UiT The Arctic University of Norway

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The use of stated preferences and bio-economic modeling in marine ecosystem service management

Case studies from Arctic Norway

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This thesis is dedicated to my father Mustafa Kemal Ahi.

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Julide Ceren Ahi

Abbreviations

ANA	Attribute non-attendance
CBA	Cost-benefit analysis
CV	Compensating variation
CVM	Contingent valuation method
DCE	Discrete choice experiment
ES	Ecosystem services
EV	Equivalent variation
FAO	Food and Agriculture Organization
ICES	International Council for the Exploration of the Sea
LCM	Latent class model
MEA	Millennium Ecosystem Assessment
MFT	Marine fishing tourism
MOSJ	Environmental Monitoring of Svalbard and Jan Mayen
MRS	Marginal rate of substitution
MXL	Mixed logit model
NEA	Northeast Arctic
RP	Revealed preferences
RUM	Random utility model
SP	Stated preferences
SSB	Spawning stock biomass
SQ	Status quo
TEV	Total economic value
UNEP	United Nations Environment Program
WTP	Willingness to pay
WTA	Willingness to accept

List of papers

Paper 1

Ahi, J. C., & Kipperberg, G. (2020). Attribute Non-attendance in Environmental Discrete Choice Experiments: The Impact of Including an Employment Attribute. *Marine Resource Economics*, *35*(3), 201-218.

Paper 2

Ahi, J. C., Kipperberg, G., & Aanesen, M., Testing the sensitivity of stated preferences to variations in choice architecture. (Manuscript submitted for publication).

Paper 3

Ahi, J. C., & Armstrong, C., Estimating the socially optimal fish stock: incorporating society's prioritization of ecosystem services. (Manuscript submitted for publication).

Summary

Regarding the growing population and escalated development on the coasts, the environmental policymakers often face the dilemma of exploiting or protecting marine and coastal ES. Therefore, the non-market valuation has become an essential instrument for supporting policymakers in eliciting preferences and welfare estimates regarding various ES, which further feed into the CBA. Among various non-market valuation techniques, the DCE methodology has gained ground in recent years for its advantages for capturing several trade-offs across multiple policy scenario alternatives and attributes. This thesis examines methodological issues regarding DCE applications on marine and coastal ES valuation and the further utilization of obtained non-market values in bio-economic models. Across three research papers utilizing DCE data collected in Arctic Norway, the results present implications for non-market valuation research and policymakers.

The first paper studies the impact of including a socio-economic attribute in environmental policy DCE studies on the attendance paid to the other attributes. We utilize split sample DCE data to elicit preferences regarding coastal development on the Arctic coast, where we present an additional socio-economic attribute indicating the number of jobs created in the region in one version. The analysis suggests that a socio-economic attribute does not significantly alter the attention dedicated to other attributes. However, the obtained WTPs significantly fluctuate across two samples, which can have important implications for the subsequent CBA.

The second paper focuses on choice architecture interventions in DCE design. The study employs a three-way split sample for studying value activation through environmental and socio-economic signposts. Employing the case of coastal cod regulations and the controversial expansion of fishing tourism in Arctic Norway, the base DCE involves the attributes of coastal cod SSB, stricter regulated user group, and cost. However, the other two versions include additional attributes of catch by fishing tourists (Treatment 1) and jobs created by fishing tourism (Treatment 2), which serve as decision signposts for value activation. The results indicate rather weak evidence for activating pre-existing pro-environmental and pro-development values through the adoption of signposts in DCE design. Nonetheless, we observe statistically significant differences in WTPs, supporting the results obtained in paper I.

Finally, the third paper expands the standard bioeconomic models to incorporate non-use values and locals' prioritization of ES uses. We gradually extend the bioeconomic model to involve the commercial fishing benefits, recreational fishing benefits, non-use benefits, and prioritization weights attached to these by the local population for optimizing the coastal cod biomass. Overall, the bioeconomic dynamic optimization results suggest that disregarding the non-use benefits attached to coastal cod results in the undervaluation of stock, which can lead to significant overexploitation and degradation.

1. Introduction

In recent decades the exploitation of the coastal ecosystems has significantly increased, which has led to tremendous socio-economic and environmental challenges (Neumann et al., 2015). As a result of the intensified exploitation and corresponding stakeholder competition for the limited resources these ecosystems offer, humans' ecological footprint on these ecosystems has greatly enlarged (UNEP, 2019). Various anthropogenic factors such as coastal development, population growth, and pollution have resulted in the loss or degradation of 50% of salt marshes, 35% of mangroves, 30% of coral reefs, and 29% of seagrasses worldwide (Barbier, 2017). Besides the problems stemming from industrial expansion on the coasts, the rising demand for fish and fish products has placed further pressure on marine and coastal ecosystems. The global fish consumption increased by 122% from 1990 to 2018, while the aquaculture industry rapidly expanded in coastal zones and raised its share to more than 10% within the total fish production (FAO, 2020; UNEP, 2019).

In line with the escalated demand, as of 2018, the fisheries and aquaculture industries' production has reached US$401 billion in first sale value, and marine fisheries are estimated to account for approximately 39 million jobs globally (FAO, 2020). However, the growth in the marine fishing industry has resulted in complex issues. Overfishing has become a major environmental and socio-economic problem, reducing biodiversity and interfering with the functioning of ecosystems (Worm et al., 2009), while the percentage of stocks below the biologically sustainable level has increased from 10% in 1990 to 32% in 2017 worldwide (FAO, 2020).

The combination of increased demand and speedy degradation of marine and coastal ecosystems highlights the need for assessing these systems' monetary value for maintaining optimal management procedures, as management decisions often involve a trade-off between economic growth and the preservation/conservation of natural resources (Nelson et al., 2009). The compromise between conservation and exploitation stresses the role of environmental policy since properly functioning markets allocate resources efficiently but cannot determine sustainability, which can only be achieved by governmental policies (Daly, 2005). Furthermore, in addition to the market-based values they provide, marine and coastal ecosystems may have significant non-use values, highlighting the essential policy task of securing these values for efficient management (Eggert and Olsson, 2009).

1.1. Ecosystem service framework and non-market valuation

For providing a benchmark for policymakers to act on the link between human well-being and ecosystems (MEA, 2005), MEA introduced the Ecosystem Service (ES) framework in 2005, where they define ES as "the benefits humans obtain from ecosystems" (MEA, 2005, p. 3). MEA's framework classifies the ES as supporting ES (e.g., soil formation, nutrient cycle), regulating ES (e.g., flood regulation, drought), cultural ES (e.g., recreational, spiritual, religious, and other non-material benefits), and provisioning ES (e.g., food, water). Among these ES, supporting ES serve as an intermediate process since they are a prerequisite for the presence of all other ES (Bastian, 2013).

Estimating the economic value of these ES is crucial for efficient policy designs, as environmental policymaking is characterized by weighing the benefits of conserving against extracting natural resources (Costanza et al., 1997). Therefore, non-market valuation techniques befit as a valuable tool for natural resource managers since they enable the value estimation for the ES that lack market price, such as the economic value of public recreational spaces or preservation of species that are under threat.

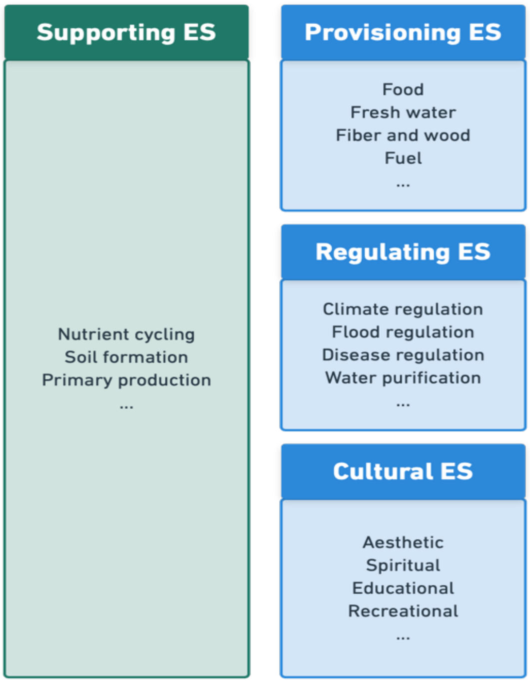


Figure 1. Ecosystem service framework (adapted from MEA, 2005).

Non-market valuation methodology enables the provision of welfare (*i.e.*, benefit) estimates for various ES, which are further utilized in policymakers' cost-benefit analyses (CBA). There are two major strands in non-market valuation techniques: revealed preferences (RP) and stated preferences (SP).

The RP method constructs a demand curve for private (*e.g.,* hedonic pricing methodology for housing market) and public goods (*e.g.,* adoption of travel cost method for estimating the value of a public beach) based on existing market data. In contrast, SP methods primarily build upon hypothetical preferences for hypothetical changes in the ES of interest.[1] This hypothetical character grants certain advantages to the SP methods as they can reflect *any* potential change from the status quo. This is of special importance when it comes to non-use ES, like existence values (Johnston et al., 2017). Accordingly, SP estimates have a significant role in environmental policymaking. The estimates coming from SP studies make up around 60% of Canada's Environmental Resource Inventory (EVRI) database and are utilized in significant policy efforts such as the US Clean Water Act (Carson and Czajkowski, 2014).

[1] It is also possible to combine the RP and SP methods, as in Contingent Behavior studies (Freeman et al., 2014).

1.2. Stated preference (SP) methods

Environmental economic theory employs the Hicksian concepts of compensating variation (CV) and equivalent variation (EV), which can be empirically measured by WTP and WTA questions in SP surveys for assessing the value of a price, quantity, or quality change (Kim et al., 2015).

In the context of environmental policy, CV is the amount of income the consumer would give up for obtaining the same utility as in SQ after implementation of the policy, while EV is the additional income the consumer would need with the SQ conditions to have the same utility after the change as equations (1) and (2) illustrate (Flores, 2017):

$$v = (p^1, q^1, y^1 - CV) = v(p^0, q^0, y^0) \quad (1)$$

$$v = (p^1, q^1, y^1) = v(p^0, q^0, y^0 + EV) \quad (2)$$

where p, q, and y represent price vector, environmental quality, and income, respectively. A major difference among these measures is the implied property rights. The CV takes SQ as the reference point and estimates the WTP to obtain the change which the individual does not have a claim for, while the EV measures the WTA to forego the change, implying that the individual has a right for the change (Markandya et al., 2002). Accordingly, WTP and WTA are equivalent ways of expressing an income change that makes the individual indifferent to an exogenously determined adjustment in the ES, which can be rewritten in terms of expenditure function (Mariel et al., 2021): [2]

$$WTP = e(p, q^0, u^0) - e(p, q^1, u^0) \text{ when } u^0 = v(p, q^0, y), \quad (3)$$

$$WTA = e(p, q^0, u^1) - e(p, q^1, u^1) \text{ when } u^1 = v(p, q^1, y) \quad (4)$$

A well-known example of how these values apply is the Exxon Valdez oil spill case. Following the Exxon Valdez spill in 1989, a state-funded SP study estimated the American public's WTP

[2] Even though WTP and WTA measure the same change, they may differ theoretically and empirically, as WTP is bound by income level while WTA is not (Mariel et al., 2021).

for avoiding a similar spill to be about USD 3 billion, which further formed the basis of settlement with Exxon (Carson, 2012). Similarly, in the aftermath of the Gulf of Mexico oil spill in 2010, NOAA commissioned an expert SP team, which priced the damage to natural resources to be USD 17.2 billion (Bishop et al., 2017).[3]

The most common SP methodologies for extracting these welfare measures are the contingent valuation method (CVM) and discrete choice experiments (Hanley and Czajkowski, 2019). In principle, these two methods are alike as they both employ random utility model (RUM) (Boxall et al., 1996), and assess the welfare change based on hypothetical changes. However, while most CVM surveys focus on a single policy scenario, DCE framework enables the valuation of individual attributes that compose an environmental good across multiple policy scenario alternatives (Hanley et al., 1998; Jin et al., 2006). [4] Accordingly, following its first application in environmental valuation by Adamowicz et al. (1994), DCE methodology has become a vital instrument in the field of non-market valuation (Hoyos, 2010).

1.3. Discrete choice experiments

With the widespread adoption of CBA studies involving non-market valuation techniques in the ex-ante assessment of public projects in recent decades (Volden 2019; Kenkel 2006), obtaining reliable and valid welfare estimates has become crucial for the management of ES under increasing pressure (Hess and Daly 2014). Considering the ability to extract welfare associated with environmental goods through several ES and the attributes they possess, discrete choice experiments (DCE) have gained ground among different SP non-market valuation techniques.

Environmental policy DCEs typically rely on extracting preferences for environmental quality through hypothetical changes in related factors. Most commonly, environmental policy DCEs offer a minimum of two alternatives, one depicting status quo (SQ), while the other alternatives suggesting changes over the SQ. The policy scenarios described across alternatives involve multiple attributes and their corresponding levels, illustrating the change in qualitative or quantitative expressions.

[3] Both Exxon Valdez and Gulf of Mexico research teams conducted CVM studies.
[4] While many CVM studies do not have the attribute-based nature of DCEs, there are also recent CVM applications that involve several attributes in the policy scenario (*e.g.,* Abate et al., 2020).

The policy scenarios communicate the environmental change often through employing relevant factors as attributes. The attribute levels fluctuate across non-SQ alternatives for depicting different policy alternatives. Except for the SQ alternative, the suggested changes in attributes come in exchange for a monetary sum for estimating the WTP for the presented attributes. In line with the neoclassical microeconomic theory, the marginal rate of substitution (MRS) between non-cost attributes and the cost attribute provides the WTP associated with each attribute (Rose and Masiero, 2010). The analyst can estimate the WTP for each attribute and how that value interacts with the level of other attributes by systematically varying the attribute levels across alternatives (Freeman et al., 2014).

To exemplify, in a rural development project, the non-SQ alternatives may present changes in attributes of grazing areas, visual aesthetic, timber production, and increased tax, which communicates the cost of the presented change. The MRS between other attributes and tax deliver the WTP for the suggested changes. Similar to this example involving cultural and provisioning ES, environmental policy DCEs often employ various ES as attributes. In addition, economic factors, often related to ES but not directly classified as ES, may also enter DCEs as attributes. Examples of such attributes are employment (Rolfe and Windle, 2015; Oviedo and Yoo, 2017) and funding of public facilities (Garcia et al., 2016). Therefore, a major challenge in DCE survey design is the trade-off between realism and complexity since environmental goods are often complex and unfamiliar (Slovic, 1995; Louviere et al., 2000; Aanesen et al., 2015; Rolfe and Windle, 2015).

1.4. Motivation

The neo-classical economic theory asserts that people have stable and complete preferences (Karlström, 2014). Consequently, one may assume that the estimated MRS for different attributes are robust to DCE design complexity and dimensionality (Caussade et al., 2005). However, a complex survey design may invoke processing strategies (i.e., *heuristics*) for reducing the complexity of assessing benefits, such as attribute exclusion, attribute non-attendance, or attribute aggregation when attributes are in common units (Hensher, 2010). Employing such processing strategies for simplifying choice tasks may lead to systematic errors in measurement (Tversky and Kahneman, 1974; Payne et al., 1993; Payne et al., 1999), as supported by growing empirical evidence (e.g., Hensher, 2006; Campbell et al., 2011; Daniel et al., 2018).

Furthermore, the need for simplicity inevitably leads to the exclusion of potentially relevant factors in DCE design as it is impossible to add all relevant factors as explicit attributes. After conducting focus groups and examining the existing literature, the researcher determines the final set of attributes presented in a DCE from a much larger pool of candidates. Nevertheless, the design process is hardly over with choosing the most relevant attributes for describing the ES. Unlike most commercial goods, the attributes of ES are multifaceted, and each can be expressed through various indicators conveying the same phenomenon (Camilleri and Larrick, 2014; Ungemach et al., 2018). For example, the researcher can express the industrial growth by adopting a socio-economic indicator, such as tax income or jobs, or by its impact on the environment. While constructing the design, the researcher's decisions are all part of the choice architecture process, as choice architecture includes all factors making up the choice context (Thaler et al., 2013; Camilleri and Larrick, 2014). Besides the well-known nudge theory coined by Thaler and Sunstein (2008), choice architecture practices can take different forms, such as reducing the number of alternatives, decision staging, and customized information, among many others (Johnson et al., 2012).

In this dissertation's first and second papers, I study the methodological and conceptual issues associated with the experimental design of non-market valuation DCEs. The first research paper performs a case study on coastal zone management in Arctic Norway. The analysis focuses on heuristics and examines whether including a socio-economic attribute leads to non-attendance toward other attributes and systematically alters the corresponding WTPs. The second paper adopts the choice architecture practice of signposting, which aims to activate the respondents' pre-existing values and align their personal objectives with their choices (Ungemach et al., 2018). The DCE designed for measuring the signpost effects elicits the preferences regarding the use of coastal cod stock in Arctic Norway. Both papers employ split samples for clear comparisons and test for statistically significant differences in WTPs between control and treatment groups.

While non-market valuation studies are beneficial for providing the welfare associated with various ES and informing CBA and policymaking procedures, they do not deliver optimized solutions regarding natural resources. Natural resource optimization involves bio-economic modeling, which is often perceived as unrelated to non-market valuation since standard optimization studies focus primarily on profit maximization and exclude non-market benefits associated with ES (Armstrong et al., 2017; Squires and Vestergaard, 2016). However, excluding non-market values results in undervaluation and potentially further degradation of natural resources (Beaumont et al., 2008). With these issues as a backdrop, the third paper combines non-market valuation and bio-economic modeling methodologies for accounting for market and non-market benefits to obtain the socially optimal coastal cod stock level in Arctic Norway.

The remainder of the thesis is structured as follows: Section 2 provides an overview of the methods employed in the dissertation and their prominence for environmental policymaking, Section 3 describes the empirical case studies, Section 4 summarizes the research articles, and Section 5 discusses the contributions and limitations of the results.

2. Econometric framework of choice models

Studying consumer motivation and welfare goes back in history as far as Jeremy Bentham's *Introduction to the Principles of Morals and Legislation,* published in 1789, where he discusses that man acts solely upon utilitarian motives focusing on self-interest and pleasure (McFadden, 2013). While the utility-seeking individual has remained an important concept in social sciences since Bentham's arguments in the following decades, Thurstone established the first conceptual choice model in 1927 (Hensher et al., 2015).

Thurstone's model assumes a multivariate normal distribution for the utility vector $U \sim Normal(\mu, \Sigma)$, where μ is the mean and Σ is the variance-covariance matrix for the vector U (Busemeyer and Rieskamp, 2014). Following Thurstone's model, Marschak (1960) have introduced the Random Utility Maximization (RUM) to economics for estimating choice probabilities through utility maximization with random elements that are unobservable for the researcher (Böckenholt, 2006; Hanemann, 1984). Finally, McFadden's phenomenal work *Conditional logit analysis of qualitative choice behavior* (1974) linked the RUM, hedonic analysis of alternatives, and random utility maximization (Holmes and Adamowicz, 2003).

A utility function as the one presented in equation (5) sets the foundation of modern choice modeling applications. Following McFadden's (1974) notation, true utility U_i consists of components V and ε, which represent the systematic component and idiosyncrasies in preferences, respectively, for attribute vector x_i associated with choice alternative Based on the RUM assumptions, the model dictates that on every occasion when $U_i > U_j$ for all $U_j \neq U_i$, the utility-maximizing individual will choose alternative i.

$$U_i = V\,(x_i) + \varepsilon_i \tag{5}$$

The choice analysis primarily consists of the interrelated tasks of specification of the behavioral model, which is often coupled with the modeling of the stochastic part and estimation of the parameters (Freeman et al., 2014; Train, 2009). When the stochastic component ε is assumed to be independently and identically (*iid*) Type I extreme value distributed, the probability of choosing alternative i becomes the logit probability (McFadden, 1974), which forms the basis of the subsequent choice probability models:

$$\Pr(i \mid j) = \frac{\exp\left(V(x_i)\right)}{\sum_j \exp\left(V\left(x_j\right)\right)} \tag{6}$$

Even though the conditional logit model has dominated the field of choice modeling for many years, its assumption of independence from irrelevant alternatives (IIA) and shortcomings in accommodating taste heterogeneity has led the researchers to seek more advanced formulations (Greene and Hensher, 2003). Following the developments in computational advances, McFadden and Train (2000) introduced the *Mixed Multinomial Logit Model* (MXL), which enables the estimation of random taste parameters with the adoption of an open-form, simulated likelihood maximization procedure. MXL has been a groundbreaking development for choice modeling as it overcame the main limitations of conditional logit by incorporating random taste variation through approximation of any distribution form, correlation in unobserved factors, and unrestricted substitution patterns (McFadden and Train, 2000; Train, 2009). Therefore, the adoption of open-form, simulated likelihood models facilitated much richer insights into preference heterogeneity associated with choices and gained significant recognition in the field (Hensher et al., 2015; Mariel et al., 2013).

3. Methods

The majority of DCE applications adopts the RUM framework, assuming that the preferences are stable, invariant to the choice tasks, and are completely known to the cognitively indefatigable respondents (Leong and Hensher, 2012). In a DCE application, these neo-classical notions of consistent and invariant consumer preferences imply that the respondents' MRS across attributes is insensitive toward experimental design procedures on dimensionality, such as the number of attributes and alternatives in a DCE (Pedersen et al., 2011). However, insights from behavioral science (*e.g.,* Kahneman and Sugden, 2005; Kahneman and Thaler, 2006) have started to pose interesting challenges to the neo-classical conception of the utility-maximizing individual with stable preferences (McFadden, 2013).

3.1. Attribute non-attendance in DCEs

The idea of non-maximizing (*i.e.,* irrational) consumer behavior is not new. The debate regarding rational vs. irrational consumer behavior may be dated to Kahn (1935), where he discusses certain factors such as ignorance and inertia as arguments for non-utility maximizing preferences. However, from the 1970s on, research on decision-making and rational behavior has received greater attention through phenomenal studies arguing that the decision-making process is cognitively biased, and the individuals often employ information processing strategies (*i.e.,* heuristics) for assessing the outcome of events, which can deviate from the optimum decision (*e.g.,* Tversky and Kahneman, 1973; 1974; 1979). Backed by mounting evidence, the theory of cognitive bias has highlighted the need to adjust the model of homo economicus (*i.e.,* rational, utility-maximizing consumer) to incorporate non-maximizing motives in modeling economic decision making (Thaler, 2000).

In line with other research fields employing choice models, the assumption of *homo economicus* is the backbone of environmental policy studies (Gsottbauer and van den Bergh, 2011). However, former research suggests that respondents employ several information processing strategies for simplifying the choice tasks for reducing the complexity and cognitive burden of DCEs, which may, in turn, affect estimated preferences and welfare measures (Hensher et al., 2005; Campbell et al., 2011; Kragt, 2013; Hole et al., 2013).

One major heuristic observed in DCEs is attribute non-attendance (ANA), where respondents ignore a particular attribute or a combination of attributes. Ignoring one or several attributes in a choice task violates the continuity axiom of consumer theory, which is the underlying assumption of DCE methodology (Logar et al., 2020). Continuity axiom asserts that individuals use compensatory decision-making processes, considering all information available, and make trade-offs between all attributes when choosing a preferred alternative (Lagarde, 2013). Therefore, capturing ANA behavior is relevant as it affects not only the model performance but also the resulting MRS and welfare measures (Grebitus and Roosen, 2018).

