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Abstract: Sensitivity to scope in nonmarket valuation refers to the property that people are willing to pay more for a higher quality or quantity of a nonmarket public good. Establishing significant scope sensitivity has been an important check of validity and a point of contention for decades in stated preference (SP) research, primarily on contingent valuation. Recently, researchers have begun to differentiate between statistical and economic significance. This paper contributes to this line of research by studying the significance of scope effects in discrete choice experiments (DCE) using the scope elasticity of willingness-to-pay (WTP) concept. We first formalize the scope elasticity concept in a DCE context and relate it to economic significance. Next, we review a selection of DCE studies from different fields and derive their implied scope elasticity estimates. We observe that scope tests as validity checks are uncommon in the DCE literature. Most studies assume unitary elastic scope sensitivities by employing linear functional forms, and when more flexible specifications are employed, the tendency is towards inelastic scope sensitivity. Then, we apply the scope elasticity concept to primary DCE data on people's preference for expanding the production of renewable energy in Norway. We find that all scope elasticity estimates are statistically significant and vary between 0.18 and 0.46, depending on attribute analyzed, model specification, geographic subsample, and unit of measurement chosen for a key attribute. While there is no strict, universally applicable benchmark for determining the economic significance of scope impacts, we deem these estimates to be of an adequate and plausible order of magnitude. Implications of the results for future DCE research are provided.

Keywords: Discrete choice experiments, scope sensitivity, willingness-to-pay, scope elasticity, economic significance

JEL classification: D01, Q51, Q57

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Samandrag

Omfangssensitivitet i miljøverdsetting inneber at folk er viljuge til å betala meir for høgare kvalitet eller kvantitet av eit ikkje-prissett miljøgode. Dokumentasjon av signifikant omfangssensitivitet har vore ein viktig validitetssjekk i fleire tiår i uttrykte preferansemetodar, primært på betinga verdsetting. I nyare tid har forsking byrja å differensiera mellom statistisk og økonomisk signifikans. Denne studien bidreg til denne forskinga ved å evaluera omfangseffektar i valeksperiment ved å nytta omfangselastisitet av betalingsviljugskap som konsept. Først formaliserer vi omfangselastisitetskonseptet for valeksperiment og relaterer det til økonomisk signifikans. Deretter gjennomgår vi eit utval av valeksperiment studiar frå ulike fagfelt for å estimera studiane sine implisitte omfangselastisitetar. Frå dette observerer vi at validitetssjekk er uvanleg i valeksperiment litteraturen, og dei fleste studiar antek at elastisiteten er ein ved å nytta lineær funksjonsform. I studiar med meir fleksibel funksjonsform observerer vi ein tendens mot uelastisk omfangssensitivitet. Vidare nyttar vi oss av omfangselastisitetskonseptet på eigne valeksperimentdata som inneheld informasjon om folk sine preferansar for å ekspandera produksjonen av fornybar energi i Noreg. Vi finn at alle beregna omfangselastisitetar er statistisk signifikante og varierer mellom 0,18 og 0,46, avhengig av attributt analysert, empirisk modellspesifikasjon, geografisk underutval og einingsmål valt for eit hovudattributt. Sjølv om det er ingen gitt universal standard for å fastslå økonomisk signifikans av omfangseffektar, ser vi på desse estimata som tilstrekkelege og truverdige. Implikasjonar av resultata våre for vidare forsking på og nyttegjering av valeksperiment blir også gjevne.

1. Introduction

Sensitivity to scope in nonmarket valuation refers to the property that people are willing to pay more for a higher quality or quantity of a nonmarket public good (Carson *et al*., 2001; Freeman *et al*., 2014). Establishing significant scope sensitivity has been an important check of validity and a point of contention for decades in stated preferences (SP) research, primarily in contingent valuation (CV) surveys (Kahneman, 1986; Mitchell and Carson, 1989; Kahneman and Knetsch, 1992; Desvousges *et al*., 1992; Diamond and Hausman (1994); Whitehead *et al*., 1998; Berrens *et al*., 2000; Heberlein *et al*., 2005; Lew and Wallmo, 2011; Hausman 2012; Kling *et al*., 2012; Haab *et al*., 2013; Whitehead, 2016).[1]

At the one extreme, some researchers have claimed general methodological invalidity in light of the failure of some studies to establish statistically significant scope effects (Hausman, 2012). Recently, however, several authors have made compelling arguments to the effect that the scope sensitivity and validity of a study cannot be assessed purely on the basis of tests of statistical significance (e.g., Amiran and Hagen, 2010; Whitehead, 2016; Lopes and Kipperberg, 2020). The extent to which estimated scope effects are *economically significant* (McCloskey and Ziliak, 1996; Thorbecke, 2004) may be equally important. Related to economic significance are the concepts of *adequacy*, i.e., whether the estimated scope effects exceed a minimum threshold, and *plausibility*, i.e., whether the estimates are believable for the particular empirical context (Arrow *et al*., 1994; Whitehead, 2016).[2][3]

A specific measure proposed for assessing the economic significance of sensitivity of scope in CV studies is *scope elasticity of willingness-to-pay* (WTP) (Amiran and Hagen, 2010). Scope elasticity of WTP measures the ratio of the percentage change in WTP for a nonmarket good relative to the percentage change in its quantity or quality. Amiran and Hagen (2010) demonstrate that in the case of strictly convex neoclassical preferences scope elasticities of WTP need only be greater than zero and less than one. One challenge, then, is that elasticities close to zero may be difficult to detect statistically. Whitehead (2016) goes on to elaborate on the economic intuition underlying the concept

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[1] See Lopes and Kipperberg (2020) for a recent overview.