3.1.1. Former work on ANA

An extensive body of research identifies experimental variation properties of complexity and dimensionality as a major source of ANA behavior. Studying the DCE dimensionality across number of choice tasks, alternatives, and attributes Caussade et al. (2005) indicates that increasing task complexity and dimensionality through including more attributes results in non-attendance propensity while contributing to higher error variance. Spinks and Mortimer (2015) show that DCE complexity measured through the number of attributes is the strongest predictor of ANA when other relevant factors such as time pressure, ordering effects, and socio-demographic features are controlled for. Similarly, Grebitus and Roosen (2018) illustrate that non-attendance becomes more of an issue with increased number of attributes, supporting the arguments that consumers switch from compensatory decision strategies to heuristics when DCEs become more complex.

Concerning how accounting for ANA affects the resulting preferences and welfare measures, former research provides mixed findings. For example, while Campbell et al. (2011) and Sandorf et al. (2017) argue that disregarding non-attendance may lead to overestimation of WTP, Hole et al. (2013) and Nguyen et al. (2015) obtain contrasting findings, suggesting that accounting for ANA does not always lead to systematic differences in welfare measures. However, regardless of the contrasting evidence, ANA behavior remains a crucial factor to have control over for ensuring unbiased welfare estimates.

The studies on ANA identification implement two methods: (i) stated ANA method for eliciting the non-attendance by asking the respondents whether they have ignored one or several attributes after each choice task or completion of the DCE, or (ii) inferred ANA method which elicits the ANA behavior analytically by econometric modeling of non-attendance (Weller et al., 2014). Over the last decade, econometric modeling of inferred ANA methodology has gone through considerable improvement. The initial investigations of ANA employ fixed parameter latent class models (LCM), where one or a combination of attribute coefficients are restricted to zero in each class for indicating non-attendance (e.g., Scarpa et al., 2009; Campbell et al., 2010; Hensher and Greene, 2010). More recent studies increasingly model the ANA behavior by employing random parameters within the LCM while fixing individual or several attributes to zero in the likelihood function for capturing the heterogeneity in ANA behavior (e.g., Hensher et al., 2013; Hess et al., 2013; Sandorf et al., 2017). Regardless of adopting a fixed parameter or random parameter approach by specifying 2^k latent classes, where k indicates the number of attributes in a DCE, one can account for all combinations of non-attendance.

In the first paper of my dissertation, I adopt a random parameter LCM model for inferring the ANA patterns in a split-sample DCE application. Specifying 2^klatent classes for both samples, I study whether including a socio-economic attribute in a non-market valuation DCE significantly alters the ANA and welfare estimates for the other attributes.

3.2. Choice architecture

The term *choice architecture* refers to all sorts of design interventions in any given choice context (Thaler and Sunstein, 2008). In this respect, doctors describing the treatment alternatives to their patients, bankers designing the investment options, or store employees organizing a window display are all examples of choice architects as they have the responsibility for creating "the context in which people make decisions" (Thaler et al., 2013, p. 428).

3.2.1. Nudges and boosts

Given the wide array of aspects in a design process, there are many choice architecture tools available for the choice architect. *Nudging* is perhaps the most renowned choice architecture intervention, which involves altering people's behavior in a predictable way without ruling out any options or changing their economic incentives, as coined by Thaler and Sunstein (2008). Some examples of nudging are providing information on social norms for influencing choices in an environmental policy context (*e.g.,* Czajkowski et al., 2019), nutrition labeling initiatives for directing people toward healthier food options (*e.g.,* Scrinis and Parker, 2016), and altering the presentation of information with the aim of making employers choose more advantageous pension programs (*e.g.,* Clark et al., 2014).

While nudging intends to help people make better choices for themselves, it has received considerable criticism on the grounds of libertarian paternalism (Hausman and Welch, 2010). Therefore, another strain of choice architecture interventions, namely *boosting,* has developed with the objective of fostering people's competence to exercise their own agency (Hertwig and Grüne-Yanoff, 2017). One such method is employing "*decision signposts",* which translate the product information for addressing various concerns and supporting the consumers in making better decisions for both the society and themselves (Ungemach et al., 2018; Hahnel et al., 2020; Mertens et al., 2020).

In the decision signpost framework, Ungemach et al. (2018) argue that every attribute in a decision context can be expressed in multiple ways through perfectly correlated translations of itself, and employment of different translations may activate different pre-existing objectives. In contrast to the nudges, by presenting product information in a fashion that highlights various aspects, signposts remind people what they care about and guide them to act on these preferences while increasing the likelihood of choosing the option congruent with personal objectives without restricting individuals' autonomy (Ungemach et al., 2018). To exemplify, Ungemach et al. (2018) express the fuel economy in different perfectly correlated metrics and demonstrate that using greenhouse gas rating as a signpost activates the already existing pro-environmental values and guides people with such concerns to make choices more aligned with their objectives.

3.2.2. Choice architecture in environmental policymaking

In the realm of environmental policy design, understanding how different interventions inspire pro-environmental behavior is crucial for "finding solutions across a diverse array of environmental problems and barriers to action" (Sawe, 2019, p.21). Correspondingly, regarding the evidence choice architecture documents for behavioral changes, numerous governments and international organizations have started to recognize the potential of choice architecture tools for designing more effective and efficient public policies (Hertwig and Grüne-Yanoff, 2017).

Given its ascendancy in the field of environmental policy and its attribute-based nature, DCE surveys provide many opportunities for examining the influence of choice architecture interventions. Primarily, the DCE design process involves various decisions on experimental variation, which associates the researcher with the role of the choice architect. The experimental variation features determining the information frame and display, the number of attributes, alternatives and their respective outcomes, and the correlation between the presented attributes all fall into the realm of choice architecture (Camilleri and Larrick, 2014).

Indeed, an emerging body of research applies nudges in environmental policy DCEs for testing systematic differences in obtained welfare measures. Czajkowksi et al. (2019) illustrate that preferences and WTP measures for household recycling vary with the level and type of social norm nudging. Wensing et al. (2020) examine the effect of various green nudges such as nature pictures, reflection questions, and information interventions on WTP for bio-based packaging. Their findings suggest that the nudges employed in DCEs are more likely to increase WTP for green products when the nudging strategy matches the consumers' cognitive style (Wensing et al., 2020). Similarly, embedding the nudge framework in a DCE for measuring preferences and WTP for fuel-efficient cars, Grover et al. (2021) exemplify that when combined with driving restrictions, a nudge-based labeling system is expected to increase the likelihood of choosing environmentally friendlier cars.

Regarding the decision signposts' effect on preferences, Ungemach et al. (2018) demonstrate that the pro-environment consumers' likelihood of choosing fuel-efficient vehicles increases when the product attributes are "translated" into green metrics, which remind consumers about their latent objectives. Following Ungemach et al. (2018), Mertens et al. (2020) employ translated attributes to study how decision signposts navigate consumers through complex DCEs and support personally and socially desirable preferences in the case of energy-efficient appliances. However, while there has been interest in studying the decision signposts' effect on choosing greener products, their influence on preferences and WTP for non-market environmental goods remain largely unexplored.

In the second paper of my dissertation, I examine the effects of decision signposts in a non-market valuation DCE. Focusing on the spawning coastal cod biomass, for determining how the preferences and WTPs for this public good vary with the use of translated attributes as signposts, I employ three split samples. Spawning coastal cod biomass, cost of regulation, and different user regulation configurations are the common attributes in all split samples. However, to test for the influence of employing signposts, I express the expansion of the fishing tourism industry in different metrics in the two of the split samples, while it's implicit in the base version. For examining the activation of pre-existing pro-environmental and pro-development values by different signposts, I use Dunlap et al.'s (2000) New Environmental Paradigm-Revised (NEPR) scale and a modified version of Choi and Sirakaya's (2005) Sustainable Tourism Attitude scale, respectively.

3.3. Bio-economic modeling

In his seminal paper, Gordon (1954) lays the foundations of bio-economic models, which form the basis of standard fishery management procedures employed to this day. Combining biological indicators and growth models with economic theory, these models seek to maximize profit through dynamic optimization of natural resources, providing the required levels of effort, natural stock, or harvest according to how the maximization problem is set up.

Traditionally, bio-economic modeling of natural resources and non-market valuation are considered as two separate fields of research within environmental and resource economics (Armstrong et al., 2017). As maximizing profit is the primary goal of bio-economic models applied in fishery management, they almost exclusively involve only the market values of marine goods. Consequently, the non-market values attached to the public goods are mostly ignored in the bio-economic optimization processes. For example, the economic literature does not dedicate much attention to the optimal management of recreational fisheries, despite the significant economic surplus generated in recreational fisheries and recreational users' crucial impact in many marine systems (Cisneros-Montemayor and Sumaila, 2010; Fenichel and Abbott, 2014). However, adopting management tools that ignore non-market values may lead to undervaluation and further degradation of already fragile marine ES (Beaumont et al., 2008).

In this regard, the social planner's maximization problem may be expanded to integrate both consumptive and non-consumptive non-market values associated with marine ES for avoiding undervaluation. An early example of such models is presented by Hartman (1976), where he argues that not only the value of timber but also the recreational values provided by forests may be considered in bio-economic optimization models used for harvest decisions. Extending the dynamic optimization models to include non-use values, Bulte et al. (1998) demonstrate that when the bio-economic model integrates the public WTP for stock conservation obtained from other relevant SP studies, the optimization procedure justifies a moratorium on minke whale harvest in Northeast Atlantic. More recently, Armstrong et al. (2017) and Xuan and Armstrong (2019) incorporate non-market values obtained from original DCE studies in bio-economic models and illustrate how the inclusion of these values influence the management decisions for habitat preservation and a new marine protected area through case studies applied in Norway and Vietnam, respectively.

In the final paper of my dissertation, I integrate non-market values with use and non-use motives in a dynamic bio-economic model for determining the optimum coastal cod stock in Northern Norway regarding different management approaches. The non-market values employed in the study come from an original DCE study designed for estimating the welfare associated with coastal cod biomass and stricter regulations for different stakeholder configurations.

4. Empirical application: Marine and coastal ES management in Arctic Norway

4.1. Background

Throughout known history, marine and coastal ES have been essential livelihood sources for the communities settled in coastal Arctic Norway (Helskog, 1982; Helskog, 1985; Renouf, 1982). While the rich cod fishery has provided subsistence for the locals, starting from the 13th century, the fish trade has become a main economic activity, and the region has become the center of commercial cod fishing, supplying preserved fish to northern and central Europe (Bertelsen et al., 1987; Perdikaris, 1999).

Today, Arctic Norway hosts various industries, including commercial fishing, aquaculture, tourism, hydroelectric energy, and mining. The public sector is the largest single employer in the region; however, fishing and aquaculture industries have been the primary drivers of economic growth in recent years.[5] Regarding the traditional fisheries sector of the region, the landings from the marine fisheries in Arctic Norway had a total value of around 1.5 billion USD in 2019, where 65% of all landings were cod and other codfishes.[6]

Though commercial fishing remains a prominent economic actor in modern times, the entry of new industries dependent on large-scale marine ES exploitation and generating considerable income creates novel challenges for the resource managers, calling for more holistic management approaches.

4.1.1. Challenges in marine ES management in Arctic Norway

The Norwegian coastal zone has experienced the rapid growth of the aquaculture industry since the 1960s (Olaussen, 2018). As part of this expansion, the number of licenses for farming rainbow trout and salmon has doubled in Arctic Norway, from 220 licenses in 1994 to 458 licenses in 2019 (Statistics Norway, 2020). Correspondingly, the export value of Norwegian

[5] Konjunkturbarometer for Nord-Norge (2019). Available at https://www.kbnn.no/artikkel/status-sysselsettingen
[6] Statistics Norway: Catch, by landing county and main group of target species. Available at https://www.ssb.no/en/statbank/table/12847

aquaculture products reached 4.8 billion USD in 2018, of which 50% was produced in Arctic Norway (Bjornsdottir et al., 2021).

Despite the significant economic benefits, industrial development in the coastal zone causes conflicts as competition for already scarce marine and coastal ES intensifies, creating winners and losers (Jentoft, 2017), where Arctic Norway is no exception. The main challenges of aquaculture expansion are environmental degradation, disruptions in social structure and traditional occupations, devastating effects on wild stocks, and increased competition for marine and coastal ES with other users (Aanesen et al., 2018; Aanesen and Mikkelsen, 2020; Bjørkan and Eilertsen, 2020). In addition to the overall environmental degradation, visual intrusion on the coasts (Falconer et al., 2013; Aanesen et al., 2018; Billing, 2018), and impacts on locals' recreational catch (Liu et al., 2011; Olaussen and Liu, 2011; Aanesen et al., 2018) are recurring themes in the conflict between local recreationists and the aquaculture establishments.

In recent decades, the management of coastal and marine ES in Arctic Norway has become more challenging with the entry of a new marine ES-based industry. In the 1990s, the Norwegian government started to promote Arctic Norway as a marine fishing destination on the international stage (Borch et al., 2011). Following the government's efforts, the region has become a marine fishing tourism (MFT) hotspot by virtue of its unique coastline, rich resources, and easy access to coastal fisheries without the requirement of a fishing license (Solstrand, 2013).[7] As of 2018, the number of MFT companies located in Arctic Norway reached 240, which reported a total catch of 713 734 fish, consisting mainly of cod with a share of 65%.[8]

Expansion of MFT has caused great controversy, as it competes for space and resources with the traditional industries of Arctic Norway. The commercial fishing industry has been the main critic of MFT expansion on the grounds of sustainability of coastal fisheries, and they have been urging for the introduction of stricter regulations for the sector (Borch, 2009). Besides the commercial fishing industry, the local community overall has disfavored the idea of sharing

[7] While marine recreational fishing does not require a fishing license, for fresh-water fishing both locals and tourists need licenses.

[8] Estimated using data available at Norwegian Directorate of Fisheries: Fangst i turistfiske https://www.fiskeridir.no/Turistfiske/Rapportering-for-turistfiskebedrifter/Fangst-i-turistfiske

their fish with foreign tourists (Solstrand, 2013). The debate around the MFT industry has intensified around themes of wasteful treatment of fish by inexperienced tourist fishers (Solstrand, 2013) and the increased fish smuggling, which has become an organized crime (Solstrand and Gressnes, 2014).

The MFT regulations have undergone several updates for addressing these issues in recent years. The current regulations allow foreign tourists registered to a legitimate MFT company to export fish or fish products up to 18 kg when leaving Norway, with a limit of twice a year. The fine for violating the quota has been raised to NOK 8000, with an additional fine of NOK 200 per kilo fish or fish product. [9] In addition to stricter regulations, in 2018, the Norwegian Directorate of Fisheries has introduced an electronic registry system for recording tourists' catch per fishing trip for obtaining better information on the MFT industry's catch.

Despite the recent efforts on increasing the efficiency of the regulatory framework, the debate over the MFT industry is still hot. To begin with, while the new regulations reduced the export quota, they still allow tourists to fish as much as they want while in Norway. Moreover, it is debated that not differentiating between fish and fish products provides incentives for wasting fish for filling the 18 kg quota by best parts of the fish, which leads to more catch per tourist within the same quota.[10] Finally, the numbers from Norwegian customs indicate that the new regulations did not eliminate the smuggling efforts. According to official statistics, 6544 kg and 9868 kg of fish were confiscated on the Norwegian border in 2018 and 2019, respectively (Norwegian Toll Customs, 2020). Regarding that the statistics account for both fish and fish fillets and that not every smuggler gets caught, the actual amount of harvest may be substantially higher.[11] As Norwegian law requires all confiscated fish to be destroyed, smugglers cause immense waste of resources.

[9] In effect from January 1, 2021, while the former quota was 20kg fish or fish product per tourist. More information available on https://www.fiskeridir.no/English/Fishing-in-Norway/Export-quota.
[10] An example of the debate by Nordskag (2020) available on https://www.fiskeribladet.no/meninger/-vil-nytt-regelverk-for-turistfiske-gi-mindre-slosing-av-ressursene-og-mindre-smugling-/8-1-71441
[11] The share of smugglers that get to leave Norway with illegal catch can be as high as 90% (see Solstrand and Gressnes, 2014).

4.1.2. The conflict over coastal cod

With the issues above as a backdrop, the coastal cod harvest of different stakeholders in Arctic Norway lies in the heart of the conflict. Traditionally, coastal cod is the most prized stock in the region (West and Hovelsrud, 2010), which is now harvested by the commercial coastal fleet, local recreational anglers, and the MFT industry. Besides being an important provisioning ES for the Arctic coastal communities through ages, coastal cod also facilitates cultural ES as it is a vital part of the tradition and cultural identity in the region (Hersoug et al., 2019).

The cod stock in coastal waters above 67°N consists of two species: migratory Northeast Arctic (NEA) cod from Barent Sea moving between the spawning areas, known as *skrei* in the region, and non-migrating coastal cod.[12] While the NEA cod stock is in good shape in terms of total and spawning stock (MOSJ, 2020), the coastal cod spawning stock biomass (SSB) has been facing considerable pressure from harvesting.

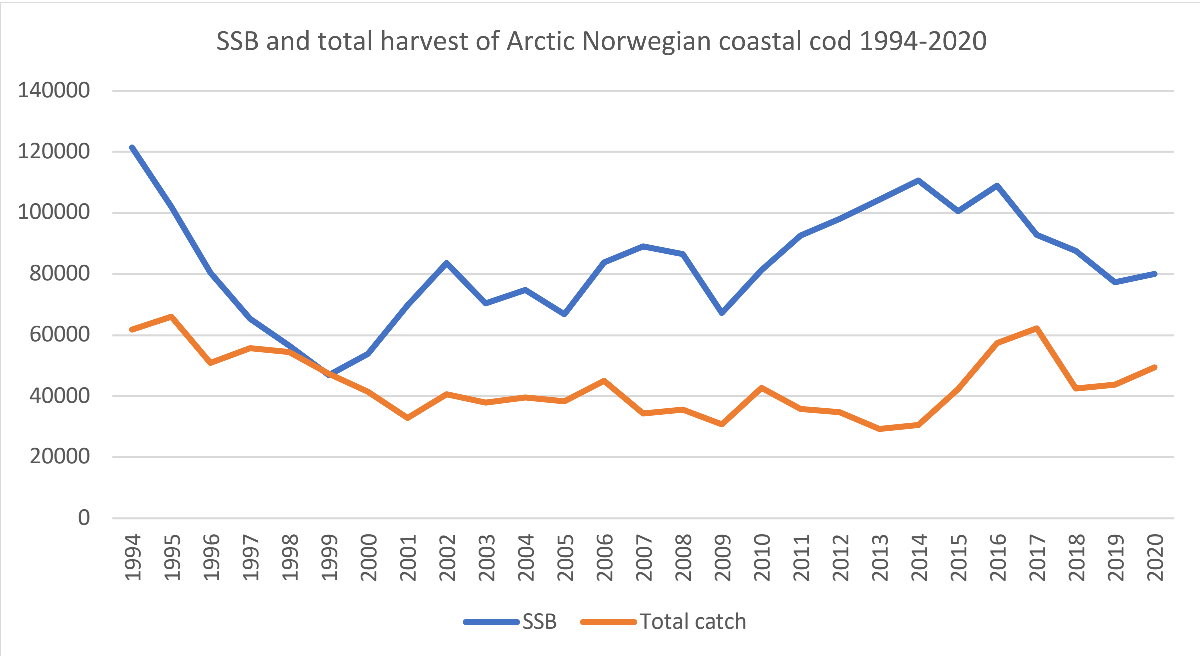


Figure 1. SSB and the total harvest of coastal cod above 67°N 1994-2020, based on data from ICES (2021).

[12] NEA cod and coastal cod are genetically distinct cod populations intermingling in coastal areas of Arctic Norway (Sarvas and Fevolden, 2005). The coastal cod is present in the coastal areas all year round (Maurstad, 2000), while the NEA cod from the Barent Sea immigrates along the Arctic Norwegian coast during spawning season and provides a rich coastal fishery, particularly in winter (Eide et al., 2013).

Figure 1 indicates a sharp decline in coastal cod SSB in the late 90s, followed by a fluctuating trend. While the combined harvest of commercial fishers, MFT industry, and local recreational anglers is below the SSB level except for 1998-1999, the gap between the two has been narrowing again in recent years. Between 2014-2019, the commercial fishing industry's estimated average coastal cod harvest is 41 370 tons, while the MFT industry and recreational fishers have an estimated annual harvest of 7 900 tons.[13] Regarding that Arctic Norwegian coastal cod TAC is 21 000 tons in total, these numbers highlight the by-catch problem in NEA cod fishery (ICES, 2021).

Considering the increased pressure the stock faces, the latest ICES (2021) advice suggests that the total annual harvest does not exceed 7 865 tons, which roughly corresponds only to the combined catch of local recreational anglers and tourists. In accordance with these warnings from the scientific community calling for drastically lowered harvest, the stock has lost its Marine Stewardship Council certificate as of August 2021[14], which may cause significant ramifications in the market. Subsequently, the conflict over coastal cod among the main stakeholders of the commercial fleet, local recreational anglers, and the MFT industry has become more intense than ever.

4.2. Data

The data employed in this dissertation comes from different sources. Data of the first paper comes from a DCE survey designed and implemented by Aanesen et al. (2018) for eliciting preferences for coastal zone development in Arctic Norway. The second paper, on the other hand, uses original data from a DCE study designed and carried out as part of this dissertation. Finally, the third paper combines the DCE data collected for the second paper, and secondary ecologic and economic data obtained from various sources.

[13] The recreational catch in ICES' reports is the combined estimated catch of the MFT industry and local recreational anglers. The presented average harvest is computed by employing ICES' (2021) estimations. The coastal cod stock above 62°N has long been assessed together with an estimated annual recreational harvest of 12 700 tons, however, recently ICES (2021) has updated their assessment by separating the stock between 62°N-67°N and stock above 67°N, which results in a reduced annual recreational harvest of 7 900 tons for coastal cod above 67°N. However, as sensitivity analysis in paper III indicates, our results are robust regarding changes in harvest estimates.

[14] "*Norway's inshore cod fishery to lose MSC stamp in August*" (Welling, 2021) available at https://www.intrafish.com/fisheries/norways- inshore-cod-fishery-to-lose-msc-stamp-in-august/2-1-1032894?utm_source=emailsharing

4.2.1. Design and data collection: paper I

Aanesen et al. (2018) implement a split-sample DCE survey for examining the preferences regarding the increased development on Arctic coastal zone and the corresponding user conflicts. Based on existing literature on coastal zone development and focus groups conducted in an Arctic-Norway region, each DCE version includes the following common attributes: industrial impact on views,[15] beach litter, recreational catches, and increased tax (*i.e.,* cost). However, for testing the impact of the creation of new jobs in the region, one version presents the additional attribute of "new jobs in Arctic Norway" (JOBS sample), while the other one omits it (NO-JOBS sample).

Table 1. Attributes and attributes levels adopted by Aanesen et al. (2018).

Attribute	Levels
Industrial impact on views	Aquaculture and MFT (BAU)
	Only MFT
	Only aquaculture
Litter	Increase by 50% (BAU)
	Increase by 25%
	No increase in litter
Recreational catches	5 kg reduction from daily catch (BAU)
	2 kg reduction from daily catch
	No reduction from daily catch
New jobs in Arctic Norway	500 new jobs (BAU)
(only in JOBS sample)	350 new jobs
	250 new jobs
	100 new jobs
Cost	0 NOK (BAU)
	500 NOK
	1000 NOK
	2000 NOK
	3000 NOK

Table 1 provides an overview of the attributes and the varying levels employed in the final design. The DCE presents each respondent with eight choice tasks, each encompassing three alternatives. In both versions of the DCE, the "business as usual" (BAU) alternative places no restrictions on MFT and aquaculture expansion on the coast. In line with increased development, there is more beach litter, more jobs (in the JOBS version), reduced daily catch, and no increase in tax. However, in alternatives "stricter regulations A" and "stricter

[15] This attribute expresses which types of industrial activity recreationists can observe when spending time in the coastal zone.

regulations B” the industrial expansion in the coastal zone is restricted in varying degrees, which come at a cost in a range of NOK 500- NOK 3000.

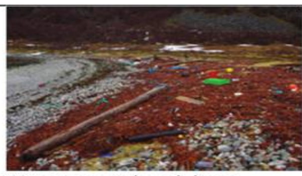
Attribute	Regulations as of today (BAU)	Stricter regulations A	Stricter regulations B
Industrial impact on views	 Fish farms and tourism facilities changes the seascape	 Only tourism facilities changes the seascape	 Only fish farms changes the seascape
New jobs in Arctic Norway	500 **new** jobs	250 **new** jobs	350 **new** jobs
Beach litter	 50% increase in beach litter	 No increase in beach litter	 25% increase in beach litter
Recreational catches from boat	5 kg less harvest per day of fishing from boat	No reduction in harvest per day of fishing from boat	2 kg less harvest per day of fishing from boat
Increase in tax	0	3000 kroner **more** per household per year	1000 kroner **more** per household per year
What do you prefer?	□	□	□

Figure 2. JOBS dataset choice card example (Aanesen et al., 2018).

Figure 2 illustrates a choice card from the final design. Following a pilot survey with 100 respondents in August 2015, the data collection took place in September 2015, which yielded 490 and 528 responses for NO-JOBS and JOBS samples, respectively, with a response rate of 47%. [16]

[16] For more details on attribute selection and data collection, please see Aanesen et al. (2018).

4.2.2. Design and data collection: paper II

Akin to the design employed by Aanesen et al. (2018), we adopt a split-sample approach for investigating the impact of choice architecture interventions on preferences and welfare associated with various marine ES policy scenarios.

For determining the relevant attributes, we conducted two focus groups in Arctic Norway. The first focus group took place on 13 February 2019 at UiT Arctic University of Norway in Tromsø, and the second one took place on 7 April 2019 at Scandic Hotel Svolvær, in Svolvær, the largest community in the Lofoten islands.

The focus group participants were recruited through a professional market research company to ensure a representative sample with age and gender balance.[17] For encouraging participation, each participant received a gift card worth NOK 300. After a short presentation of the study objectives, we devoted most of the meeting time to open discussion on themes of MFT expansion, recreational catch, and coastal cod regulations exercised on the commercial fleet. Many discussants expressed that while the MFT industry has facilitated economic growth and new jobs, it has also taken a large toll on the already declining coastal cod stocks. In both groups, the recurring themes were degrading coastal cod stocks, fish smuggling, and uneven regulations exercised on different stakeholders. The only difference in the meeting structures was that in the last part of the second meeting, we asked the second focus group to respond to a trial DCE we had developed after the first focus group meeting. Based on the focus group discussions and relevant literature, we designed a DCE survey with eight choice tasks and three alternatives. In addition to the focus group meetings, we consulted fishery scientists, MFT companies of different sizes, and commercial fishers in Tromsø and Svolvær before designing the final version of the survey.

[17] https://www.norfakta.no/

Table 2. Attributes and levels of DCE designed for paper II.

Attribute	Levels
Spawning coastal cod biomass (in tons)	15 000 tons (SQ) 20 000 tons 40 000 tons 60 000 tons 80 000 tons
User group(s) facing new stricter regulations	No new stricter regulations (SQ) Only commercial fishermen Only fishing tourists Commercial fishermen and recreational anglers Commercial fishermen and tourists All user groups
Number of coastal cod caught by the tourists per year **(Treatment 1)**	500 000 (SQ) 125 000 more (+25%) 50 000 more (+10%) 125 000 less (-25%) 50 000 less (-10%)
Jobs created by MFT in the region **(Treatment 2)**	1000 (SQ) 250 new jobs created (+25%) 100 new jobs created (+10%) Loss of 250 jobs (-25%) Loss of 100 jobs (-10%)
Annual household tax	0 NOK (SQ) 500 NOK 1000 NOK 1500 NOK 2000 NOK 3000 NOK

Table 2 presents the attributes and levels in the final set of choice tasks. We employ three split samples to investigate whether the WTP estimates significantly vary with choice architecture interventions. In all versions, three attributes are common: coastal cod SSB, *stricter* regulated user group, and cost. In the base version, including only these three attributes, we communicate restrictions on MFT's expansion implicitly through stricter regulations applied to this industry. In treatments 1 and 2, however, the DCE presents an additional attribute indicating potential effects of the MFT industry, either as the number of coastal cod caught by tourist fishers or as the number of new jobs created by the MFT industry. These two attributes serve as decision signposts for pro-environmental and pro-development sentiments and enable us to investigate whether the WTP measures and SQ-choice propensity vary with choice architecture interventions as a result of value-activation.

In all treatments, the SQ alternative presents the policy scenario with no new restrictions on any users. Accordingly, there is no improvement on coastal cod SSB and no tax increase. In

Alternative 1 and Alternative 2, coastal cod SSB always improves, and a single user or a combination of users faces stricter regulations; however, this comes at a cost in the range of NOK 500-NOK 3000. By design, MFT's coastal cod harvest and new jobs created by the industry cannot increase when the MFT is in the configuration of users facing new, stricter regulations. Besides the DCE part, the survey included several non-choice questions regarding respondents' participation in commercial and/or recreational fishing, views on the MFT industry, overall pro-environmental and pro-development tendencies, and DCE consequentiality.

Both the pilot version and final DCE has a d-efficient design generated by NGENE software (Choicemetrics, 2014). The recruitment occurred through the pre-recruited household panel of a major Norwegian survey company.[18] The pilot survey took place in November 2019 with 100 respondents. Following minor verbal edits on the choice cards, we launched the actual DCE in December 2019. The survey was available for about ten days, and by the closing date we had 251 respondents for the base DCE and Treatment 1 each, and 252 respondents for Treatment 2, adding up to 754 respondents in total.

[18] https://norstat.no

Which alternative do you prefer?

	STATUS QUO	ALTERNATIVE 1	ALTERNATIVE 2
Spawning coastal cod biomass 	15 000 tons ¼ of the minimum level recommended	60 000 tons Recommended minimum level	80 000 tons 1/3 over the recommended minimum level
Stricter regulated user groups 	No change No new regulations	Commercial fishermen	Marine fishing tourism
Annual coastal cod harvest of marine fishing tourists 	No change (approximately 500000 per year)	125 000 <u>more</u>	125 000 <u>less</u>
Annual cost for your household 	0 NOK	500 NOK	2000 NOK

Figure 3. Example choice card from Treatment 1 (translated from Norwegian original).[19]

[19] All images have standard licenses- stock.adobe.com

4.2.3. Data collection: paper III

Paper III employs DCE data from paper II's base version and secondary biologic and economic data from several sources, incorporating WTP estimates in a bioeconomic dynamic optimization setting.

DCE data collected for paper II allows the estimation of people's WTP for raising the spawning coastal cod survey biomass in Arctic Norway from the SQ level to each level presented in the DCE. While the obtained WTP values represent the non-market benefits associated with the coastal cod stock, for obtaining net benefits of commercial and recreational users, we use price, cost, and harvest data from the Norwegian Directorate of Fisheries, Norwegian Fishermen's Sales Organization, and ICES. Similarly, we compute the catchability parameter based on these organizations' reports on coastal cod abundance and harvest.

For obtaining the total economic value (TEV) of coastal cod, we gradually expand the bioeconomic model to incorporate different users' benefits. This approach enables us to compare the TEV generated by models that focus solely on use-values with the models that incorporate non-use values and the local population's prioritization of different uses of coastal cod.

5. Summary of the papers

5.1. Paper I: Attribute non-attendance in environmental discrete choice experiments: the impact of including an employment attribute

Inclusion of socio-economic attributes, such as numbers of jobs or tax revenue created by development, in non-market valuation studies receives both support and criticism from economists. The supporters claim considering such effects provide a more realistic valuation setting, and people have significant preferences for market attributes that should not be ignored (Blamey et al., 2000; Morrison et al., 1999), while the opposition argues that these values can simply be adapted from available market information and the inclusion may lead to double-counting of benefits (Diamond and Hausman, 1994). This discussion, however, is not the topic for paper 1 of the Thesis.

Paper 1 investigates the impacts of including an employment attribute in a coastal development non-market valuation setting, with a primary focus on ANA behavior. We utilize Aanesen et al.'s (2018) DCE data, consisting of two split-samples: NO-JOBS dataset omitting the employment attribute and JOBS dataset with the employment attribute. The common attributes in both versions of the survey are visual intrusion from coastal development, beach littering, recreational harvest, and cost. Using these datasets, we seek to address the questions of (1) How large is the proportion of the respondents attending to the employment attribute when included? (2) How does the inclusion of employment attribute affect ANA for the other attributes? (3) How do WTP estimates for environmental attributes compare across the two subsamples? (4) How do WTP estimates compare between models that incorporate ANA relative to models that do not?

For studying the WTP and ANA patterns, we specify both MXL and random parameter LCM models, with 16 and 32 latent classes for NO-JOBS and JOBS sub-samples, respectively. In all models, we obtain a negative and significant cost attribute. Overall, we observe considerable preference heterogeneity indicated by the statistical significance of standard deviation parameters and a high degree of ANA in LCM models, ranging between 31%-63%.

Regarding the first research question, the findings indicate that people have a relatively high attendance rate for employment attribute with an ANA share of 33%. Furthermore, the residents of Arctic Norway indicate significant and positive preferences for creating more jobs in the region. Regarding the second question on whether the inclusion of employment has an impact on ANA for other attributes, the results suggest that the employment does not take attention away from other attributes.

Considering the research questions (3) and (4) on WTP estimates deriving from the two sub-samples, we observe that the WTP for all attributes are different in a statistically significant manner, with no specific trend regarding increase or decrease. Finally, WTP measures provided by models accounting for ANA are lower than in standard models, supporting former research in ANA methodology, arguing that disregarding ANA may cause overestimation of welfare (*e.g.,* Scarpa et al., 2013; Hess et al., 2013).

5.2. Paper II: Testing the sensitivity of stated preferences to variations in choice architecture

Among several stated preferences tools, DCEs have become prominent for policymakers to assess the welfare associated with various public goods as the DCE methodology provides the researcher significant flexibility in scenario design. Nonetheless, there are also many challenges in the DCE design process. In a standard design process, after reviewing existing literature, interviewing experts, and conducting focus groups, the researcher determines the final set of attributes. However, how to express any given attribute also involves several decisions by the researcher, as all attributes can be expressed in multiple ways (Ungemach et al., 2018). Furthermore, Ungemach et al. (2018) argue that the researchers can activate respondents' pre-existing values by employing perfectly correlated translations of an attribute, namely the "*signposts*", and guide the respondents to make choices that are more aligned with their personal objectives.

We conduct a three-way split sample DCE in Arctic Norway regarding the management of coastal cod stocks for testing whether the signposts do activate pre-existing values and lead to significant changes in stated preferences and WTP estimates. Utilizing the controversial expansion of the MFT industry in the region as our point of departure, we design three DCE surveys, which also include indices measuring pro-environmental and pro-development values.

The base version of the DCE involves only the common attributes of spawning coastal cod biomass, stricter regulated user group, and cost in the form of an increase in annual household tax. In this version, we express the further MFT development implicitly by not including it into the user configurations that are to face stricter regulations. In Treatment 1 and Treatment 2, however, we present the MFT expansion explicitly by communicating it through the total coastal cod harvest of the MFT and new jobs created by the MFT industry, respectively. By design, the levels of these attributes increase only when MFT is not in the combination of users facing stricter regulations. Therefore, these perfectly correlated translations of MFT expansion serve as signposts for already existing pre-environmental and pre-development values.

Our findings indicate that the residents of Arctic Norway have significant WTP for improving the coastal cod stock in the region regardless of the treatments, and the WTP for increasing the biomass is not statistically different across datasets. However, the WTP for regulating different users fluctuates significantly across treatments, suggesting that welfare associated with regulating user groups depends on how the MFT expansion is communicated. While we find rather weak evidence for value-activation for choice of non-SQ alternatives, auxiliary regression analyses on conditional WTP estimates reveal several significant interactions between treatment dummies and individual welfare, highlighting the importance of experimental variation in DCE design.

5.3. Paper III: Incorporating society's prioritization of ecosystem services: Arctic coastal cod management

Use and non-use values together determine the TEV of an ES (Costanza et al., 1997; Turner and Schaafsma, 2015). However, standard bioeconomic models often disregard non-use values, which can lead to the depreciation of vital ES. In pursuit of comparing the standard models with models that account for non-use values and people's prioritization of different stakeholders, we specify a standard bioeconomic model and gradually expand it to accommodate several non-market factors.

We use the case of the Arctic coastal cod stock for illustrating our framework. The main stakeholders for the coastal cod in the region are the commercial fishing fleet and recreational fishers, the latter including both local anglers and tourists. These two user groups receive benefits primarily by their direct use (*i.e.,* harvest) of the stock. However, as coastal cod is an important cultural and traditional icon struggling under the threat of overexploitation, we argue that people may have non-use benefits associated with the stock, which can significantly alter the findings of standard models.

We run several bio-economic models with different combinations of the market and non-market benefits considered in the dynamic optimization. Overall, our findings suggest that disregarding non-use values cause substantial underestimation of TEV of the coastal cod stock. The results indicate that today's management scheme generates the lowest TEV of NOK 1.5 billion. The highest TEV derives from the models based on a hypothetical closure of the commercial fishery, optimizing only recreational use, and recreational use together with non-use values. In more realistic cases involving both users and non-use values in the optimization, we obtain a TEV of approximately NOK 6.1billion when we account for people's ranking of coastal cod use. The TEV remains the same for the model excluding people's prioritization. However, the model accounting for the ranking generates a slightly higher optimum stock level.

6. Contributions

This dissertation examines DCE design interventions that may affect the quantification of public goods' economic benefits and expands the traditional bioeconomic models for accommodating non-market values and people's prioritization of stakeholders. Therefore, the presented research contributes to the existing academic literature on non-market valuation and bioeconomic modeling while addressing practical issues for resource managers.

Given the speedy development of coastal areas, resource managers and policymakers frequently face the crucial question of whether to exploit or conserve marine and coastal ES. As such, robust and reliable WTP elicitation is of great importance for further CBA analyses often employed for public projects. The discussions in the first two papers examine experimental variation and choice architecture in DCE design for testing the attendance to attributes and robustness of the obtained preferences and WTP measures.

Contributing to the discussions over saliency vs. simplicity in DCE design, paper I empirically explores non-attendance behavior in DCE surveys while investigating the inclusion of market attributes, which may both influence the estimated WTPs. Results uncover the rather high share of non-attendance to the attributes, statistically significant differences in WTP when employment is considered, and potential overestimation of welfare when ANA is not accounted for. These findings provide valuable insights to non-market valuation practitioners and policymakers regarding the importance of experimental variation in DCE design.

As a continuation of the design issues addressed in paper I, in paper II we apply the choice architecture framework to marine ES valuation for assessing the robustness of WTP measures to design interventions. In line with the results of paper I, the WTPs indicate sensitivity to context and attribute combination concerning the sustainable management of coastal cod stocks. These findings indicate how the economic benefits associated with the same phenomenon may shift when presented using different aspects. While we abstain from advising the DCE practitioners on whether to use environmental or socio-economic indicators for representing development, the findings serve as a reminder for the context-sensitivity of preferences and welfare.

There are also persistent WTP patterns in both DCE studies. Overall, the DCE studies' findings suggest that the residents of Arctic Norway associate significant welfare with the creation of new jobs in the region and have robust WTP for improving the coastal cod biomass, regardless of the interventions. As these results may be case-specific given the remoteness of the region with relatively slow job creation and the historical importance of coastal fishery, they are difficult to generalize. Nonetheless, these tendencies have implications for similar cases and the authorities in Arctic Norway as they highlight not just economic growth but also conservation and sustainable management of ES have meaningful monetary benefits that should not be neglected.

Obtaining reliable welfare measures is vital for sustainable and efficient ES management (Hess and Daly, 2014); however, it is often not enough for a holistic management approach. While the WTPs indicate the unit welfare of the non-market and non-use ES, they cannot deliver recommendations on optimized use of the ES. However, most optimization procedures consider only the economic benefits based on exploitation disregarding the non-use benefits of marine ES. Contributing to the small body of research investigating the impact of involving non-use values in bioeconomic dynamic optimization, in paper III we feed the welfare gain associated with the protection of Arctic Norwegian coastal cod stock in a bio-economic model. As a novel approach, we extend the model further by including the local population's prioritization for different uses of coastal cod through the weighting parameters obtained in paper II. Comparing our extended models with the current regulatory framework and standard optimization models, we expose the immense undervaluation of coastal cod stock's TEV, which may lead to overexploitation and grave deterioration of this crucial ES. While this snapshot of the coastal cod management in Arctic Norway reveals the troublesome outcomes of disregarding non-use benefits in bio-economic models, our single-stock approach has certain limitations as coastal cod by-catch in the NEA cod fishery is an important problem the policymakers struggle with while managing the coastal cod stock.

To conclude, this dissertation is a humble attempt to contribute to the sustainable management of marine and coastal ES, which is among the most important missions of our age. While my application of non-market valuation and further combining the findings with bio-economic modeling have caveats and limitations, I believe they will assist fellow researchers and decision-makers in future studies. This research is not about advocating stated preferences valuation methods. However, as a reminder on why quantifying the economic benefits of non-market ES matters and why we should constantly seek to address the methodological issues surrounding non-market valuation, I'd like to close my research with an argument by Carson et al. (2001) highlighting the importance of stated preference valuation methods and their application in decision-making tools: "Without stated preference survey methods, though, economists have to admit that they are not measuring the passive use aspects of environmental and other non-market goods, and that these are the aspects about which people may care about most. A benefit-cost analysis that omits these considerations will at best be incomplete and at worst completely misleading." (Carson et al., 2001, p. 197).

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Appendix A: Papers I-III

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 subsamples 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: Attribute non-attendance, coastal ecosystem services, discrete choice experiments, employment effects, stated preferences.

JEL codes: C25, H41, Q5, Q51, Q52.

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

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trade-off is the fact that attributes important to some respondents may not be relevant for others because of 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 (ANA)* is directly linked to the design considerations of simplicity and saliency and respondent heterogeneity. In general, ANA 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 oversimplified, 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 ANA. 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 ANA literature has established that nontrivial 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 ANA 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 *nonmarket* 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 ANA estimations.

The main contribution of our paper is to combine research on ANA 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, 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 ANA 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 ANA for the other attributes? (3) How do WTP estimates for environmental attributes compare across the two subsamples? (4) How do WTP estimates compare between models that incorporate ANA 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) job creation/losses, and (5) change in annual tax payments. Approximately half the respondents received choice cards without the employment attribute. For both subsamples, we estimate panel mixed logit models with multivariate normally distributed non-cost parameters. We explore ANA 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 ANA 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, ANA 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 ANA 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 ANA 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 ANA 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 an example, suppose one attribute in a DCE for coastal zone management is the 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) are 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 nonmarket benefits that would not be reflected in the market information. For example, a 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 their own employment opportunities are affected (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 to 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 nonmarket valuation techniques to measure the welfare effects of job creation or losses. Furthermore, when market impacts are included in DCEs, 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 neoclassical 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 DCEs.

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 a 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) explicitly treat the employment of others 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) finds that a job loss attribute is significant and

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.

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 ecosystem protection in Arctic Norway. They conclude that new jobs are 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 nonuse 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 subsample 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 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, that is, included a market attribute and discussed ANA, though without drawing a connection between the two issues (Campbell, Venn, and Anderson 2018).

EMPIRICAL APPLICATION: ARCTIC COASTAL ZONE MANAGEMENT

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 with the southern parts of the country, partly because 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 one-third 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 have led to lower rates of economic development in this region than in the rest of the country. In light of these regional

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2. Ahi (2018) provides an exploration of the role and impact of the job attribute, but without focusing on ANA.

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 2000–18 for up to 10 DCE studies from each journal. A detailed summary is available upon request.

characteristics, the pristine nature and the 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-1990s (Borch 2009; Solstrand 2014). However, despite the fact that 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 the 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 backdrop, 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 ANA, 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 nongovernmental organizations. In the focus groups, the discussions centered around the use of the coastal zone for recreational and commercial purposes, and the participants expressed their opinions about the development of 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 the aquaculture industry. 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 whether 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 the 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 subsample receiving the employment attribute, while the other subsample did not see this attribute. The survey treatments were identical in all other aspects for the two subsamples. 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 because of 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 a 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.

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 with the current situation	25% increase compared with 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 in 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	1,000	2,000	3,000

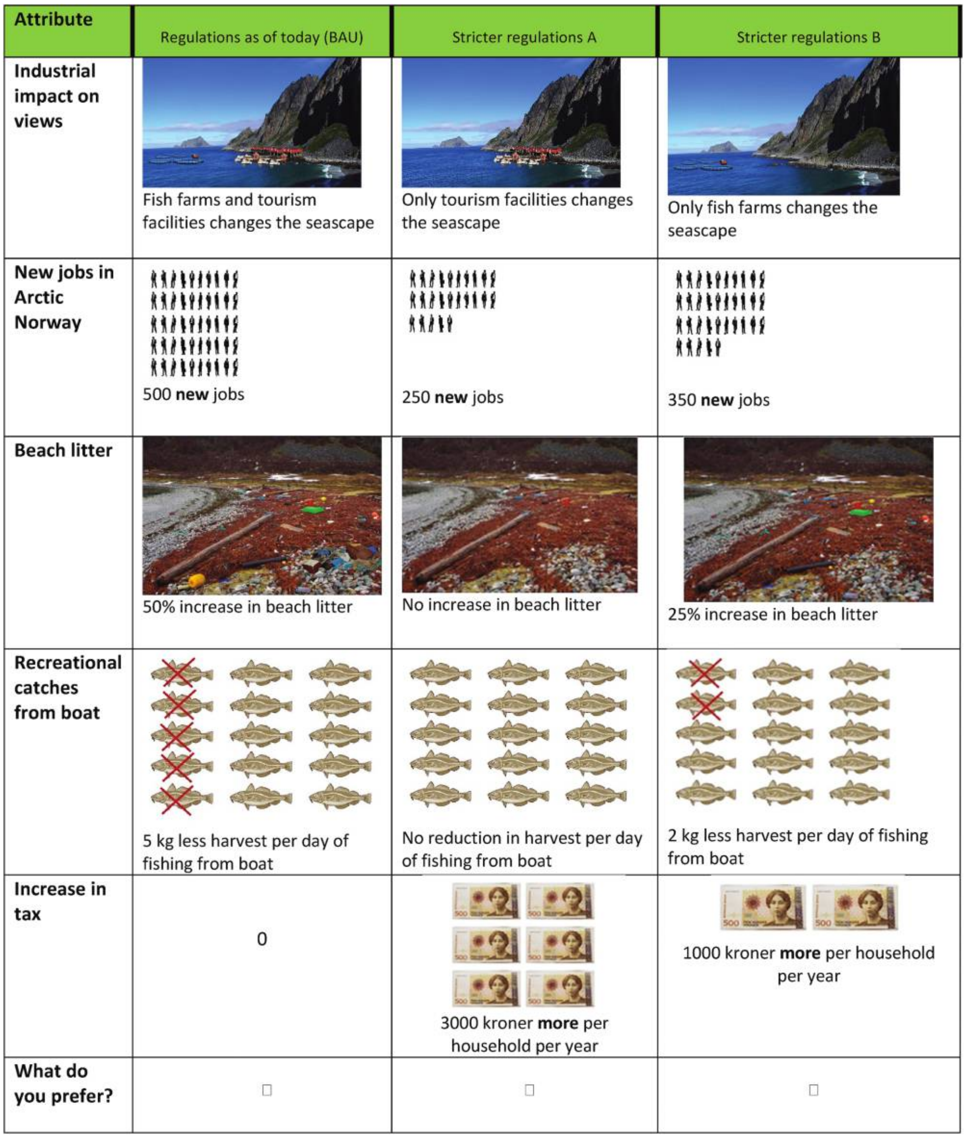

Figure 1. Sample Choice Card (with employment attribute version). A color version of this figure is available online.

As the descriptive statistics in table 2 indicate, the two subsamples are virtually identical in terms of their socioeconomic profiles. Hence, any difference in results across the two subsamples is likely to be attributable to the design version, not to differences in the underlying characteristics of the survey participants.

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

Table 2. Demographics of the Two Subsamples

Demographics	Job Subsample ($n = 518$)	No-Job Subsample ($n = 490$)
Male (%)	45	51
Age (years)	49	51
University degree and above (%)	60	64
Member of recreational organization (%)	18	19
Member of environmental organization (%)	6	7
Annual household income NOK 400K–599K (%)	19	19
Annual household income NOK 600K–799K (%)	21	23
Annual household income NOK 800K–999K (%)	24	20
Full-time employee (%)	51	52
Student (%)	9	7
Retiree (%)	21	21

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 0 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:

$$\Pr_{int} = \frac{\exp(V_{int})}{\sum_{j=1}^{J} \exp(V_{jnt})}. \tag{2}$$

In our analysis, we estimate and compare results from two types of econometric models: (1) panel mixed logit (MIXL) and (2) ANA latent class mixed logit (LC-MIXL). The MIXL model is a powerful and sophisticated approach to analyzing discrete choice data because 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:

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

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 ANA. In contrast, the LC-MIXL model, first proposed by Hess et al. (2013), is a flexible way of exploring the ANA phenomenon. It combines discrete and continuous mixing distributions. First, it allows for any pattern of ANA, from non-attendance to single attributes to non-attendance to subsets of attributes (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. Second, 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:

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

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 nonzero elements for the $S = 2^K$ different attendance classes. With an assumption of independent ANA behavior across attributes, the model requires estimation of only K number of ANA probabilities, instead of estimating the whole set of $2^K - 1$ probabilities (Hole 2011). Therefore, the modeling of π under the ANA 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 ANA combination s that consists of attendance for attributes 1 and 2 and ANA 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 subsample:

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

For the no-job subsample, $\beta_4 = 0$ by design. We apply Hess et al.'s (2013) LC-MIXL framework for identifying the ANA patterns for both subsamples, where the 2^K LC-MIXL model results in 32 and 16 classes of ANA combinations for the job and no-job 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 subsample) 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 ANA behavior.[4]

Neither model 3 nor model 4 has a closed-form solution. Hence, they must be must approximated through simulated maximum likelihood estimation. All models presented below are

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.

estimated by making appropriate adaptations/modifications to the R package Apollo (Hess and Palma 2019), with each employing 1,000 scrambled Sobol draws for simulation.[5]

ESTIMATION RESULTS

Table 3 summarizes the main results from the MIXL and LC-MIXL estimations for the two subsamples. 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 the 1% level. Exceptions are the mean SCENIC coefficient in the LC-MIXL NO JOBS estimation and the mean HARVEST coefficient in the LC-MIXL JOBS estimation.

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 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 ANA models (LC-MIXL). Previous research in the ANA field has mixed results regarding the substantial changes in coefficient size. However, there are examples of notable increases in a cost coefficient's size when switching from full-attendance models to ANA 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 ANA shares from the LC-MIXL estimations. The probability of non-attendance is relatively high, with ANA shares ranging from 31% to 63% across subsamples and attributes. The lowest ANA share (31%) is associated with COST in the job subsample, while the highest share (63%) is associated with SCENIC in the no-job subsample. These statistically estimated ANA 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 subsample indicated that visual impacts from aquaculture (marine fishing tourism) is not important to them. The discovery of substantial ANA is also comparable to that of a previous study in similar Norwegian environmental valuation context by Sandorf, Campbell, and Hanley (2017). These authors estimate ANA shares between 23% and 62% in a study on cold-water corals in Arctic Norway.

Regarding attendance to the additional employment attribute, we observe that ANA is relatively low for JOBS at 33%. Similarly, the cost attribute, which is essential for the identification

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

6. The negative sign on the HARVEST coefficient may seem counterintuitive. 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.

Table 3. Mixed Logit Estimation Results

	MIXL NO-JOB		MIXL JOBS		LC-MIXL NO-JOB		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. ANA SCENIC	—	—	—	—	0.63***	—	0.51***	—
					(0.04)		(0.06)	
Prob. ANA LITTER	—	—	—	—	0.58***	—	0.55***	—
					(0.03)		(0.04)	
Prob. ANA HARVEST	—	—	—	—	0.48***	—	0.35***	—
					(0.05)		(0.05)	
Prob. ANA COST	—	—	—	—	0.44***	—	0.31***	—
					(0.02)		(0.05)	
Prob. ANA JOBS	—	—	—	—	—	—	0.33***	—
							(0.05)	
LL (0)	–19,351		–20,254.05		–19,351		–20,254.05	
Log likelihood	–6,735.8		–7,495.9		–5,187.6		–5,526.2	
AIC	13,489		15,013		10,414.6		11,103.6	
N	450		471		450		471	

Note: ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively.

of welfare measures, is the attribute with lowest ANA share, and therefore, highest implied attendance share, in both subsamples.

Finally, we observe that the ANA shares appear to be lower in the job subsample. 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 subsamples. Note that WTP estimations from the LC-MIXL models only make use of 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 subsamples in comparison to preferences for other attributes.

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, 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 subsample.

Next, we investigate the impact of accounting for ANA. We observe drastic differences in mean WTP between the MIXL and the LC-MIXL models. In the no-job subsample, WTP for SCENIC is lowered by 98%, followed by a reduction of 93% in WTP for HARVEST when ANA 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 subsample, 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 subsamples 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 ANA impact welfare measures.

DISCUSSION AND CONCLUDING REMARKS

The DCE design procedure involves challenging trade-offs between the simplicity and the saliency of the choice sets. This paper utilized data from a split-sample DCE to investigate the impact of

7. For results of the convolution tests, please see table A1 in the appendix.
8. For details on WTP differences and results of the convolution tests, please see table A2 in the appendix.

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	1,608	1,018	24	362
	1,525, 1,691	968, 1,067	20, 29	355, 373
LITTER	–1,980	–2,152	–2,499	–1,418
	–2,039, –1,777	–2,223, –2,081	–2,552, –2,440	–1,437, –1,365
HARVEST	5,120	2,280	326	–49
	4,998, 5,242	2,196, 2,365	301, 353	–66, –31
JOBS	—	2,400	—	122
	—	2,337, 2,464	—	110, 134

Note: All estimates are reported on an annual per household basis. (1 NOK = $0.11). The WTPs reflect welfare change associated with (1) presence of both marine fishing tourism and aquaculture on the coast (SCENIC); (2) a doubling of beach litter (LITTER); (3) a one-kilo reduction in the recreational catch limit (HARVEST); and (4) 100 new jobs (JOBS).

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 ANA for the other attributes? (3) How do WTP estimates for environmental attributes compare across the two subsamples? (4) How do WTP estimates compare between models that incorporate ANA 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 ANA 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 ANA rates are lower in the job subsample estimation than in the no-job subsample estimation. Importantly, attention towards the cost attribute is not adversely affected by the additional attribute dimension. This is reassuring for the identification of welfare measures in ANA models, as the cost parameter plays an essential 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 ANA (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 ANA 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 ANA phenomenon by simultaneously studying the implications of including an employment attribute in the DCE designs, or more generally, increasing DCE complexity (Hensher 2006a, 2006b; Weller et al. 2014). We refrain from making a judgment 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 subsamples 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.

APPENDIX

Table A1. Significance Tests for Differences in ANA Shares

ANA 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).

Table A2. Significance Tests for Differences in Mean Welfare Estimates

	SCENIC		LITTER		HARVEST		JOBS	
Models	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 2,840	0.00	—	—
LC-MIXL NO-JOB vs. LC-MIXL JOBS	NOK 338	0.00	NOK 1,081	0.00	NOK 375	0.00	—	—
MIXL NO-JOB vs. LC-MIXL NO-JOB	NOK 1,584	0.00	NOK 519	0.00	NOK 4,794	0.00	—	—
MIXL JOBS vs. LC-MIXL JOBS	NOK 656	0.00	NOK 734	0.00	NOK 2,329	0.00	NOK 2,278	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.

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Testing the sensitivity of stated environmental preferences to variations in choice architecture

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Abstract

We conduct a three-way split sample discrete choice experiment (DCE) to investigate welfare estimates for attributes related to the management of coastal cod stocks in Arctic Norway. In a base DCE design, respondents face three core attributes: (1) coastal cod spawning biomass as an indicator of the sustainability of the cod stocks, (2) stricter regulations on primary user groups (commercial fishers, local recreational anglers, the marine fishing tourism industry), and (3) annual household cost. In two experimentally varied DCE designs, respondents receive a fourth attribute that explicitly describes the expansion of the marine fishing tourism industry in the region. In treatment 1, the expansion is represented by the number of coastal cod caught by marine fishing tourists as an indicator of the industry's environmental impact. In treatment 2, the expansion is represented by the number of new jobs as an indicator of the industry's socio-economic impact. These two attribute translations, designed to be perfectly correlated, serve as an instrument for testing a choice architecture framework recently proposed in the management science literature. Results from mixed logit estimation indicate that the mean welfare estimates associated with sustainable management of the coastal cod stocks are statistically indistinguishable across DCE versions, while preferences for specific regulatory configurations are design-dependent. Additional regression analyses of conditional willingness-to-pay estimates and the respondents' propensity to choose the status quo option uncover further choice architecture impacts and provide mixed evidence of value activation. Overall, our findings suggest that DCE researchers should recognize their role as choice architects when offering advice to public resource managers and policymakers.

Keywords: *stated preferences; discrete choice experiments; ecosystem service valuation; willingness-to-pay; status quo; choice architecture; value activation.*

JEL codes: *Q22, Q51, Q57, C25.*

1. Introduction

Public planning and management often involve complex environmental and industrial tradeoffs, affecting various stakeholders in idiosyncratic manners. In recent decades, cost-benefit analysis (CBA) has become a standard tool for *ex-ante* evaluation of public policy and investment decisions due to its ability to place the welfare changes of society at large and different groups of people into perspective by incorporating estimates of willingness-to-pay (WTP) for nonmarket goods (Volden 2019; Kenkel 2006). Obtaining valid and reliable welfare estimates has become essential to optimal management of natural resources under increasing pressure (Hess and Daly 2014).

The discrete choice experiment (DCE) method is one of the most widely used techniques for assessing the welfare impact of changes in environmental quality induced by public policies (Mariel et al., 2020). It combines behavioral theories and statistical methods and relies upon constructed markets wherein people express preferences or make contingent choices that uncover their implicit tradeoffs and monetary valuations (Hoyos, 2010). Given the hypothetical nature of DCEs, design is inherently a complex and multi-layered process. A key challenge is identifying appropriate attributes, attribute levels, alternatives, choice sets, and information provision (Meyerhoff et al., 2015). These design considerations can be examined within a *choice architecture* framework, a general term that defines the context and process of decision-making (Thaler and Sunstein, 2008; Johnson et al., 2012; Camilleri and Larrick, 2014; Thaler et al., 2014).

Deciding on the number and representation of attributes invariably involves a tradeoff between realism and complexity, as the tasks in environmental valuation studies are often unfamiliar and complicated (Slovic, 1995; Rolfe and Windle, 2015). Most attribute selection procedures seek guidance from the existing literature and input from focus groups with affected stakeholders. However, as it is impossible to add all aspects of an environmental issue to the

DCE design, the ultimate set of attributes is an outcome of the researcher's judgment. In this sense, the DCE researcher can be viewed as a *choice architect* (Johnson et al., 2012). The verdict of the researcher, i.e., the choice architect, in the final step of design is crucial since each attribute can be expressed in multiple ways through the adoption of different indicators or metrics (Camilleri and Larrick, 2014; Ungemach et al., 2018). This insight is vital to public policy and environmental management since the attributes of nonmarket goods are not as straightforward as the attributes of commercial goods and services. For example, one could communicate the socio-economic impacts of a new industrial establishment as an increase in regional tax revenues, new jobs, regional population growth, or a combination of these dimensions, depending on the case. Similarly, ecosystem impacts from environmental and industrial policies may be communicated through an index, a vector of correlated effects, or through the changes in the level of one "representative" ecosystem dimension.

Under the neoclassical economics paradigm, one would expect that people have stable, well-behaved preferences and that marginal rates of substitution are insensitive to variation in DCE framing and dimensionality (Caussade et al., 2005; Pedersen et al., 2011; Homar and Cvelbar, 2021). However, a large body of behavioral research on decision-making processes has accumulated evidence that people tend to adapt their decisions in response to characteristics of the choice context (McFadden et al., 1999; Swait and Adamowicz, 2001; Campbell et al., 2008; Kragt and Bennett, 2012; McFadden, 2014). Correspondingly, choice architecture practices and interventions that shape DCE dimensionality and context may have implications for resulting preference expressions and welfare estimates.

Previous research on dimensionality and context robustness of DCEs presents mixed results. Caussade et al. (2005) and Meyerhoff et al. (2015) examine the impacts of DCE dimensionality and report that the number of attributes plays a significant role in choice consistency, while it does not systematically change WTP estimates. Zhang and Adamowicz

(2011) find that increasing the number of tradeoffs is associated with a lower likelihood of choosing the status quo (SQ) alternative. The proposed reason is that adding attributes with varying levels increases the likelihood that respondents will find a non-SQ option that matches their preferences. In contrast, Oehlmann et al. (2017) conclude that the propensity to choose SQ is unaffected by the number of attributes.

Concerning context robustness, Jacobsen et al. (2008) study the effects of using different ecological indicators to express environmental quality changes. These authors show that the WTP estimates are sensitive to whether the environmental good is "iconized" or defined simply by quantitative measures. However, in a similar study, Zhao et al. (2013) find that preferences and WTP estimates are robust when it comes to the ecological indicator used as attribute representation. Extending the issue of indicator selection to socio-economic attributes, Rolfe and Windle (2015) find that varying their combination leads to significant impacts on preference expressions and welfare estimates in a land-use policy DCE. Finally, Ungemach et al. (2018) analyze attribute selection explicitly within a choice architecture framework and illustrate how one can communicate the same attribute in various manners through highly (or perfectly) correlated translations. According to Ungemach et al. (2018), using one translation over another, or combining representations, may have implications for activation of pre-existing values, thereby directing respondents towards choice alternatives that are congruent with their objectives. These authors refer to this as a *signpost effect*, where using a specific expression or metric for an attribute may lead to more coherence between pre-existing values and choices.

This article examines choice architecture impacts in the empirical context of studying preferences for the management of coastal cod stocks in Arctic Norway. The main objective of the underlying DCE survey is to investigate the regional population's tradeoff between conservation and use of coastal cod stocks, focusing on the sustainability of the coastal cod biomass. As a methodological contribution, we test whether stated preferences and related welfare estimates are robust across the number and representation of attributes in a marine resource management setting. Furthermore, we investigate the implication of different choice architectures for activating pre-existing values.

Our research agenda is addressed through a three-way split sample DCE design. Specifically, one sub-sample receives a parsimonious, base version of the DCE with three core attributes: (1) coastal cod spawning biomass as an indicator for the health of the coastal cod stocks, (2) different configurations of stricter regulations on the three primary cod user groups, namely, commercial fishers, local recreational anglers, and the marine fishing tourism industry, and (3) change in annual household cost. In two experimental treatment sub-samples, the participants receive a fourth attribute that explicitly captures the expansion of the marine fishing tourism (MFT) industry in Arctic Norway. In Treatment 1, the expansion is described by the number of coastal cod caught by marine fishing tourists. In Treatment 2, the expansion is represented by new regional jobs created by the MFT industry.

A motivation for including an explicit attribute for the MFT industry, and subjecting it to choice architecture variation, is that the growth of this industry in Arctic Norway is controversial due to reports of overfishing and illegal exports. At the same time, the coastal cod stocks are declining and are currently considered to be below sustainable levels. The first version of the MFT attribute (the coastal cod harvest of marine fishing tourists) communicates the industry's expansion in terms of environmental impact and is expected to be negatively valued by the population of Arctic Norway. In contrast, the second version of the attribute (new jobs created in MFT) communicates the expansion with a socio-economic impact focus, expected to evoke positive preferences. Our triple split-sample DCE allows us to test the design sensitivity (or robustness) of welfare estimates associated with different coastal cod management regimes. In addition, the two treatment versions provide us a unique opportunity to study the potential activation of pre-existing pro-environmental or pro-development values, following the signpost framework proposed by Ungemach et al. (2018). We first employ standard mixed logit techniques to compare mean welfare estimates across sub-samples. Then we conduct additional regression analyses of conditional WTP estimates and the respondents' propensity to choose the SQ option to explore further the influence of DCE characteristics and test for the activation of pre-existing values.[1]

This study is the first to test value activation by employing translated attributes in a nonmarket valuation context. Our application deviates from and extends the original work of Ungemach et al. (2018) in three specific ways. Firstly, while Ungemach et al. (2018) study preferences for a private good (i.e., personal vehicles), we focus on a public good (i.e., renewable resource management). Secondly, Ungemach et al. (2018) focus solely on signpost effects related to the probability of choosing an environmentally friendlier vehicle option. We extend the analysis to investigate the potential impact of value-activation on welfare estimates. Thirdly, Ungemach et al. (2018) investigate value activation by employing different indicators for the underlying attribute of vehicle fuel economy. In contrast, we investigate the impact on preferences for an ES dimension (i.e., coastal cod spawning biomass) and its regulatory framework (i.e., various configurations of user groups subjected to stricter regulations) when these attributes are accompanied by different versions of an additional attribute, both implying the same phenomenon (i.e., expansion of the MFT industry).

The specific research questions that we seek to answer are the following: (1) What are the Arctic Norwegian population's preferences for improving the coastal cod stocks and managing their use by different stakeholders? (2) Are the welfare estimates context-specific or robust across choice architecture treatments? (3) Do choice architecture variations influence

[1] The sufficiency of the base DCE for the overall purpose of eliciting preferences for managing the coastal cod stocks was established through a careful design and pretesting process. Hence, the base DCE can be considered a *control* design in our study. Additional pretesting of the experimental treatment versions with one extra attribute did not uncover any issues of concern (e.g., elevated protest propensity). Hence, we deem these designs as valid for the purpose of exploring choice architecture and signpost effects in our particular valuation context.

individual-specific WTPs and SQ choice probabilities? (4) Can attribute translations (i.e., signposts) activate pre-existing values in a marine ES valuation setting?

The rest of the article is organized as follows: Section 2 presents the background for the empirical application, while Section 3 describes the DCE design process, analytical framework, and data collection. In Section 4, we report and discuss econometric estimation results. Section 5 summarizes and provides some concluding remarks.

2. Empirical application: Coastal cod stocks in Arctic Norway

The counties of Troms and Finnmark and part of the county of Nordland comprise the area known as Arctic Norway. Harsh climate conditions, scarce population, and pristine nature are the main characteristics of this area. Historically, climatic and geographic obstacles have led to commercial underdevelopment compared to southern Norway. The economic activities have relied heavily on traditional sectors such as fisheries and small-scale agriculture until the recent decades (Aanesen et al., 2018). However, following the Norwegian government's efforts to promote Arctic Norway as a fishing tourism destination in the European market, the region has experienced rapid growth of the MFT industry in recent years (Borch, 2009; Solstrand and Gressnes 2014). The number of registered MFT companies in Arctic Norway has increased from 205 enterprises in 2011 (Borch et al., 2011) to 341 as of January 2020.[2]

While the MFT companies contribute to the regional economy, the fast expansion of this industry has resulted in stakeholder conflicts. A major source of conflict is that the MFT industry relies heavily on the Norwegian coastal cod, an essential species within the deeply rooted tradition of coastal fishing activities in Arctic Norway (West and Hovelsrud, 2010).[3] Recent reports by ICES (2018a; 2018b) indicate that the coastal cod spawning biomass levels

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[2] Norwegian Directorate of Fisheries, 26.01.2020 https://www.fiskeridir.no/Turistfiske/Registrering-av-turistfiskebedrift/Registrerte-turistfiskebedrifter

[3] Apart from the rich cod fisheries along the coast, the region is also a major spawning location for *skrei (i.e. Atlantic cod)*, which means *wanderer* in Old Norse, migrating from the Barents Sea to spawn along the Norwegian coast (Sundby and Nakken, 2008).

are well under what is necessary for ensuring the sustainability of this crucial ES. In addition to sustainability concerns, stakeholder conflicts have intensified due to an asymmetric regulatory framework, lack of monitoring, and claims of overfishing and smuggling in the MFT industry (Borch, 2009; Borch et al., 2011; Solstrand and Gressnes, 2014). The latter, fish smuggling by tourists, is a recurring theme in the local media, intensifying the debate around poor environmental monitoring and inefficient regulations (Solstrand and Gressnes, 2014). The regional population is sensitive to this issue as both local recreational anglers and commercial fishers rely on the declining coastal cod stocks, which adds an emotional dimension to the conflict.

The Norwegian Directorate of Fisheries has recently introduced a new set of regulations for the MFT industry to address these conflicts. According to the new rules, unregistered tourists can bring 10 kg of fish product per person out of the country, while tourists registered at MFT companies can export a maximum of 20 kg per person. Additionally, the Directorate of Fisheries established an online catch registry to monitor the catch of tourists. The fine for a smuggling offense doubled to NOK 8000 per incident plus NOK 200 per kilo fish.[4] However, the new regulations have fallen short of addressing the core of the conflict. Under the new regulatory regime, the tourists are still free to fish as much as they wish during their stay, independent of how much they export. The new regulatory framework has also fueled a new debate about wasteful resource utilization. The rules define export limits generically in terms of "fish product", which may incentivize tourists to only take the best part of the fish (i.e., fish fillets) rather than whole fish. In turn, this may actually result in more catch within the revised export quota. Another source of conflict is that tourists and recreational anglers have access to restricted areas that the commercial fleet cannot utilize due to equipment restrictions and boat size limitations.

[4] NOK 1 = USD 0.11

With the above sustainability concerns and unresolved regulatory issues as back-drop, Arctic Norway presents a fascinating setting for investigating the impact of choice architecture interventions in a DCE application.

3. Methods

3.1. DCE design

The design process started with a preliminary literature review followed by focus groups and interviews in Arctic Norway to identify the appropriate policy framing and relevant attributes for a DCE on coastal cod management. We held focus groups in Tromsø and Svolvær in the Lofoten islands, the latter being a hotspot for MFT activities. Both sessions had recreational anglers among participants. In addition, face-to-face interviews with fishery experts, coastal fishers, and MFT company employees were conducted to inform the DCE design.

The main themes that came up in the focus groups and interviews were the use of coastal cod by different stakeholders, current and potential regulations, and the rapid expansion of the MFT industry. The focus group participants expressed ambivalence towards the industry. On the one hand, they were aware of its social and economic contributions. The positive aspects highlighted were job opportunities for young people, availability of regional flights all year round, and new local businesses generating more vibrant communities. On the other hand, the participants also expressed concerns over the environmental impact of the industry expansion on the declining coastal cod stocks. A frequently mentioned topic in both the focus groups and the interviews was the current regulatory framework, which was seen as unjust and leading to mismanagement of the coastal cod resource due to various asymmetries and loopholes.

Based on prior research, input from the focus groups and interviews, and a careful pre-testing and piloting process, the final DCE design ended up with three core attributes, namely, (1) spawning coastal cod biomass, (2) stricter regulations on primary user groups, and (3) increase in annual household taxes. To test for preference and WTP sensitivity related to attributes (1) and (2), two experimentally varied versions of the DCE include a fourth attribute that explicitly describes the expansion of the MFT industry. Treatment 1 presents *coastal cod caught by marine fishing tourists,* while Treatment 2 presents *new jobs created by the MFT industry* as an additional attribute in the choice tasks. These two attribute versions highlight the environmental and socio-economic aspects of the industry expansion, respectively. Following Ungemach et al. (2018), we restrict the attribute levels of these two attribute representations to be perfectly correlated in the experimental design.

Table 1 introduces attribute names and summarizes attribute levels. The SQ level of 15 000 tons for the coastal cod spawning biomass (BIOMASS) is based on ICES (2018a, 2018b). By design, this attribute takes on increasing levels in the alternative management regimes (20 000 to 80 000 tons), with 60 000 tons designated as the sustainable level. The stricter regulatory framework attribute (NEWREG) is categorical (i.e., qualitative) and identifies the affected stakeholders. Examples of potential new regulations described in the attribute information include seasonal and zonal restrictions and user group quotas. The SQ category for this attribute reflects the current situation with no additional restrictions planned for any of the three primary user groups (i.e., business as usual). In selecting the other levels or categories for this attribute, the initial idea was to include all possible configurations, including one with only local recreational anglers facing new restrictions. However, feedback from fishery experts overruled this idea due to concern over protest responses as recreational fishing is a significant coastal activity for the regional population. The final set of categories, deemed unlikely to invoke choice task rejection, are as follows: new regulations for the commercial fishers only (REGCOM), new regulations for the MFT industry only (REGMFT), new regulations for local users, i.e., commercial fishers and recreational anglers (REGLOC), new regulations for industries, i.e., commercial fishers and the MFT industry together (REGIND), and regulating all users (REGALL). Finally, the third core attribute (COST) is a monetary attribute framed as an incremental local tax imposed annually at the household level. The rationale for this tax is the need to finance costly monitoring and enforcement associated with alternative coastal cod management regimes.

For Treatment 1, we utilized the harvest registry system of the Norwegian Directory of Fisheries to identify an SQ level of 125 000 for the additional attribute of coastal cod caught by marine fishing tourists (CATCH). In Treatment 2, the SQ level of 1000 for the number of jobs in the MFT industry is based on Borch et al. (2011).[5] Both attribute versions have a range of ± 25% around the SQ level, which we deem as experimentally sufficient and reasonable in describing the potential development path of the MFT industry in the region.

The DCE has eight choice tasks, each with three policy alternatives.[6] The SQ option represents a scenario without additional regulations and without improvement in the coastal cod spawning biomass. In contrast, policy alternatives 1 and 2 represent improvements over the current situation, achieved through stricter regulations financed by the annual household tax payments to the local authorities.[7] The experimental design imposed several restrictions on permissible combinations of attribute levels, given feasible relations between attributes. For example, as new regulations would aim to improve stock conditions, the SQ level of biomass is not available in alternatives 1 and 2. Furthermore, in DCE Treatments 1 and 2, an increase in cod caught by marine fishing tourists or more jobs in the MFT industry (representing an expansion) is not permitted when this industry is subjected to stricter regulations.

[5] The harvest estimate includes both offshore and coastal catch. Nonetheless, we take this to be a reasonable approximation for our study as most tourists are fishing in the coastal zone. There are no precise employment statistics for the MFT industry in Arctic Norway. Many MFT companies are small family-owned businesses with seasonal employees and most have a varied range of tourism activities from northern light tours to ocean safari.

[6] Please see Appendix A for an example choice card from each DCE version.

[7] Since a new coastal cod management regime would take several years to achieve a targeted improvement in the coastal cod stocks, one could argue that the current situation is not the appropriate comparison. However, what we describe in the DCE as the SQ option is a technically feasible future state of the world, relevant for comparisons with outcomes from new management regimes. Furthermore, pre-testing the DCE did not raise any concerns related to this configuration of choice alternatives. Lastly, most environmental management DCEs do not seek to identify time preferences by stating and experimentally varying the time horizon for the policy implementation. Neither did we, as this would have added choice task complexity and potential protest behavior and detracted from our specific conceptual and methodological research objectives.

Table 1. Attributes and levels of Base and Treatment DCEs.

Attribute	Levels
Coastal cod spawning biomass (in tons) (BIOMASS)	15 000 tons (SQ) 20 000 tons 40 000 tons 60 000 tons 80 000 tons
Stricter regulatory framework focusing on different user groups (NEWREG)	No new stricter regulations (SQ) Only commercial fishers (REGCOM) Only MFT (REGMFT) Commercial fishers and recreational anglers (REGLOC) Commercial fishers and MFT (REGIND) All user groups (REG_ALL)
Treatment 1: Number of coastal cod caught by marine fishing tourists per year (CATCH)	500 000 (SQ) 125 000 more (+25%) 50 000 more (+10%) 125 000 less (-25%) 50 000 less (-10%)
Treatment 2: Jobs created by MFT in the region (JOBS)	1000 (SQ) 250 new jobs created (+25%) 100 new jobs created (+10%) Loss of 250 jobs (-25%) Loss of 100 jobs (-10%)
Increase in household taxes (annual) (COST)	0 NOK (SQ) 500 NOK 1000 NOK 1500 NOK 2000 NOK 3000 NOK

A pilot study with 100 respondents from Arctic Norway was carried out in December 2019 to check the DCE survey's overall quality, i.e., comprehensibility and realism. Diagnostics on the acceptability of each choice architecture treatment were made possible by randomizing the pilot respondents into the three DCE versions. Following the pilot study, the DCE underwent minor changes. An extra description was added to the BIOMASS attribute on the choice cards, relating its level to the recommended sustainable level of 60 000 tons (ICES 2018a; 2018b). For example, the revised design supplementary expresses the SQ level of 15 000 tons of spawning biomass as *¼ of the minimum level recommended* (60 000 tons). We also added a budget reminder to the information given before the choice tasks to enhance DCE consequentiality.[8]

3.2. Value activation

In addition to extracting the monetary benefits of improved management of the coastal cod stocks and testing their sensitivity to choice architecture treatments, this study also investigates the presence of value activation through translated attributes. For this purpose, the survey included items from two validated attitudinal value scales to examine whether the two versions of the MFT attribute (CATCH and JOBS) invoke different pre-existing values. Specifically, we use the *Revised New Environmental Paradigm* scale by Dunlap et al. (2000) for measuring pro-environmental inclination (referred to as NEPR) and the *Development of Sustainable Tourism* scale by Choi and Sirakaya (2005) for measuring pro-development views (referred to as PRODEV).[9] Following Ungemach et al. (2018), we investigate value-activation through the interaction of the participants' pro-environment and pro-development scores with dummy variables indicating the presence of an environmental or socio-economic translated attribute (DTREAT1 and DTREAT2), respectively.

3.3. Analytical framework

The random utility model (RUM) forms the basis for our econometric analysis of the DCE data (Mariel et al., 2020). Specifically, we estimate mixed logit models in WTP space (Train and Weeks, 2005). According to the RUM framework, the total utility individual n obtains from alternative i in choice situation t (U_{nit}) consists of a systematic part (V_{nit}) and a stochastic part (ε_{nit}). Individual n is assumed to choose alternative i in choice occasion t if $U_{nit} > U_{njt}$, for

[8] As is common practice, we employed a D-efficient design with zero priors for the pilot survey. Then, the estimated coefficients from analysis of the pilot data were used as priors in the final D-efficient design. The pilot and final experimental designs were generated using the NGene software (Choicemetrics, 2014).

[9] We only employed eight items from each scale in the survey as the choice tasks and follow-up questions are cognitively challenging and quite time consuming. Please see Appendix B for the statements we used to construct the NEPR and PRODEV indices for this study. In our data, the Cronbach's alpha is 0.71 for NEPR and 0.78 for PRODEV, exceeding the standard minimum level of 0.70 (Cortina, 1993).

all $j \neq i$. Commonly, total utility is assumed separable in its two components and the systematic part approximated by an additively linear combination of observed variables (x_{nit}) weighted by unknown individual-specific parameters (β_n) following density $f(\beta)$ in the population. Furthermore, the model can be adjusted to separate monetary and non-monetary attributes, enabling direct estimation of welfare measures within the random utility specification. This approach is referred to as *utility in WTP space* (Train and Weeks, 2005). Let $x_{nit} = (p_{nit}, z_{nit})$ and $\beta_n = (\alpha_n, w_n)$, then total utility can be specified in WTP space as:

$$U_{nit} = \alpha_n(-p_{nit} + w_n' z_{nit}) + \varepsilon_{nit}. \quad (1)$$

In equation (1), α_n represents the preference weight on the negative of the cost attribute (p_{nit}) and w_n is a vector that represents the individual's monetary valuation of the non-cost attributes (z_{nit}). The unobserved random term (ε_{njt}) is assumed to be distributed iid extreme value and captures the researcher's ignorance and the decisionmaker's imperfection (McFadden, 1973; Revelt and Train, 1998; Train, 2009). With these assumptions, the probability that individual *n* chooses alternative *i* in choice occasion *t* can be expressed by a standard logit formula:

$$L_{nit}(\beta_n, x_{nit}) = \frac{exp[\alpha_n(p_{nit}+w_n' z_{nit})]}{\sum_j exp[(\alpha_n(p_{njt}+w_n' z_{njt})]} \quad . \quad (2)$$

However, this probability can only be computed under known values for β_n or estimated directly under the assumption of homogenous preferences, i.e., individual-invariant parameters. Furthermore, it does not account for the panel nature of our data. For these reasons, we estimate a mixed logit model (MIXL) to accommodate preference heterogeneity across individuals and correlated choices. The unconditional probability of observing a sequence of choices $Y_n = \{Y_{n1}, \dots, Y_{nT}\}$ made by individual n becomes the integral of the product of logit probabilities, one for each choice occasion, over all possible values of β_n (Train, 2009):

$$\Pr(Y_n | x_{nit}) = \int \prod_{t=1}^{t=T} \left(\frac{exp[\alpha_n(p_{nit}+w_n' z_{nit})]}{\sum_j exp[(\alpha_n(p_{njt}+w_n' z_{njt})]} \right) f(\beta|\theta) d\beta \quad . \quad (3)$$

Here, θ represents estimable moments (means; variances; covariances) characterizing the probability distribution $f(\beta|\theta)$ of the unknown preference parameters. Estimation is achieved through simulated maximum likelihood procedures; see Train (2009) for details.

Based on estimated moment coefficients ($\hat{\theta}$) and information on the individuals' actual choices (Y_n), it is possible to predict conditional (*i.e.,* individual-specific) WTPs by applying Bayes' theorem (Greene et al., 2005; Train, 2009). In our case, a vector $\widehat{w}_n$ representing respondent-specific WTPs for the non-cost attributes is computed over R draws as follows:

$$\widehat{w}_n = \frac{\sum_{r=1}^{R}[\Pr(Y_n|w_r)w_r]}{\sum_{r=1}^{R}\Pr(Y_n|w_r)} \quad . \tag{4}$$

In the application below, we estimate separate models for each sub-sample. We assume that the parameters on all non-cost attributes follow a multivariate normal distribution, which permits predictions of welfare gains and losses associated with a change in attribute levels. The parameter on the negative of cost is specified as log-normally distributed, which ensures that all respondents disfavor a rise in the cost level, in line with microeconomic theory. Each model is estimated with a full covariance matrix to accommodate all sources of correlation (Hess and Train, 2017). The maximum likelihood simulation employs 5000 scrambled Sobol draws (Czajkowski and Budziński; 2019).

Relating this econometric approach to the attributes presented in Table 1: We model the attributes of BIOMASS, CATCH, and JOBS as linear continuous, where their parameters denote the incremental WTP per 1000-ton increase in spawning coastal cod biomass, 50 000 units of coastal cod caught by marine fishing tourists, and 100 new jobs created by the MFT industry, respectively. We incorporate the regulatory framework attribute (NEWREG) in the deterministic utility with a set of dummy variables representing different combinations of user groups facing stricter regulations.[10,11] Equations (5a), (5b), and (5c) describe the deterministic utility in WTP space estimated for the base DCE, Treatment 1, and Treatment 2, respectively:

$$V_{Base\ DCE} = \beta_{1n} * SQ + ln(\beta_{2n}) * (-COST_{int} + \beta_{3n} * BIOMASS_{int} + \beta_{4n} * REG\ COM_{int} + \beta_{5n} * REG\ MFT_{int} + \beta_{6n} * REG\ IND_{int} + \beta_{7n} * REG\ LOC_{int} + \beta_{8n} * REG\ ALL_{int}) \quad (5a)$$

$$V_{Treatment\ 1} = \beta_{1n} * SQ + ln(\beta_{2n}) * (-COST_{int} + \beta_{3n} * BIOMASS_{int} + \beta_{4n} * REGCOM_{int} + \beta_{5n} * REG\ MFT + \beta_{6n} * REG\ IND_{int} + \beta_{7n} * REG\ LOC_{int} + \beta_{8n} * REG\ ALL_{int} + \beta_{9n} * MFT\ CATCH_{int}) \quad (5b)$$

$$V_{Treatment\ 2} = \beta_{1n} * SQ + \ln(\beta_{2n}) * (-COST_{int} + \beta_{3n} * BIOMASS_{int} + \beta_{4n} * REG\ COM_{int} + \beta_{5n} * REG\ MFT_{int} + \beta_{6n} * REG\ IND_{int} + \beta_{7n} * REG\ LOC_{int} + \beta_{8n} * REG\ ALL_{int} + \beta_{9n} * MFT\ JOBS_{int}) \quad (5c)$$

The analysis below employs the complete combinatorial test suggested by Poe et al. (2005) for statistical inference regarding impacts of DCE dimensionality and framing on the unconditional welfare estimates. Furthermore, following Yao et al. (2019), we investigate whether DCE features and socio-demographic variables can explain sub-sample variation through second-stage regressions.[12] We study the impact of choice architecture treatments on conditional WTP estimates by employing standard linear regression techniques (Wooldridge, 2015). Following Ungemach et al. (2018), we specify a random intercept logistic regression model (Cameron and Trivedi, 2005) to examine the effect of choice architecture treatments and value activation on SQ choice probabilities.

3.4. Data collection

The data collection took place in December 2019 through the pre-recruited household panel of *NORSTAT*, a major Norwegian survey company.[13] The sampling procedure employed a

[10] We also include a dummy variable for the SQ alternative. Choice of SQ often captures systematic unobservable effects and estimation of a so-called alternative-specific-constant (ASC) for this alternative often suffers from various biases (Hess et al., 2005; Hasund et al., 2011). For this reason, we keep the ASC in utility space and give it a qualitative interpretation of preference tendencies (i.e., towards or away from status quo) rather than a quantitative monetary welfare interpretation.
[11] For identification, regulating all three user groups (REGALL) is set as the base level.
[12] An alternative approach is to incorporate pro-environmental and pro-development values in the estimation of a hybrid choice model. However, some prior studies have suggested that complex hybrid specifications increase the computational burden significantly without necessarily outperforming the MIXL. Also, the two methods seem to have similar predictive power (Kløjgaard and Hess, 2014; Mariel and Meyerhoff, 2016).
[13] https://norstat.no/

randomized split-sampling scheme, where people received either the base DCE or one of the treatment versions.

The survey was open for about ten days and yielded a total of 754 responses, 251 for the base DCE, 251 for Treatment 1, and 252 responses for Treatment 2. The overall survey response rate was 26%. The descriptive statistics in Table 2 indicate that the respondents have relatively similar socio-demographic profiles across the three sub-samples. Nevertheless, we control for respondent characteristics in the regression analyses of conditional welfare estimates and propensity to choose the SQ option.

Table 2. Demographics of the sample (n=754).

	Base DCE (n= 251)	**Treatment 1 (n=251)**	**Treatment 2 (n=252)**
Female	47%	50.6%	44.8%
Age	47.1	46.7	49.3
Bachelor's degree or higher	41.8%	40.8%	44.4%
Employed full-time	48.6%	56.1%	55.5%
Employed part-time	12.3%	10.7%	9.1%
Student	8.7%	9.1%	6.3%
Personal income NOK 300 000-400 000	11.1%	14.7%	11.9%
Personal income NOK 400 000-500 000	21.1%	21.1%	17.4%
Personal income NOK 500 000-600 000	15.5%	13.5%	17.8%
Personal income above NOK 600 000	19.1%	21.9%	26.1%
Recreational anglers	41%	43%	44.8%

4. Results

4.1. Mixed logit estimations

Table 3 reports MIXL estimation results for each sub-sample.[14] McFadden's ρ^2 is above 0.3 in all models, suggesting a very good fit (McFadden, 1977, Louviere et al., 2000). The cost attribute is significant across models.[15] The estimated mean coefficient on SQ is significant and negative, suggesting that the average respondent is dissatisfied with the current coastal cod management regime and may prefer stricter regulations. The qualitative results for mean attribute preferences (i.e., the signs on estimated mean WTPs) appear robust across sub-

[14] All MIXL models are run in R using the Apollo package (Hess and Palma, 2019).

[15] As the cost parameter is specified as log-normally distributed, the positive sign relates to the absolute size, rather than the sign of the log-normal coefficient (Hess et al., 2013).

samples. The average respondent has a positive valuation of improving the coastal cod biomass (BIOMASS), more MFT jobs (JOBS), and regulating the MFT alone (REGMFT) or together with commercial fishers (REGIND). An exception is the sign-reversal observed for REGMFT in Treatment 1. When the DCE design explicitly includes coastal cod caught by marine fishing tourists (CATCH in Treatment 1), mean preferences for regulating only the MFT industry become negative. Interestingly, while the mean coefficient on CATCH is positive, it is not statistically significant. This result suggests that some respondents blend employment impacts into their interpretation of this attribute. In contrast, when the DCE design explicitly controls for new jobs in the MFT industry (JOBS in Treatment 2), the mean preferences for regulating this industry are strengthened. The average respondent has negative preferences for placing new restrictions on commercial fishers alone (REGCOM) or commercial fishers and local recreational anglers together (REGLOC). Lastly, the relatively high and mostly significant standard deviation coefficients associated with the non-cost attributes indicate substantial preference heterogeneity in the population.

Turning to quantitative interpretations, i.e., the welfare estimates, we first observe that the mean WTP to improve the coastal cod spawning biomass (BIOMASS) is NOK 4.2, NOK 9.5, and NOK 8.9 in the base DCE, Treatment 1, and Treatment 2, respectively. These welfare estimates represent annual incremental WTP for a 1000-ton increase in biomass. Regarding the treatment attributes representing the regional expansion of the MFT industry, the estimation results indicate WTPs of NOK 332 per 100 new jobs and NOK 34 per 50 000 units reduction in cod harvest. However, the latter estimate is statistically indistinguishable from zero. Finally, while the welfare estimates associated with the regulatory framework categories should be interpreted cautiously, we note that they are substantial, ranging from negative NOK 1718 (REGCOM in Treatment 1) to positive NOK 1451 (REGMFT in Treatment 2).

Table 3. Results from the mixed logit estimation.

Coefficients in preference space	Base DCE	Treatment 1 (CATCH)	Treatment 2 (JOBS)
SQ: Mean coefficient	-4.01***	-2.92***	-2.06***
(t-ratio)	(-7.93)	(-5.44)	(-3.73)
SQ: Standard deviation	4.22***	6.61***	5.79***
(t-ratio)	(6.46)	(9.14)	(7.43)
ln(COST): Mean coefficient	0.54***	-0.31**	-0.49**
(t-ratio)	(3.84)	(-2.02)	(-2.47)
ln(COST): Standard deviation	0.18***	0.22*	0.85***
(t-ratio)	(5.30)	(1.88)	(6.30)
Coefficients in WTP space (NOK)	**Base DCE**	**Treatment 1 (CATCH)**	**Treatment 2 (JOBS)**
BIOMASS: Mean WTP	4.2***	9.5***	8.9***
(t-ratio)	(-4.65)	(-3.24)	(-6.90)
BIOMASS: Standard deviation	26.1***	15.5***	42.7***
(t-ratio)	(10.14)	(5.20)	(12.07)
REGCOM: Mean WTP	-656.7***	-1718.1***	-1219.2**
(t-ratio)	(4.93)	(5.29)	(2.13)
REGCOM: Standard deviation	349.7***	982.9***	180.6*
(t-ratio)	(5.08)	(-5.13)	(-1.74)
REGMFT: Mean WTP	220**	-559.3***	1451***
(t-ratio)	(-2.53)	(2.91)	(-6.16)
REGMFT: Standard deviation	338.5***	375.2***	672.8***
(t-ratio)	(-3.59)	(3.50)	(6.74)
REGIND: Mean WTP	552.4**	439.1	703.1**
(t-ratio)	(-2.38)	(-1.14)	(2.07)
REGIND: Standard deviation	125.3	890.5**	615.3***
(t-ratio)	(1.06)	(2.24)	(8.06)
REGLOC: Mean WTP	-432.9***	-1219.5***	-794.6***
(t-ratio)	(3.64)	(4.09)	(5.59)
REGLOC: Standard deviation	446.7***	100.7	1539.9***
(t-ratio)	(13.21)	(-1.09)	(6.06)
CATCH: Mean WTP	-	-33.7	-
(t-ratio)		(0.53)	
CATCH: Standard deviation	-	46*	-
(t-ratio)		(1.67)	
JOBS: Mean WTP	-	-	331.8***
(t-ratio)			(-6.15)
JOBS: Standard deviation	-	-	28.3
(t-ratio)			(0.56)
Log-likelihood (0)	-2206	-2206	-2214
Log-likelihood	-1450	-1447	-1512
AIC	2970	2983	3112
BIC	3166	3229	3358
McFadden's ρ^2	0.3426	0.3438	0.3173
Number of observations	2008	2008	2016
Number of parameters	35	44	44

4.2. Differences in WTP estimates across DCE versions

Table 4 provides statistical tests of differences in mean WTP across sub-samples (Poe et al., 2005). The high p-values (> 0.1) indicate that the differences in mean WTP for biomass improvement are not statistically significant across DCE versions. The same is the case for regulating industrial users (REGIND). In contrast, the welfare estimates associated with REGMFT vary significantly across sub-samples. Placing restrictions on the commercial fishers only (REGCOM) is associated with a higher estimated welfare loss in Treatment 1 and Treatment 2 relative to the base DCE. Stricter regulations on commercial fishers and local recreational anglers together (REGLOC) result in a significantly larger welfare loss estimate in Treatment 1 than in the base DCE. Altogether, these statistical tests provide moderate evidence of choice architecture impacts in our empirical context.

Table 4. Poe test results for differences in unconditional mean WTP across subsamples.

	(Base DCE – Treat. 1) p-value	**(Base DCE- Treat. 2) p-value**	**(Treat. 1- Treat. 2) p -value**
BIOMASS	0.824	0.176	0.533
REGCOM	**0.005**	**0.088**	0.206
REGMFT	**0.001**	**0.000**	**0.000**
REGIND	0.404	0.365	0.673
REGLOC	**0.016**	0.108	0.155

4.3. Conditional welfare estimates and value activation

To further examine variation in welfare estimates across the DCE designs, we regress the conditional WTPs extracted from the MIXL models on treatment indicators (DTREAT1 and DTREAT2), the personal value indices discussed in Section 3.2 (NEPR and PRODEV), interactions terms (DTREAT1 x NEPR and DTREAT2 x PRODEV), and a vector of respondent characteristics. Table 5 reports key results from pooled data regressions.[17]

We first discuss the results for the main DCE attribute, namely, BIOMASS. As can be seen, the estimated coefficient of 3.77 on DTREAT1 is marginally significant, suggesting that the respondents' valuation of improving the coastal cod stocks is higher when an environmental

[17] Table 5 omits details on the variables capturing respondent characteristics to maintain focus on the research questions related to choice architecture. Appendix C provides complete output. For example, the results for these variables suggest that WTP for biomass improvement is decreasing in age, lower for female respondents, increasing in education, and higher for those who live in Tromsø.

attribute (CATCH) explicitly represents the MFT industry development in the region. Furthermore, the conditional WTP increases with the NEPR score, meaning those with stronger pro-environmental values have a higher valuation of the BIOMASS attribute.

According to the value activation hypothesis proposed by Ungemach et al. (2018), we would expect that those who score higher on the NEPR index have higher WTPs in the Treatment 1 sub-sample relative to the other two sub-samples. However, the estimated coefficient on the interaction term (DTREAT1 x NEPR) is not statistically significant. Neither are the estimated coefficients associated with DTREAT2, PRODEV, and, most importantly, their interaction term (DTREAT2 x PRODEV). Hence, while we observe some indication of choice architecture impact on BIOMASS, we do not find statistical support of a "signpost effect" (i.e., value-activation) for this attribute.

When it comes to the regulatory framework categories, the results are mixed. For example, the conditional WTPs for regulating only one user group (REGCOM and REGMFT) or two user groups (REGIND and REGLOC) are lower in Treatment 1 as indicated by the negative and significant coefficients on DTREAT1. On the other hand, WTP for regulating one group is lower while WTP for regulating two groups is higher in Treatment 2, *ceteris paribus*. The sign and significance of the estimated coefficients on the two personal value indices are mixed and difficult to interpret. However, the interaction term DTREAT1 x NEPR is significant for all four regulatory framework categories, suggesting signpost effects. Higher NEPR scores are associated with lower welfare estimates from regulating one or two user groups instead of all user groups when an environmental attribute translation (CATCH) represents the MFT industry development. Furthermore, higher scores on either of the two personal value indices are associated with a higher valuation of new regulations targeting local commercial fishers and recreational anglers when the MFT industry development is explicitly controlled for, as seen by the positive and statistically significant coefficients on the interaction terms in the REGLOC regression. These results are consistent with the activation of pre-existing environmental and pro-development values, respectively, and generally support the hypothesis that variation in DCE design interventions can trigger signpost effects.

Table 5. OLS regression results for conditional WTP (NOK) estimates of all sub-samples (n=754).

	BIOMASS (t-value)	REGCOM (t-value)	REGMFT (t-value)	REGIND (t-value)	REGLOC (t-value)
Intercept	2.75 (0.61)	-161.39 (-0.84)	78.8 (0.53)	414*** (4.49)	378.95*** (3.58)
DTREAT1	3.77* (1.90)	-1029*** (-12.09)	-773.9*** (-11.68)	-79.44*** (-19.41)	-147.72*** (-3.14)
DTREAT2	2.45 (1.23)	-498.21*** (-5.84)	-347.28*** (-5.24)	1186*** (28.98)	116.7** (2.48)
NEPR	1.15*** (5.17)	-15.99* (-1.67)	15.28** (2.05)	4.92 (1.07)	8.7* (1.65)
PRODEV	0.003 (0.03)	11.51 (1.48)	14.46** (2.38)	-2.23 (-0.59)	-11.07*** (-2.58)
DTREAT1 x NEPR	0.04 (0.12)	-58.57*** (3.79)	-19.89* (-1.65)	-30.61*** (-4.12)	24.40*** (2.86)
DTREAT2 x PRODEV	0.06 (0.20)	-8.9 (-0.62)	-0.70 (-0.06)	-9.25 (-1.34)	18.31** (2.32)
RESPONDENT CHARACTERISTICS	YES	YES	YES	YES	YES
R^2	0.135	0.257	0.197	0.767	0.134
Adjusted R^2	0.115	0.240	0.178	0.761	0.114
F-statistic	6.763***	15.0***	10.64***	142.5***	6.74***

4.4. Choice of SQ and value activation

The SQ alternative is of particular interest in our application as it represents a scenario with no new regulations to support the sustainability of the coastal cod stocks. While the experimental treatments do not aim specifically to nudge respondents away from the status quo alternative, we do seek to test whether the propensity to select the lowest regulation level depends on whether the MFT industry development is explicit and how it is communicated. This examination is in the same spirit as Ungemach et al. (2018), who investigated the influence of different attribute translations and environmental value activation in the context of consumers' vehicle purchasing decisions.

Table 6 presents sub-sample frequencies for the selection of the SQ alternative. As seen in the first row, 38.3% of the respondents chose this alternative in the base DCE versus 36.9% in the treatment DCEs, a difference of 1.4 percentage points. However, this difference is not statistically significant according to the high p-values (> 0.1) from the Chi-square tests. The second row of the table reports equivalent analysis for the subset of choice tasks with alternative regulations suggesting an improvement of the biomass to at least the recommended level of 60 000 tons. Here, the SQ choice propensities are much lower in all sub-samples and substantially lower in the JOBS sub-sample than the other two sub-samples. This descriptive result suggests that the MFT employment attribute may bring more attention to the cod attribute.

Table 6. Selection of SQ alternative across sub-samples.

	Base DCE	Treatment 1 (CATCH)	Treatment 2 (JOBS)	Base DCE vs. Treat. 1	Base DCE vs. Treat. 2	Treat. 1 Vs. Treat. 2
All choice tasks	38.3%	36.9%	36.9%	P = 0.37	P = 0.38	P = 0.99
Tasks with a sustainable alternative	14%	13.4%	4.2%	P = 0.77	P = 0.00	P = 0.00

Next, we conduct an econometric exploration of the presence of choice architecture impacts on the probability of choosing SQ. Even though the sub-sample frequency statistics above suggest no difference across DCE designs, it is still possible that there are systematic differences at the respondent level. Relatedly, the above descriptive analysis does not inform value activation. We estimate a random intercept logit model for the pooled data since we have multiple observations for each respondent. As in the conditional WTP regressions, we include treatment indicators to test general choice architecture effects. However, the MFT attribute levels (CATCH or JOBS) can go in both directions in the alternatives to the SQ option. Therefore, we also add a dummy variable (DIMPROVE), indicating whether the regulation alternatives included a potentially welfare-improving change in the additional attribute, i.e., a lower number of cod caught by marine fishing tourists or more jobs in the industry. Again, the value activation hypothesis is tested through interaction terms between the treatment indicators and their associated value index. Table 7 reports the main results.[18]

Table 7. Random intercept logistic regression and logistic regression results for SQ choice probability in the pooled dataset (n=754).

Random effects	**Variance**	**Standard deviation**
Respondent	16.04	4.00
Choice task	0.05	0.23
Fixed effects	**Coefficient**	**t-value**
Intercept	-0.192	-0.20
DTREAT1	-0.143	-0.33
DTREAT2	0.064	0.15
DTREAT1 x DIMPROVE	-0.590**	-2.16
DTREAT2 x DIMPROVE	0.108	0.47
NEPR	-0.276***	-5.57
PRODEV	0.041	1.05
DTREAT1 x NEPR	-0.090	-1.16
DTREAT2 x PRODEV	-0.137*	-1.94
RESPONDENT CHARACTERISTICS	YES	
Number of observations	6032	
AIC	4515.7	
Pseudo R^2	0.439	

The negative and significant interaction between DIMPROVE and DTREAT1 indicates a lower probability of choosing the SQ option when the MFT industry development is expressed in environmental terms at the same time as the alternatives include a potential welfare improvement. Stronger environmental values also reduce the propensity to select the current regulatory scheme, as indicated by the negative and statistically significant coefficient on NEPR. However, the evidence for choice architectural activation of pre-existing values through translated attributes is weak. The negative interaction term between DTREAT1 and the NEPR index is insignificant, while the interaction between DTREAT2 and the PRODEV index is only marginally significant. The negative sign of the coefficient on the latter term implies that

[18] Results from the complete random effects model including socio-economic covariates can be found in Appendix D. For example, the propensity to choose SQ is increasing in age and higher for female respondents, while it is decreasing in education and household income.

respondents who score higher on the pro-development value index are less likely to choose the SQ option in Treatment 2.

5. Concluding remarks

This study set out to investigate four research questions: (1) What are the Arctic Norwegian population's preferences for improving the coastal cod stocks and managing their use by different stakeholders? (2) Are the welfare estimates context-specific or robust across choice architecture treatments? (3) Do choice architecture variations influence individual-specific WTPs and SQ choice probabilities? (4) Can attribute translations (i.e., signposts) activate pre-existing values in a marine ES valuation setting? The first question is empirically important for Arctic Norway and similar sparsely populated coastal regions worldwide facing tradeoffs between economic development and environmental protection. The second and third questions are methodological and relate to the validity and reliability of welfare estimates from SP studies. The fourth question is conceptual and addresses the relevance of emerging choice architecture insights from management science to nonmarket environmental valuation research.

Concerning the first research question, our MIXL analysis indicates that people in Arctic Norway place an economically significant value on the sustainable management of the coastal cod stocks. The lowest (highest) estimated mean annual household WTP for a 1000-ton improvement in the spawning biomass is NOK 4.2 (NOK 9.5). This estimate implies a yearly total WTP of NOK 190 (NOK 428) for going from the current biomass level of 15 000 to the sustainable level of 60 000 tons. Multiplying that welfare estimate with the approximately 35 000 households living in Arctic Norway yields a total annual value of NOK 6.65 million (NOK 15 million). However, the regulatory framework also matters. There appear to be positive preferences for stricter regulations of the MFT industry (either alone or together with the commercial fishing industry) and negative preferences for regulating commercial fishing by itself or along with local recreational angling. A caveat is that the analysis of the conditional welfare estimates extracted from the MIXL models suggests varying preferences for different regulatory configurations across DCE versions and respondents. Finally, the mean WTP estimates associated with the treatment attribute representing the MFT industry development in the region indicate welfare gains from new MFT jobs, while the welfare impact associated with the harvest by marine fishing tourists is insignificant.

Concerning the second research question, in line with previous studies of Caussade et al. (2005) and Meyerhoff et al. (2015), the mean unconditional WTP for improving the coastal cod spawning biomass from the MIXL models is statistically indistinguishable across DCE versions. However, the point estimate difference may still be significant in economic terms. Employing a mean WTP of NOK 4.2 (Base DCE) versus NOK 9.5 (Treatment 1) could alter the conclusion of a cost-benefit analysis and subsequent public management decisions. Furthermore, the analysis of the conditional WTPs indicates that Treatment 1 is associated with NOK 3.77 per 1000-ton higher valuation of an improvement in the spawning biomass relative to the base DCE. The welfare estimates for different regulatory configurations also vary significantly across DCE versions, i.e., depending on whether and how the MFT industry expansion is represented. A noteworthy finding is that there appears to be a welfare gain associated with regulating only the MFT industry in Treatment 2, while an implied welfare loss is associated with this regulatory category in Treatment 1. The latter may potentially be explained by the Treatment 1 respondents accounting for employment impacts even though these are not explicit in this DCE version.

Concerning the third research question, the average propensity to choose the status quo option does not seem to vary across DCE versions, unlike some previous findings (Zhang and Adamowicz, 2011; Rolfe and Windle, 2015). However, the analysis uncovered lower SQ propensity in Treatment 1 when the alternative management regimes reduce the coastal cod harvest by marine fishing tourists. In addition, the conditional WTPs vary across DCE versions and respondent characteristics. Treatment 1 is associated with consistently negative preferences for regulatory configurations that do not involve all three user groups. One possible explanation is that by explicitly quantifying and connecting the MFT industry to the shared natural resource (i.e., the coastal cod stocks), one may trigger egalitarian values congruent with the Scandinavian *allmennsrett tradition* (the right to open access) (see Søreng, 2007; 2008).

Concerning the last research question, our analysis provides no direct evidence for pre-existing value activation reflected in WTP estimates for the spawning biomass attribute. However, several significant interactions between treatment dummies and the personal value indices in the additional regression analyses are indicative of signpost effects, though their interpretations are not as straightforward as in Ungemach et al. (2018). At this point, we recommend that further investigations be undertaken in additional environmental valuation contexts to fully assess the relevance and usefulness of the proposed value activation (signpost) framework.

Overall, our study illustrates how preference expressions and welfare estimates may shift with different representations of the same phenomenon. While we refrain from advising public planners and policymakers on whether various environmental and socio-economic impact translations should be employed in marine ES valuation, our findings demonstrate the importance of incorporating ***experimental variation in the experimental design*** of DCEs. In general, SP researchers need to be cognizant of their role as choice architects. Not only should one consider the uncertainties associated with econometric model selection and statistical estimations. It is also pertinent to acknowledge implied "confidence bands" related to variation in the choice architecture of the valuation instruments.

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Appendices

Appendix A: Choice card example from each sub-sample

Base DCE
Which alternative do you prefer? [14]

	STATUS QUO	ALTERNATIVE 1	ALTERNATIVE 2
Spawning coastal cod biomass 	15 000 tons ¼ of the minimum level recommended	60 000 tons Recommended minimum level	80 000 tons 1/3 over the recommended minimum level
Stricter regulated user groups 	No change No new regulations	Commercial fishermen	Marine fishing tourism
Annual cost for your household 	0 NOK	500 NOK	2000 NOK

[14] All images have standard lisences- stock.adobe.com

Treatment 1: Environmental translation (CATCH) present.

Which alternative do you prefer?

	STATUS QUO	**ALTERNATIVE 1**	**ALTERNATIVE 2**
Spawning coastal cod biomass 	15 000 tons ¼ of the minimum level recommended	60 000 tons Recommended minimum level	80 000 tons 1/3 over the recommended minimum level
Stricter regulated user groups 	No change No new regulations	Commercial fishermen	Marine fishing tourism
Annual coastal cod harvest of marine fishing tourists 	No change (approximately 500000 per year)	125 000 <u>more</u>	125 000 <u>less</u>
Annual cost for your household 	0 NOK	500 NOK	2000 NOK

Treatment 2: Socio-economic translation (JOBS) present.

Which alternative do you prefer?

	STATUS QUO	ALTERNATIVE 1	ALTERNATIVE 2
Spawning coastal cod biomass 	15 000 tons ¼ of the minimum level recommended	60 000 tons Recommended minimum level	80 000 tons 1/3 over the recommended minimum level
Stricter regulated user groups 	No change No new regulations	Commercial fishermen	Marine fishing tourism
New jobs created in North Norway by MFT industry 	No change (approximately 1000)	250 more	250 less
Annual cost for your household 	0 NOK	500 NOK	2000 NOK

Appendix B: Value indices employed in the survey

B1. Pro-environment value index (NEPR index) adapted from Dunlap et al.'s (2000) NEPR scale (5 = strongly agree, 4 = agree, 3= unsure, 2= disagree, 1 = strongly disagree)

Do you agree or disagree with the following statements?
Humans have the right to modify the natural environment to suit their needs
When humans interfere with nature it often produces disastrous consequences
Human ingenuity will ensure that we do NOT make the earth unlivable
Humans are severely abusing the environment
The earth has plenty of natural resources if we just learn how to develop them
Plants and animals have as much right as humans to exist
The balance of nature is strong enough to cope with the impacts of modern industrial nations
If things continue on their present course, we will soon experience a major ecological catastrophe

B2. Pro-development index (PRODEV index) adapted from Choi and Sirakaya's (2005) Development of Sustainable Tourism Attitude scale (5 = strongly agree, 4 = agree, 3= unsure, 2= disagree, 1 = strongly disagree)

Do you agree or disagree with the following statements?
My quality of life has deteriorated because of tourism in my community
I believe the quality of environment in my community has deteriorated in my community because of tourism
Community recreational resources are overused by the tourists
Tourism grows too fast
I believe tourism is a strong economic contributor to the community
Tourism benefits other industries in communities
Tourism generates substantial tax revenues for the local government
I think tourism businesses should hire at least ½ of their employees within the local community

Appendix C: OLS regression on conditional WTP estimates

C1. List of variables employed in OLS regression on conditional WTP-estimates

Variable	
Age	Age of the respondent
Female	Dummy indicating gender
Education	Total years of education
Tromsø	Dummy indicating whether respondent is from Tromsø, where MFT is not as visible as other regions in North Norway.
Household income	Annual household income
Full-time employment	Dummy indicating full time employment
Recreational angler	Dummy indicating whether the respondent is a local recreational fisher
Knowledge on regulations	Self-reported knowledge level on regulations
Employment in MFT	Categorical variable indicating whether the respondent and/or the immediate family works within MFT industry
Employment in commercial fishing	Categorical variable indicating whether the respondent and/or the immediate family works within commercial fishing industry
NEPR	Centered NEPR score
PRODEV	Centered pro-development score
DTREAT1	Dummy indicating whether CATCH is present
DTREAT2	Dummy indicating whether JOBS is present
DTREAT1 x NEPR	Interaction indicating pre-existing pro-environmental value activation
DTREAT2 x PRODEV	Interaction indicating pre-existing pro-development value activation

C.2. Complete results of the OLS regression on conditional WTP estimates (n=754).

	BIOMASS (t-value)	REGCOMM (t-value)	REGMFT (t-value)	REGIND (t-value)	REGLOC (t-value)
Intercept	2.75 (0.61)	-161.39 (-0.84)	78.8 (0.53)	414*** (4.49)	378.9*** (3.58)
Age	-0.14*** (-2.64)	1.31 (0.56)	-5.07*** (2.83)	-1.83* (-1.65)	-0.87 (-0.68)
Female	-6.85*** (3.92)	231.71*** (3.09)	-79.32 (1.35)	21.04 (0.58)	-86.23** (-2.08)
Education	2.88 *** (3.85)	-116.0 *** (-3.61)	8.59 (0.34)	-22.20 (-1.43)	51.83*** (2.92)
Tromsø	4.36** (2.60)	-129.5* (-1.79)	-40.05 (-0.71)	-20.50 (-0.59)	81.2** (2.04)
Household income	0.37 (1.20)	-15.0 (-1.11)	6.85 (0.65)	2.91 (0.45)	3.05 (0.41)
Full-time employment	-0.06 (0.36)	60.72 (0.76)	75.09 (-1.21)	31.11 (0.81)	21.2 (0.48)
Recreational angler	-2.91 * (1.70)	20.43 (0.28)	-102.01* (-1.78)	-77.36 (-0.22)	27.5 (0.68)
Knowledge on regulations	2.77** (2.36)	-162.77*** (-3.23)	-86.57** (-2.21)	-31.40 (-1.29)	63.61** (2.29)
Employment in MFT	-2.05 (0.38)	126.40 (0.54)	178.0 (0.98)	109.59 (0.98)	-47.05 (-0.36)
Employment in commercial fishing	4.38 (1.12)	-248.05 (-1.48)	81.29 (0.62)	-68.7 (-0.85)	96.48 (1.04)
NEPR	1.15*** (5.17)	-15.99* (-1.67)	15.28** (2.05)	4.92 (1.07)	8.7* (1.65)
PRODEV	0.003 (0.03)	11.51 (1.48)	14.46** (2.38)	-2.23 (-0.59)	-11.07 *** (-2.58)
DTREAT1	3.77 * (1.90)	-1029*** (-12.09)	-773.9*** (-11.68)	-79.44*** (-19.41)	-147.72*** (-3.14)
DTREAT2	2.45 (1.23)	-498.21*** (-5.84)	-347.28*** (-5.24)	1186*** (28.98)	116.7** (2.48)
DTREAT1 x NEPR	0.04 (0.12)	-58.57*** (3.79)	-19.89* (-1.65)	-30.61*** (-4.12)	24.40*** (2.86)
DTREAT2 x PRODEV	0.06 (0.20)	-8.9 (-0.62)	-0.70 (-0.06)	-9.25 (-1.34)	18.31** (2.32)
R-squared	0.135	0.257	0.197	0.767	0.134
Adjusted R-squared	0.115	0.240	0.178	0.761	0.114
F-statistic	6.763***	15.0***	10.64***	142.5***	6.74***

Appendix D: Random-effects regression on SQ Choice probability

D1. List of variables employed in random-effects regression on the probability of choosing SQ

Variable	
Age	Age of the respondent
Female	Dummy indicating gender
Education	Total years of education
Tromsø	Dummy indicating whether respondent is from Tromsø, where MFT is not as visible as other regions in North Norway.
Household income	Annual household income
Full-time employment	Dummy indicating full time employment
Recreational angler	Dummy indicating whether the respondent is a local recreational fisher
Knowledge on regulations	Self-reported knowledge level on regulations
Employment in MFT	Categorical variable indicating whether the respondent and/or the immediate family works within MFT industry
Employment in commercial fishing	Categorical variable indicating whether the respondent and/or the immediate family works within commercial fishing industry
NEPR	Centered NEPR score
PRODEV	Centered pro-development score
HIGH_COST	Dummy indicating whether alternative 1 and alternative 2 present higher than average cost levels
DTREAT1	Dummy indicating whether CATCH is present
DTREAT2	Dummy indicating whether JOBS is present
DIMPROVE	Dummy indicating whether regulation alternatives offer an improvement from SQ in the means of less catch (environmental improvement) or more jobs (development improvement)
DTREAT1 x DIMPROVE	Interaction indicating whether choice probability of SQ changes if alternatives offer an improvement in CATCH
DTREAT2 x DIMPROVE	Interaction indicating whether choice probability of SQ changes if alternatives offer an improvement in JOBS
DTREAT1 x NEPR	Interaction indicating pre-existing pro-environmental value activation
DTREAT2 x PRODEV	Interaction indicating pre-existing pro-development value activation

D.2. Complete results of the random intercept logit model for selecting the SQ alternative.

Random effects	**Variance**	**SD**
Respondent	16.04	4.00
Choice task	0.05	0.23
Fixed effects	**Coefficient**	**t-value**
Intercept	-0.192	-0.20
Age	0.029**	2.52
Female	1.552***	4.07
Education	-0.732***	-4.45
Tromsø	-0.188	-0.52
Household income	-0.136**	-0.202
Full-time employment	0.558	1.41
Recreational angler	0.143	0.38
Knowledge on regulations	-0.965***	-3.76
Employment in MFT	-0.237	-0.21
Employment in commercial fishing	-1.643*	-1.94
NEPR	-0.276***	-5.67
PRODEV	0.041	1.05
HIGH_COST	0.625***	4.96
DTREAT1	-0.143	-0.33
DTREAT2	0.064	0.15
DTREAT1 x DIMPROVE	-0.590**	-2.16
DTREAT2 x DIMRPOVE	0.108	0.47
DTREAT1 x NEPR	-0.090	-1.16
DTREAT2 x PRODEV	-0.137*	-1.94
Number of obs	6032	
AIC	4515.7	
Pseudo R^2	0.439	

Estimating the socially optimal fish stock: Incorporating society's prioritization of ecosystem services

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Abstract

Standard optimization procedures in fisheries management often neglect non-market benefits and society's prioritization of various ecosystem services (ES), which can lead to underestimation and overexploitation of resources. Our study expands the commonly applied bio-economic models by integrating non-market benefits and society's priority weights associated with a public good in the dynamic optimization process. For our applied analysis, we examine the case of coastal cod stocks in Arctic Norway, which provides an interesting background as the stocks are utilized by multiple stakeholders and face increasing pressure. We estimate several models, expanding gradually from standard applications to the inclusion of non-market benefits and weighting parameters. The findings indicate that while the socially optimum stock level does not shift greatly across models, total economic value (TEV) varies significantly, which can significantly influence the policy-making process.

Keywords: optimization, coastal cod, choice modeling, marine, ecosystem services.
JEL codes: C61, Q22, Q26, Q58, C35

1. Introduction

Global demand for fish and fish products has been rising in recent decades (Kobayashi et al., 2015). However, as the marine and coastal ecosystem services (ES) are under increasing pressure from coastal development, nutrient loadings, climate change, and overfishing, it is unclear if marine fisheries can satisfy the demand even with the expanding aquaculture production (Alcomo et al., 2005; Timmermann et al., 2014). Considering the intensified burden these anthropogenic factors place on marine and coastal ES, efficient management of fisheries has become crucial for ensuring the flow of these ES.

Fisheries management accommodates intertwined environmental, social, economic, and political aspects, involving several stakeholder groups engaged in extractive and non-extractive ecosystem services (ES) (Chambers and Kokorsch, 2017; Ruiz-Frau et al., 2015). For example, while commercial and recreational fishers exploit provisioning and cultural marine ES, respectively, by obtaining benefits from the direct use of a fish stock, society overall may derive non-use benefits from the same stock for its mere existence. As the exploitation of fisheries advances, the competition for various ES among their respective stakeholders escalates. Therefore, there is often a trade-off concerning different stakeholders, creating winners and losers (Jentoft, 2017; Rodriguez et al., 2006). However, the multifaceted benefits of marine ES create a further dimension in the management regarding the quantification of stakeholder benefits for determining the trade-offs since they require different valuation methods. The commercial value of fisheries is relatively straightforward to obtain, as the market prices of extracted resources facilitate the benefit estimation. In contrast, estimating the recreational use values and non-use values require non-market valuation techniques. These use and non-use values are both vital for sustainable management of fisheries since they make up the total economic value (TEV) of the fishery (Costanza et al. 1997; Turner and Schaafsma, 2015).

Traditional fishery management procedures often focus on commercial profit maximization and overlook or underrepresent the external, non-market benefits that society receives from marine goods and services (Pascoe et al., 2018; Squires and Vestergaard, 2016). However, the explicit inclusion of all stakeholders makes values intrinsic to ES, and the ES framework provides a way to assess trade-offs among different stakeholders, regardless of whether their benefits are monetized or not (Brauman et al., 2007). Therefore, this indifference toward society's non-market benefits is troublesome, as it may lead to the underestimation of TEV of the fishery and therefore cause overexploitation and degradation (Beaumont et al. 2008). Within this perspective, policymakers have started to recognize fisheries as an integrated part of the marine environment, and their focus has shifted from solely maximizing economic rents to optimizing the sustainable use of marine resources by society (Kronbak et al. 2014), accounting for the benefits of a larger group of stakeholders.

In line with the increased interest in producing socially optimal solutions, novel efforts have been made to incorporate non-market values alongside commercial values in bioeconomic optimization studies. For example, Bulte et al. (1998) build a dynamic optimization model for minke whales in the Northeast Atlantic and demonstrate that the status-quo is suboptimal and a moratorium on harvesting is economically efficient by incorporating non-use benefits in a separable fashion. In a follow-up study, Bulte and Van Kooten (1999) argue that the policy decision between harvesting or conserving the minke whales is highly dependent on the willingness-to-pay (WTP) for conserving the stock fed into the bioeconomic model.

In addition to the former research focusing on socially optimal use of a particular stock, few studies also seek optimal management regimes for habitat-fishery interactions by involving both commercial and non-market benefits. Barbier and Strand (1998) and Barbier (2000) set up a bioeconomic model for maximizing the benefits from the commercial shrimp fisheries, where the non-market value of support function between shrimp production and mangrove forests enters as an input in the optimization procedure. Correspondingly, these applications obtain indirect use-values, as well as direct use-values of the habitats. Further expanding the approach of accounting for direct and indirect uses of public goods, non-market valuation has witnessed an increased prevalence of discrete choice experiments (DCE), which enable elicitation of both use and non-use values in various policy settings through multiple attributes. Armstrong et al. (2017) present the first application of integrating non-use values from a DCE study in a dynamic optimization model and examine the interaction between cold-water corals and cod stocks in the Northeast Arctic. Their theoretical model is further extended by Xuan and Armstrong (2019) to investigate the trade-off between fisheries and tourism in the case of introducing a marine protected area (MPA) in Khanh Hoa province in Vietnam.

Based on Armstrong et al. (2017) and Xuan and Armstrong (2019), this study develops a dynamic bioeconomic fishery framework for estimating the socially optimal coastal cod biomass, which incorporates both non-use values deriving from a DCE and the benefits of coastal commercial fishers and recreational anglers. Our bioeconomic framework examines the case of Arctic Norwegian coastal cod stock as it provides an interesting background, where multiple stakeholders extracting both use and non-use benefits from a marine ES under pressure. The DCE survey tool we employ not only informs on the local population's WTP for improving the coastal cod stocks but also provides their position regarding the distribution of the stock among different stakeholders and conservation. Therefore, while it enables us to feed the often-neglected non-use values into the system, it expands the former studies combining bio-economic models and stated preferences by comparing the optimal biomass based on society's standpoint and the current situation. Accordingly, our primary contribution to the existing literature is estimating a critical marine ES's socially optimal level by incorporating both non-use values and the regional population's prioritization of stakeholders in a dynamic bioeconomic optimization model. Specifically, we address whether the inclusion of non-use values and the local population's weighting of various ES and the corresponding stakeholders result in different socially optimal stock levels.

The article is organized as follows: We first describe the dynamic bioeconomic model for optimal management of coastal cod fisheries and DCE framework and continue with the details regarding the case study of Northern Norway and the DCE. Thereafter, we move on to the analyses and conclusions.

2. Background

The coast of Northern Norway has been recognized as a major cod spawning area since the ninth century, where coastal cod remains an essential species within the vital economic activity of coastal fishing to this day (Sundby and Nakken, 2008; West and Hovelsrud, 2010).

The coastal cod above 67°N constitutes the Northern Norwegian coastal cod. The stock provides a wide range of ES in the region. Concerning the exploitation-based ES, the primary stakeholder is the commercial fishing industry, with an estimated average annual harvest of 43 000 tons between 2013-2018 (ICES, 2013:2018). Recreational fishers also take a significant share, particularly in the fjords where commercial fishing activity is low (ICES, 2020), as fishing is common among the local population (Aas and Skurdal, 1996). In addition to these two traditional main stakeholders, there is also a growing marine fishing tourism (MFT) industry since the 1990s, following the government's efforts to make Northern Norway a major fishing tourism destination (Borch, 2009). While there are no official statistics of coastal cod harvest taken by non-commercial users, the combined catch of recreational fishers and MFT is suggested to be approximately 12 700 tons per year (ICES, 2020). Considering similar fishing motivations and lack of data for these two stakeholders, we examine them as "recreational users" from here on. In addition to these extractive commercial and recreational ES, the stock also provides non-use benefits. Some people may benefit from its mere existence, which is investigated within *bequest and existence values*.

While the total allowable catch (TAC) was 40 000 tons per year between 1977-2003, it was reduced to 20 000 tons in 2004 with rebuilding considerations (Aglen et al., 2020). As of 2021, TAC is 21 000 tons per year, with no separate quotas for different vessels. Accordingly, a major challenge in the stock management is bycatch within the Northeast Atlantic cod fishery, which is reflected in catch by gear statistics. For example, the trawlers had a total coastal cod landing of approximately 5 000 tons in 2020, roughly corresponding to ¼ of the TAC (ICES, 2021).

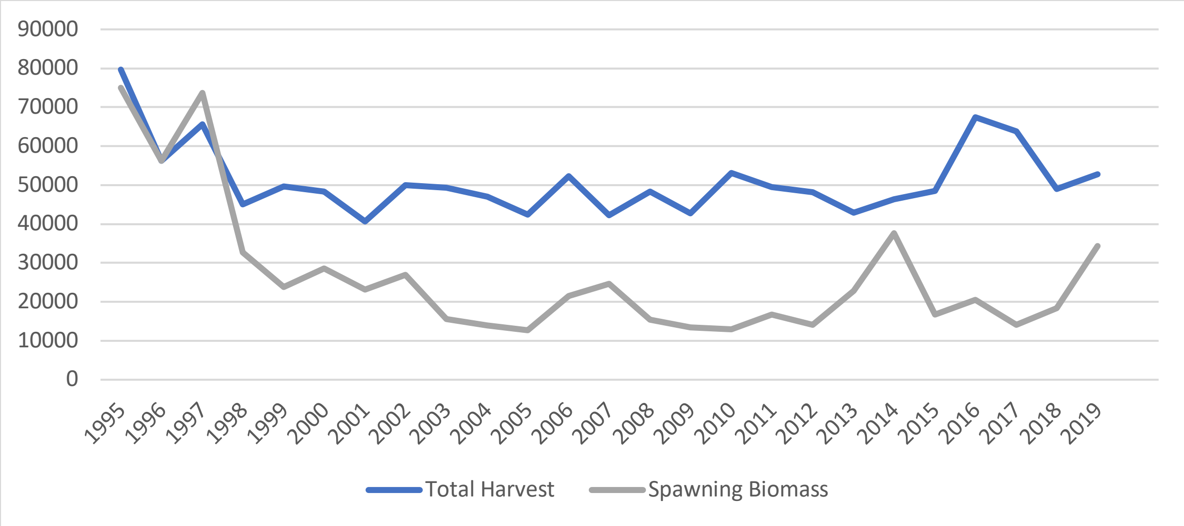

Figure 1. Total harvest and acoustic survey index for coastal cod spawning biomass 67°N between years 1995-2019, based on data from ICES (2020).[1]

Figure 1 illustrates the combined commercial and recreational harvest and acoustic survey indices regarding coastal cod spawning biomass during the period 1995-2019. The presented data indicates a steep reduction in the spawning biomass since the late 1990s. Furthermore, the numbers indicate that the spawning biomass is constantly lower than the estimated harvest, highlighting the need for recovery plans to ensure the stock's sustainability (ICES 2013:2020).

Considering this decline, the Norwegian Ministry of Fisheries and Coastal Affairs introduced in 2010 a rebuilding plan for coastal cod north of 67°N, which aims to raise the survey index of spawning coastal cod to above 60 000 tons for two successive years by drastically reducing the fishing mortality (ICES, 2018). However, after ten years of being in effect, the results of the plan do not meet the target. As Figure 1 indicates, the recent index values for spawning biomass are well below the target of 60 000 tons, which has raised calls for more efficient sustainable management interventions.

Therefore, following the most recent estimations of the spawning stock and harvest levels, the ICES advice on the stock has been changed to not harvesting the coastal cod above 67°N at all (ICES, 2021). Furthermore, given the poor condition of the stock, Norwegian coastal cod lost

[1] We present the acoustic survey indices as they form the basis of the rebuilding plan introduced by Norwegian Ministry of Fisheries and Coastal Affairs. However, catch-based VPA analysis provide larger biomass estimates with a similar trend. For more details, please see ICES (2018:2020).

its Marine Stewardship Certificate (MSC) in effect from August 2021[2], which may have major repercussions in the market.

3. Methods

3.1. A bioeconomic model of coastal cod fishery

Our bioeconomic model builds on the previous work of Armstrong et al. (2017). However, while Armstrong et al. (2017) investigates the interaction between the Northeast Arctic cod fishery and cold-water coral habitat through use and non-use values, we optimize social welfare obtained from a single stock. Furthermore, our model extends Armstrong et al. (2017) by accounting for distributional issues among different stakeholders.

The generalized model assumes a two-user system, where commercial and recreational fishers harvest the renewable stock of coastal cod. We employ standard profit functions to estimate the net benefits of harvesting cod for commercial and recreational fishers. The economic value of coastal cod harvest for the commercial fleet is represented by exogenous price p_c obtained from market data. The unit value of recreational harvest, p_R, on the other hand, involves both market and non-market benefits, which we will describe in detail in the next section. Accordingly, $c_C(x)$ and $c_R(x)$ represent the unit cost of harvesting coastal cod for commercial and recreational fishers, respectively. Both users' unit harvest costs are dependent on stock size x, so that $c_{cx} < 0$, $c_{Rx} < 0$, $c_{cxx} > 0$, and $c_{Rxx} > 0$ (Clark, 2010).

The harvest of the commercial fleet and recreational anglers is h_C and h_R, respectively. The resource manager aims to achieve optimum levels of stock and harvest, which maximize the present value of net benefit stemming from the stock regarding the distribution among three ES; commercial use, recreational use and conservation (i.e., non-use). Let $Rec(x)$ be the net benefit of recreational fishers, and $Com(x)$ be the net benefit of commercial fishers. Correspondingly, the objective function of the optimal control problem becomes:

$$NPV = \int_0^\infty e^{-\delta t} \{(p_C - c_C(x))h_C + (p_R - c_R(x))h_R\}dt \quad \text{s.t.,} \tag{1}$$

$$\dot{x} = F(x) - h_C - h_R \tag{2}$$

[2] "*Norway's inshore cod fishery to lose MSC stamp in August*" https://www.intrafish.com/fisheries/norways-inshore-cod-fishery-to-lose-msc-stamp-in-august/2-1-1032894?utm_source=emailsharing

$$x(t) > 0 \tag{3}$$

where δ is the social rate of discount and $F(x)$ is the natural growth of the stock. Consequently, the Hamiltonian for the maximization problem becomes:

$$H = e^{-\delta t}\{(p_C - c_C(x))h_C + (p_R - c_R(x))h_R)\} + \lambda(F(x) - h_C - h_R) \tag{4}$$

We treat h_C and h_R as control variables, whereas the multiplier λ denotes the shadow price for the state variable, the coastal cod stock (x).[3] The unit harvest cost for commercial and recreational fishers are both a function of stock level x, and catchability q, such that $c_c(x) = \frac{\mu c_c}{q_c x}$, and $c_R(x) = \frac{\mu c_R}{q_R x}$, where μc_C and μc_R reflect the cost of effort for these two uses. Accordingly, first order necessary conditions are:

$$\frac{\partial H}{\partial h_C} = e^{-\delta t}\{(p_C - c_C(x))\} - \lambda = 0 \tag{5}$$

$$\frac{\partial H}{\partial h_R} = e^{-\delta t}\{(p_R - c_R(x))\} - \lambda = 0 \tag{6}$$

The maximization problem presented in equations $(1) - (6)$ depends on the relationship between the commercial and recreational users from harvesting the stock x. If the benefit of commercial and recreational users is equal (i.e., $Com(x) = Rec(x)$), the optimization problem becomes unsolvable as there is only one state variable, as seen in equations (5) and (6).

The maximization problem arrives at a corner solution in the more realistic scenario of one user extracting more benefit than the other. For example, if $Com(x) > Rec(x)$, the recreational harvest h_R becomes 0, and commercial users take all harvest such that $h^* = h_C$. Likewise, if $Rec(x) > Com(x)$ for all values of x, this would imply it is economically optimal to allocate the whole harvest to the recreational users, and optimal harvest becomes $h^* = h_R$. However, the recreational users' maximum harvest capacity $h_{R,max}$ may not meet the level h^*. In this case, the natural growth of the stock $F(x)$ surpasses $h_{R,max}$ as it is below h^* that is required to keep the growth of stock at the steady state, and the system becomes unstable. Therefore, when

[3] Another candidate for control variable is the fishing effort. However, as we are interested in distributional issues regarding the stock, we prefer to base the estimate on the harvest levels of different stakeholders.

$h_{R,max} < h^*$, the resource manager's optimization problem becomes the determination of an optimum harvest level h_C^* for commercial fishers, given that recreational fishers harvest at rate $h_{R,max}$ (Bishop and Samples, 1980; Clark, 2010).

Our application of the presented framework to the Northern Norwegian coastal cod fishery illustrates a situation where recreational users' benefit greatly surpasses the commercial fishers' benefit for all values of x, i.e. $Rec(x) > Com(x)$, and the optimal harvest is lower than the maximum recreational harvest, i.e., $h_{R,max} < h^*$. Furthermore, we expand our bioeconomic model in equation (1) by accounting for non-use values $V(x)$ for obtaining the total economic value of the fishery.[2] We identify the weighting parameters α, γ, and θ for expressing society's prioritization of the use and non-use benefits. Employing these weighting parameters accommodates model flexibility for investigating various distributional scenarios, as an increased weight for one stakeholder inevitably means lower priority for at least one of the other two stakeholders, and vice versa. Given the application and these extensions, the maximization problem and corresponding Hamiltonian presented in equations (1) – (4) become:

$$NPV = \int_0^\infty e^{-\delta t} \left\{\alpha(p_C - c_C(x))h_C + \gamma(p_R - c_R(x))h_{R,max} + \theta V(x)\right\}dt \quad \text{s.t.,} \tag{7}$$

$$\dot{x} = F(x) - h_C - h_{R,max} \tag{8}$$

$$x(t) > 0 \tag{9}$$

$$H = e^{-\delta t}\left\{\alpha(p_C - c_C(x))h_C + \gamma(p_R - c_R(x))h_{R,max} + \theta V(x)\right\} + \lambda(F(x) - h_C - h_{R,max}) \tag{10}$$

where $h_{R,max} < F(x)$. As the optimization problem reduces to choosing only h_C, the first order necessary condition and adjoint function are as in equations (11) and (12), respectively:

$$\frac{\partial H}{\partial h_C} = e^{-\delta t}\{(p_C - c_C(x))\} - \lambda = 0 \tag{11}$$

$$\frac{d\lambda}{dt} = -\frac{\partial H}{\partial x} = -\left[e^{-\delta t}\left\{-\alpha c_{Cx} h_C - \gamma c_{Rx} h_{R,max} + \theta V_x + F_x\big(\alpha(p_C - c_C(x))\big)\right\}\right] \tag{12}$$

[2] The estimation of non-use value V(x) is conducted separately, using a DCE, which we describe later.

Concerning the stock growth, we assume a Pearl-Verhulst logistic growth model as in equation (13):

$$F(x) = rx(1 - \frac{x}{K}) \tag{13}$$

where K is the carrying capacity of the coastal cod stock and r is the intrinsic growth rate. Solving the system of equations presented delivers the Golden Rule, which specifies an economically optimal equilibrium biomass level x^*, and a corresponding level of harvest h_C^* (Clark, 2010), as in equation (14):

$$F_x + \frac{\theta V_x - \gamma c_{Rx} h_{R,max} - \alpha c_{Cx}(F(x) + h_{R,max})}{\alpha\big(p_C - c_C(x)\big)} = \delta \tag{14}$$

Here, the marginal productivity of the stock is equal to the discount rate δ, where the resource manager is indifferent toward harvesting or conserving the stock. Different from standard natural resource optimization applications, the marginal productivity in equation (14) involves both market and non-market use values, along with the non-use values.

3.2. Estimation of non-use values

Estimation of choice models is typically performed by employing random utility theory (RUT). According to RUT, two elements compose the individual's total utility (U): systematic component V, which is observable and can be estimated, and stochastic component ε (McFadden, 1973; Train, 2009). In this view, separable in monetary and non-monetary attributes, individual *n*'s total utility obtained from alternative *j* in choice occasion *t* is expressed as:

$$U_{njt} = \alpha_n p_{njt} + b_n x_{njt} + \varepsilon_{njt} \tag{15}$$

where p_{njt} is the cost attribute, x_{njt} is the vector of non-cost attributes, ε_{njt} is the error term, and α_n and b_n are the taste parameters for cost and non-cost attributes, respectively. The utility from cost and non-cost attributes forms the systematic part of utility such that $V_{njt} = \alpha_n p_{njt} + b_n x_{njt}$. The WTP for non-cost attributes is often obtained by the ratio of the non-cost attribute to the cost attribute. However, this application may lead to extreme values and unrealistic distributions of the WTP (Sonnier et al., 2007). To avoid such problems, the utility can be specified in the WTP-space for obtaining the WTP values directly (Train and Weeks, 2005):

$$U_{njt} = \alpha_n(p_{njt} + \beta_n x_{njt}) + \varepsilon_{njt} \tag{16}$$

In equation (16), $\beta_n = b_n/\alpha_n$ expresses the welfare deriving from the vector of attributes x_{njt}. In line with RUT, the individual n chooses alternative i in choice occasion t if $U_{nit} > U_{njt}$ for all $i \neq j$. Therefore, the probability of choosing alternative *i* in can be expressed by the logit probability (McFadden, 1973), as in equation (17):

$$\Pr\left(Y_n = i|\beta_n\right) = \frac{\exp\left(V_{nit}\right)}{\sum_J \exp\left(V_{njt}\right)} \tag{17}$$

The logit model above assumes homogeneous preferences by estimation of fixed parameters. To introduce heterogeneity among individuals, one can employ the mixed logit model (MIXL), which accommodates taste heterogeneity among individuals through random parameters approximating various distributions and estimating the full covariance matrix. In this case, the unconditional probability of observing the sequence of choices Y_n becomes the integral of $\Pr(Y_n|\,\beta_n\,)$ over all values of β_n weighted by its density (Train, 2001):

$$\Pr_n(Y_n) = \int \Pr(Y_n|\,\beta_n\,)\, \mathrm{g}(\beta_n|m,\Omega)d\beta_n \tag{18}$$

Here, β_n is the vector of jointly distributed marginal WTP estimates according to $\mathrm{g}(\beta_n|m,\Omega)$, where m and Ω express the mean and variance of this distribution. As the integral in equation (18) does not have a closed-form solution, the log-likelihood is approximated by simulation (Train, 2009). Conducting the Hierarchical Bayes (HB) simulation, the probability becomes:

$$\Lambda(\beta_n|m,\Omega) \propto \prod_n \Pr(Y_n|\,\beta_n\,)\ \mathrm{g}(\beta_n|m,\Omega) \tag{19}$$

Based on (19), the information on the posterior is obtained by taking draws from the posterior and calculating the moments over these draws (Scarpa et al., 2008).

Our model assumes all non-cost attributes follow a multivariate normal distribution to accommodate both welfare gain and loss from the changes in attribute levels. In line with microeconomic theory, we specify the negative of the COST parameter to be log-normally distributed to ensure that all respondents have welfare loss from an increase in COST. We employ 1 000 000 burn-in iterations, followed by 100 000 draws from the posterior for HB estimation. The specification imposes normal diffuse priors on m, such that it is distributed normally with $N(m|\,0,\theta)$, while the priors for the covariance matrix Ω derive from Hierarchical Inverse Wishart (Huang and Wand, 2013).

We estimate all coefficients except for SQ and COST in WTP-space. In order to obtain WTP for each level, the BIOMASS attribute enters the estimation in a piece-wise fashion, where the SQ level of BIOMASS is the reference. Similarly, the NEW_REG attribute indicating different regulated user group configurations is estimated by employing dummy variables, each representing the welfare in reference to REG_ALL, where every user group faces new, stricter regulations.

Subsequently, following Armstrong et al. (2017), we employ these WTP estimates for BIOMASS[3] and specify a non-linear, non-use value function. However, as the respondents' WTP in the survey is not for improving the total biomass but for improving the spawning biomass index, we adjust the levels such that the WTPs correspond to total biomass levels of 200 000, 400 000, 600 000, and 800 000 tonnes since the spawning biomass index is approximately 10% of the total coastal cod biomass in the region according to VPA estimates (ICES 2017; 2018; 2020).

4. Empirical application: Coastal cod fishery in Arctic Norway

4.1. DCE Data

We utilize a DCE survey conducted on Northern Norwegian households for obtaining the non-use values associated with the coastal cod stocks. The main objective of the employed survey is to study the regional population's trade-off between conservation and use of coastal cod stocks, with a focus on the sustainability of the coastal cod. To address this issue, the DCE presents the following attributes: *(1) spawning coastal cod biomass as an indicator for the health of the coastal cod stocks, (2) different configurations of stricter regulations on three*

[3] We employ the WTP for all levels of BIOMASS, including SQ, which we assume to be 0, as it is free of charge.

main user groups; commercial fishers, local recreational anglers, and marine fishing tourism, and *(3) change in annual cost in the form of a household tax.*

The rationale for using the level of spawning biomass instead of total biomass for indicating the stock status is that the current regulatory regime for improving the stock condition targets raising spawning coastal cod biomass indices to 60 000 for two subsequent years (ICES, 2018; 2020).

Table 1. Attributes and levels employed in the DCE

Attribute	Levels
Spawning coastal cod biomass (in tons) (BIOMASS)	15 000 tonnes (SQ) 20 000 tonnes 40 000 tonnes 60 000 tonnes 80 000 tonnes
Stricter regulatory framework focusing on different user groups (NEW_REG)	No new stricter regulations (SQ) Only commercial fishermen (REG_COM) Only marine fishing tourism (REG_MFT) Commercial fishermen and recreational anglers (REG_LOC) Commercial fishermen and MFT (REG_IND) All user groups (REG_ALL)
Annual household tax (COST)	0 NOK (SQ) 500 NOK 1000 NOK 1500 NOK 2000 NOK 3000 NOK

In the status quo (SQ) alternative, the spawning biomass (BIOMASS) remains the same, there are no new regulations (NEW_REG), and the corresponding tax increase (COST) are introduced for managing the stock. Alternative 1 and Alternative 2, however, offer improvement on the current situation through an annual increase in the household tax. We inform the respondents that to achieve the target biomass level, one or more user groups are to face new regulations, and by DCE design, the coastal cod spawning biomass improvement always comes at the expense of the regulated groups' harvest. Therefore, the trade-offs that favor increasing the stock level highlight the non-use (i.e., conservation) values.

Figure 2. Example choice card.[4]

<table>
<tr><th></th><th>STATUS QUO</th><th>ALTERNATIVE 1</th><th>ALTERNATIVE 2</th></tr>
<tr><td>Coastal cod spawning biomass
</td><td>15 000 tonnes

¼ of the minimum level recommended</td><td>60 000 tonnes

Recommended minimum level</td><td>80 000 tonnes

1/3 over the recommended minimum level</td></tr>
<tr><td>Stricter regulated user groups
</td><td>No change

No new regulations</td><td>Commercial fishermen</td><td>Marine fishing tourism</td></tr>
<tr><td>Annual cost for your household

</td><td>0 NOK</td><td>500 NOK</td><td>2000 NOK</td></tr>
</table>

Following a pilot study with 100 respondents, the final DCE was generated using a Bayesian efficient design[5] and launched in December 2019 through a pre-recruited household panel company.[6] In the final version of the survey, each respondent received eight choice cards. The data collection yielded 251 responses, generating 2008 observations in total, with a response rate of 26%. Table 2 illustrates the socio-demographic background of the sample.

[4] Standard licensed visuals from stock.adobe.com
[5] Both the pilot and final design are generated using the NGene software (Choicemetrics, 2014).
[6] https://norstat.no/

Table 2. Socio-demographics of the sample and population.

	Survey sample (n=251)
Female	47%
Age	47.1
Bachelor's degree or higher	41.8%
Employed full-time	48.6%
Employed part-time	12.3%
Student	8.7%
Personal income NOK 300 000-400 000	11.1%
Personal income NOK 400 000-500 000	21.1%
Personal income NOK 500 000-600 000	15.5%
Personal income above NOK 600 000	19.1%
Recreational fishers	41%

4.2. Ecologic and non-choice economic data

Table 3 presents the economic and ecological data employed for the optimization. Our data sources consist of primary data obtained from the DCE survey and secondary data from the Norwegian Directorate of Fisheries, ICES, and former research.

Table 3. Data applied in bioeconomic model of coastal cod.

Parameter	Measure	Unit	Explanation/Source
$\boldsymbol{\delta}$	0.05		Vondolia et al. 2020
$\boldsymbol{r}$	0.5		Vondolia et al. 2020
K	1 200 000	Tons	Estimated from ICES (2014:2020)[7]
$\boldsymbol{q_c}$	0.000132		Estimated using reports of Norwegian Directorate of Fisheries (2014, 2015, 2016, 2017, 2018)
$\boldsymbol{p_C}$	17 377	NOK/Tons	Norwegian Fishermen's Sales Organization (2018)
$\boldsymbol{\mu c_C}$	12 826	NOK	Estimated using reports of Norwegian Directorate of Fisheries (2014, 2015, 2016, 2017, 2018)
$\boldsymbol{\alpha}$	0.56		Priority weight attached to commercial use Obtained from DCE survey
$\boldsymbol{\gamma}$	0.26		Priority weight attached to recreational use Obtained from DCE survey
$\boldsymbol{\theta}$	0.18		Priority weight attached to non-use value Obtained from DCE survey
$\boldsymbol{q_R}$	8.50785e-08		Estimated from ICES (2020)
$\boldsymbol{p_R}$	81 020	NOK/Tons	Estimated by employing the average retail cod fillet prices and recreational value of fishing trip by Carlén et al. (2019)
$\boldsymbol{h_{R,max}}$	12 700	Tons	ICES (2014:2020)
$\boldsymbol{\mu c_R}$	16 510	NOK	Estimated from ICES (2020) and Hyder et al. (2018)
HH	2 409 257		Number of households in Norway as of 2018 (SSB, 2020)[8]

We estimate the commercial fishers' net benefit by employing available secondary market data. However, recreational fishers' benefit involves both market and non-market values, as the recreational fishing in Norway has a harvest-oriented, subsistence-like character due to its historical link to livelihood (Aas and Kaltenborn, 1995). Therefore, we sum the market and non-market values of recreational fishing for reflecting both aspects of recreational fishers' benefit. For obtaining a proxy market value for recreational fishing, we average the 2018 retail prices for cod fillet in various Norwegian retail chains. Next, we employ the Norwegian Directorate of Fisheries' conversion factor for obtaining the market value of the recreationally harvested cod, which results in a per kg benefit of NOK 72.6.

[7] Given that the coastal fishery in Arctic Norway has been exploited for almost 1000 years, it is difficult to determine the carrying capacity when there is no fishing activity (Diekert et al., 2010). As the current regulations aim to reach 60 000-ton spawning biomass in the survey index, we estimate the target MSY to be 600 000 tons from the relationship between survey index and total biomass over the years, which yields a corresponding carrying capacity of 1 200 000 tons. In a recent work, Vondolia et al. (2020) employs a K of 596 250 tons, based on Kahui et al.'s (2016) estimation for NEA cod carrying capacity of 4.5 million tons.

[8] https://www.ssb.no/en/statbank/table/09747/

Regarding the non-market value of the fishing trip, we apply a simple value transfer based on the former work of Carlén et al. (2019), which studies the recreational fishing trip value in Sweden. Adjusting their findings for Norwegian prices, we estimate the non-market value of recreational fishing to be NOK 151.3 per trip. Given the average per trip coastal cod harvest of 17.6 kg indicated by our survey respondents, the non-market value becomes NOK 8.6 per kg catch. Summing up these market and non-market values, we obtain a total benefit of NOK 81.02 per kg catch. As the current regulatory framework does not restrict recreational harvest, we employ the estimated annual harvest of 12 700 tons (ICES, 2017; 2018; 2020) as the maximum recreational harvest.[9]

The prioritization weights α, γ and θ derive from a non-choice question of the DCE survey. We ask the respondents to distribute the coastal cod stock among commercial, recreational, and non-use motived ES such that the weights sum up to 1. The respondents' ranking of these ES provides the weights of 0.56, 0.26, and 0.18 for commercial, recreational, and non-use benefits, respectively.

5. Analysis

5.1. HB MIXL estimation

Table 4 presents the results of the HB MIXL estimation. Overall, the findings indicate that the average respondent favors enforcement of new, stricter regulations for sustainable management of coastal cod stocks, as reflected by the SQ coefficient's negative sign. However, except for regulating only the MFT industry, the respondents associate introducing new, stricter regulations only for some users with a loss in benefits, as the negative sign on REG_COM, REG_LOC, and REG_IND coefficients reveal. This pattern implies that the respondents would rather regulate all users in a stricter fashion instead of singling out these user configurations since all users face new, stricter regulations in the reference level (REG_ALL).

[9] The amount estimated by ICES accounts both for local recreational fishers' and marine fishing tourists' coastal cod harvest.

Table 4. Results of Hierarchical Bayes MIXL estimation in WTP-space.[10]

Coefficients in preference-space	**Posterior Mean (s.e.)**	**Standard Deviation (s.e.)**
SQ	-2.510	0.757
	(0.119)	(0.068)
COST	-0.112	0.287
	(0.038)	(0.030)
Coefficients in WTP-space (in 1000 NOK)	**Posterior Mean (s.e.)**	**Standard Deviation (s.e.)**
BIOMASS_20	0.074	0.348
	(0.012)	(0.015)
BIOMASS_40	0.459	0.371
	(0.017)	(0.017)
BIOMASS_60	1.590	0.427
	(0.032)	(0.023)
BIOMASS_80	0.143	0.658
	(0.052)	(0.035)
REG_COM	-0.907	0.402
	(0.022)	(0.015)
REG_MFT	0.359	0.306
	(0.024)	(0.016)
REG_LOC	-0.891	0.471
	(0.027)	(0.022)
REG_IND	-1.100	0.580
	(0.038)	(0.031)
Number of respondents	251	
Number of observations	2008	
LL (0)	-2206.1	
LL final	-866.3	
Root likelihood post burn-in	0.692	

Regarding our main attribute of concern, the results indicate a benefit of NOK 74, NOK 459, NOK 1590, and NOK 143 for raising BIOMASS from SQ to 20 000, 40 000, 60 000, and 80 0000, respectively.[11] It is noteworthy that the WTP for BIOMASS peaks at the regulatory target of 60 000 and decreases after hitting this point. Overall, the large and statistically significant standard deviation coefficients suggest considerable heterogeneity among respondents for both BIOMASS and regulation dummies.

[10] The choice model is estimated using R package Apollo (Hess and Palma, 2019).
[11] 1 NOK = 0.12 USD approximately.

5.2. Value function

HB MIXL estimation provides the posterior mean WTP of each respondent for all BIOMASS levels, enabling us to fit a non-use value function across 1255 data points. The results indicate that the welfare increases as BIOMASS surpasses the SQ level and peaks when it rises from SQ to 60 000 tonnes. However, after hitting the target level of 60 000, the welfare lowers for raising BIOMASS from SQ level to 80 000 tonnes. Therefore, we specify a value function in the quadratic form for reflecting the non-linear nature of the respondents' benefit from increased BIOMASS:

$$V(x) = Ax^2 + Bx + C \tag{20}$$

Estimating (20), we obtain -0.000009353, 0.009699, and -1430 for A, B, and C, respectively (R^2 = 0.17, p < 0.001). Since WTP values reflect non-use benefits regarding coastal cod stocks in Northern Norway, we can multiply $V(x)$ with the number of households in Norway and compute the total non-use benefit for further incorporation into our bioeconomic model.

5.3. Optimization results

Employing the data presented in Table 3, we estimate a set of bioeconomic models which capture both standard use-based scenarios and a more holistic approach incorporating non-use benefits and the weights the society attaches to different ES of coastal cod.

Table 5. Overview of optimization scenarios with respect to different ES.

	h_r (tonnes)	h_c (tonnes)	x (tonnes)	TEV (NOK)
$V(x)$ excluded				
REC_ONLY	149 623	-	569 947	8 113 779 555
REC_COM	12 700	149 108	553 728	3 509 114 325
$V(x)$ included				
REC_NON	148 936	-	549 468	13 571 319 412
REC_COM_NON	12 700	147 801	527 350	6 091 982 140
$V(x)$ and α, γ, θ included				
W_REC_COM_NON	12 700	148 143	533 247	6 096 038 013
Advised use of coastal cod				
NON_USE_ONLY	-	-	518 496	2 873 990 784
Current use of coastal cod				
STATUS_QUO	12 700	43 000	290 153	1 593 151 799

Table 5 presents an overview of the results obtained from the different models. We first analyze the optimum solution for the conventional case presented in equation (1), which disregards the non-use benefits of coastal cod. As discussed previously in section 3.1, the solution depends on the relationship between benefits $Com(x)$ and $Rec(x)$. Given that the recreational users have a substantially larger monetary benefit per ton coastal cod harvest, such that $Rec(x) > Com(x)$ for all values of x, the optimization arrives at a corner solution, which we call REC_ONLY.[12] In this case, the optimum stock level x^* is 569 947 tonnes, and the recreational users are allocated all the harvest h_R, which we estimate to be 149 623 tonnes. Since this

[12] In the hypothetical opposite case of $Com(x) > Rec(x)$ for all values of x, the optimum stock and harvest levels are 542 472 and 148 621 tons, respectively, generating a TEV of NOK 2.5 billion.

optimal harvest level greatly exceeds the recreational fishing capacity of 12 700 tonnes per year (*i.e.,* $h_{R,max}$), we assume that the recreational fishers harvest at the constant rate of $h_{R,max}$ and optimize the harvest of the commercial fleet. Following this model (REC_COM), the optimum stock level declines to 553 728 tons, while the commercial fleet is allocated 149 108 tons coastal cod harvest. The total monetary benefit of recreational and commercial fishers is NOK 937 million and NOK 2.5 billion, generating a TEV of NOK 3.5 billion.

When we include the non-use values through the value function $V(x)$, the corner solution results in an optimum stock level x^* of 549 468 tons, as model REC_NON illustrates. The benefit of recreational users at this point is approximately NOK 11 billion. The non-use values, estimated through the incorporation of $V(x)$ in the optimization, deliver a benefit of NOK 2.5 billion. Therefore, the TEV of coastal cod, in this case, is approximately NOK 13.5 billion. As h_R greatly exceeds the estimated annual recreational harvest of 12 700 tons again, we re-estimate the optimum stock level concerning a more likely scenario, which we name REC_COM_NON. In this scenario, the recreational users harvest at $h_{R,max}$, and we optimize the harvest of commercial users, h_C. This application results in an optimum stock level x^* of 527 350 tonnes, and h_C of 147 801 tonnes.[13] These harvest levels generate NOK 2.5 billion and NOK 932 million for commercial and recreational users, respectively. In line with the increased stock level, the non-use values rise to NOK 2.6 billion. In sum, the system provides a TEV of NOK 6.1 billion for the ES related to coastal cod, almost twice as large as the TEV of REC_COM, which disregards non-use values.

Next, in model W_REC_COM_NON, we incorporate the regional population's prioritization weights of these ES to reflect the society's views on coastal cod distribution. Applying the golden rule presented in equation (14), we obtain an optimum stock of 533 247 tonnes and a corresponding commercial harvest of 148 143 tonnes, while the recreational users are allowed to harvest at their maximum capacity. These stock and harvest levels generate NOK 2.6 billion, NOK 933 million and NOK 2.5 billion for commercial, recreational and non-use benefits. Overall, this configuration provides a TEV of approximately NOK 6.1 billion.

[13] Note that the golden rule for this case is equivalent to golden rule presented in equation (14), but without the prioritization weights.

For comparison purposes, we also optimize the stock according to ICES' most recent advice of no harvest (NON_USE_ONLY). Based on the value function $V(x)$, the biomass increases to 518 496 tonnes with a value of NOK 2.8 billion in this scenario.

Finally, model STATUS_QUO indicates that the current regulations' prioritization of coastal cod ES generates a TEV of approximately NOK 1.6 billion, where recreational and commercial users obtain NOK 854 million and NOK 736 million, respectively. Since we have the current stock and landings numbers, we can plug these values into the golden rule (14) and solve for the implied weight for non-use values within the present-day regulatory framework. Assuming a weight of 1 for α and γ, as the benefits of commercial and recreational users capture their prioritization in the current situation, and re-solving the golden rule for today's stock level, we obtain the designated weight of 0.002 for the non-use values.

5.4. Sensitivity analysis

Table 6 presents the results' sensitivity for a 10% increase in the related parameters. Overall, the optimum stock level and the corresponding commercial harvest appear to be robust to changes in optimization variables. Intrinsic growth rate r is the only exception concerning ecologic parameters, leading to a difference marginally greater than 10% in all models. A 10% increase in the value function parameter B results in the most significant shifts with a corresponding increase of 21% in TEV. However, these relatively more extensive changes in TEV may be due to the non-linear form of the value function.

Table 6. Sensitivity analysis (sensitive results indicated in bold).

	REC_COM			REC_COM_NON			W_REC_COM_NON		
10% increase	**% change in x^***	**% change in h_c**	**% change in TEV**	**% change in x^***	**% change in h_c**	**% change in TEV**	**% change in x^***	**% change in h_c**	**% change in TEV**
$\boldsymbol{\delta}$	-1.03	-0.15	-1.03	-0.27	-0.06	-0.02	-0.55	-0.11	-0.03
$\boldsymbol{r}$	0.76	**10.10**	7.43	0.33	**10.07**	4.21	0.60	**10.13**	4.21
$\boldsymbol{K}$	9.58	9.93	7.56	2.23	7.89	3.21	4.69	8.73	3.24
$\boldsymbol{p_c}$	-0.21	-0.03	7.35	0.05	0.01	4.22	0.06	0.01	4.22
$\boldsymbol{p_R}$	0.00	0.00	2.93	0.00	0.00	1.65	0.00	0.00	1.68
$\boldsymbol{c_c}$	0.04	0.00	-0.05	0.01	0.00	-0.03	0.02	0.00	-0.03
$\boldsymbol{c_R}$	0.19	0.03	-0.23	0.06	0.01	-0.15	0.05	0.01	-0.15
$\boldsymbol{q_c}$	-0.03	0.00	0.04	-0.01	0.00	0.03	-0.02	0.00	0.02
$\boldsymbol{q_R}$	-0.18	-0.03	0.21	-0.05	-0.01	0.14	-0.04	-0.01	0.14
$\boldsymbol{h_{r,max}}$	0.19	0.02	2.69	0.05	0.01	1.53	0.05	0.01	1.53
$\boldsymbol{A}$	-	-	-	0.00	0.00	-5.65	0.00	0.00	-5.65
$\boldsymbol{B}$	-	-	-	0.00	0.00	**21.52**	4.81	0.77	**21.31**
$\boldsymbol{C}$	-	-	-	-6.95	-1.88	**-10.09**	-4.71	-1.12	**-10.06**
$\boldsymbol{\alpha}$	-	-	-	-	-	-	0.24	0.05	0.01
$\boldsymbol{\gamma}$	-	-	-	-	-	-	0.14	0.03	0.00
$\boldsymbol{\theta}$	-	-	-	-	-	-	-0.16	-0.03	0.00
$\boldsymbol{HH}$	-	-	-	-	-	-	-0.13	-0.02	4.27

6. Concluding remarks

This study optimizes the coastal cod stocks in Northern Norway with respect to commercial, recreational, and non-use benefits while accounting for society's prioritization of these different ES and the corresponding stakeholders.

The results are robust toward changes in bioeconomic model variables, with exceptions regarding intrinsic growth rate and value function parameters. However, even these variables do not generate substantially different stock and harvest levels. Except for corner solutions, the analyses suggest that commercial stakeholders' harvest can be raised over the current amount by increasing the stock to the optimum level and then harvesting the growth at that point. Furthermore, the optimum stock level and TEV increase substantially when the bioeconomic model accounts for the non-use benefits, indicating that the rent is not the only value associated with marine ES. This finding supports former arguments of Beaumont et al. (2008), Bulte and Van Kooten (1999), and Armstrong et al. (2017), regarding the undervaluation of natural resources when focusing only on use-values, and that the management decision between extracting or conserving a resource is dependent on non-use monetary benefits as well.

The models findings illustrate that the current regulatory framework and the resulting harvest levels produce the lowest TEV among the presented models. However, this result is not surprising considering the lower harvest of the stakeholders due to the suboptimal stock level, and that model STATUS_QUO excludes non-use benefits.

The stock levels generated by the optimization models are almost twice higher than today's coastal cod stock, enabling commercial harvest levels that are more than thrice as much. The most significant TEVs result from models REC_NON and REC_ONLY, which are impractical as they exclude the commercial stakeholders. The models accounting for both stakeholder groups' extraction-based benefits and the society's non-use benefits present similar amounts of TEV and harvest, regardless of whether we apply society's weighting parameters or not. This harmony between REC_COM_NON and W_REC_COM_NON suggest that the value created by different ES are robust to preferring an equal weights or society's weighting for prioritization, as supported by the sensitivity analysis.

When we model the stock according to ICES' advice of no harvest, non-use benefits estimated through the value function generate a TEV that is still much greater than the current economic value. It is noteworthy that the benefit, in this case, is lower than the other optimization scenarios, reflecting the non-linear nature of society's welfare associated with recovered coastal cod stocks. As already reflected in the polynomial shape of the value function, the non-use benefits tend to decrease after a certain point, implying that the society would instead harvest the stock. Therefore, scenarios involving multiple stakeholders generate higher benefits than the pure conservation case.

Overall, optimization procedures suggest that the models which account for all stakeholders with both use and non-use benefits create the largest, achievable stock and welfare levels.[14] The considerable difference in the estimated TEV between the models those that include non-use values and those that do not illustrate how undervalued the stocks are within the regulatory framework in effect. While underestimating marine and coastal ES is troublesome, the total exclusion of existence values may lead to the false perception that no-harvest recommendations for recovering vital resources produce no value.

[14] The models REC_ONLY and REC_NON are not considered achievable since excluding commercial stakeholders is not realistic for this case.

Regarding the optimum stock level, it is noteworthy that except for STATUS_QUO all models generate results in proximity to the assumed MSY level. This consistency in the results suggests that regardless of the model specifics, any of the presented management options is preferable to the current management of coastal cod stocks.

One weakness of our analysis is that we treat the local recreational anglers and marine fishing tourists as one within recreational fishing ES due to lack of data. While the estimated total harvest of these users (i.e., $h_{R,max}$) does not impact the findings significantly as shown in the sensitivity analyses, the cost and benefit of both international and domestic tourists requires more attention in the future research. Furthermore, our study provides a single-stock analysis of a potentially complex system. Whereas the estimations deliver a clear and achievable target for the coastal cod stocks of Northern Norway, concerning the bycatch problem in the NEA cod fishery, a more comprehensive model accounting for the NEA harvest may provide a more in-depth analysis of this specific stock.

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