[2] Estimated scope effects in economic models can be statistically significant without being economically significant and vice versa. In the latter case, lack of statistical precision may lead to failure to reject the null hypothesis of no impact, even when point estimates are indicative of economic significance. Ideally, of course, a well-designed study with sufficient power can establish both statistical and economic significance.

[3] In this paper, we focus on the economic significance of the change in welfare estimates in relation to the discussion of methodological validity rather than the economic significance of the welfare estimates themselves. For example, an environmental amenity could be associated with a substantial non-market value, deemed economically significant, which does not vary much with its provision level. Conversely, another environmental amenity may have a modest value that nonetheless increases substantially at higher provision levels.

of scope elasticity and applies it in a re-assessment of several CV studies that initially had their scope sensitivity questioned. He argues that the implied scope elasticities of WTP in these studies are within a plausible range and satisfy economic significance.[4]

The issue of sensitivity to scope has also been explored in the discrete choice experiment (DCE) literature, but to a much lesser extent than for CV (e.g., Layton and Brown, 2000; Lew and Wallmo, 2011; Johnston *et al*., 2017). As in CV studies, sensitivity to scope in DCEs implies that people are willing to pay more for a larger quantity or better quality of a good. For a good, as opposed to a bad, this is usually indicated as higher attribute levels, all else held equal. Depending on the experimental design, variation in the levels of quantitative attributes facilitates scope sensitivity examination through the estimation of indirect utility functions with linear and non-linear functional forms. For example, Layton and Brown (2000) estimate a piecewise linear indirect utility function to test whether the WTP to avoid larger forest losses due to climate change is higher than the WTP to avoid smaller losses. Lew and Wallmo (2011) perform scope tests across a number of protected endangered species as well as their protection levels. Both studies establish statistically significant scope effects. Neither study discusses adequacy, plausibility, or economic significance, though Layton and Brown (2000) refer to their results as "*economically sensible*" and "*economically reasonable*".[5]

It is important from both a methodological point of view and a policy perspective to further develop and include scope tests in DCE studies as well as in CV research. Methodologically, scope sensitivity continues to be discussed in relation to SP validity. As pointed out in the SP guidance by Johnston *et al*. (2017, p.374): "*Underlying the challenge for SP validity testing is the lack of general agreement on whether results from individual studies (or sets of studies) should be interpreted as evidence for or against the validity of the method in general. Recognizing this lack of agreement over what constitutes an acceptable validity test for SP studies, we recommend continued investigation of both current and new tests as an important area for future research.*" From a practical resource management perspective, policymakers are typically interested in assessing different policy alternatives and associated attributes varying in magnitude (e.g. degree of environmental protection), with increasing opportunity costs. If the social benefits of the policy should turn out to be invariant to the public good provisioning levels, the optimal decision would be simple. The policymakers should choose the lowest

[4] The scope elasticity concept can be applied generally to assessment of the sensitivity of welfare measures to scope, both WTP and willingness to accept (WTA). For simplicity, we only refer to the scope elasticity of WTP here.

[5] The presence of scope sensitivity in SP studies can be assessed by means of external or internal tests. In DCEs, scope significance is typically identified by means of a combination of within- and across-respondent variation in attribute levels (e.g., Layton and Brown, 2000). The split-sample, external scope test in the DCE of Lew and Wallmo (2011) is an exception.

cost alternative. In many circumstances, such a finding would seem implausible and not be useful for decision-making.

In this paper, we investigate scope effects through the lens of the scope elasticity of WTP concept. To our knowledge, no other DCE study have used this analytical framework. We provide a theoretical discussion, methodological perspectives, and a unique empirical application. We begin by formalizing scope elasticity of WTP both generally and specifically in the DCE context (Section 2). Then we review a selection of DCE studies from different fields and derive their implicit elasticity estimates (Section 3). The literature analysis leads to the following three observations: i) explicit investigations of scope sensitivity in DCE studies seem uncommon; ii) many studies assume unitary elastic scope sensitivities through their choice of a restrictive functional form; and iii) studies that utilize flexible functional forms tend to find inelastic effects, consistent with diminishing marginal utility from attribute improvements.

Following the literature discussion, we apply the scope elasticity of WTP concept to study preferences for renewable energy expansion in Norway (Sections 4 and 5). We provide baseline results for two quantitative attributes (new renewable energy production and new wind power installations) and investigate whether elasticity estimates vary across model specifications, geographic subsamples with different levels of familiarity and exposure, and experimental variation in the unit of measurement of the wind power attribute. This analysis is generally motivated by the lack of attention to DCE scope effects revealed by the literature review. More specifically, the exploration of familiarity and exposure is motivated by the existing literature on habituation (e.g., Wilson and Dyke, 2016; Zerrahn, 2017) while the exploration of unit of measurement is motivated by emerging research on choice architecture and attribute translations (e.g., Hertwig and Grüne-Yanoff, 2017; Ungemach *et al*., 2018).

Overall, the analyses in this paper show that scope sensitivity can vary between attributes and across conceptual, methodological and empirical dimensions of studies, which suggests that economic significance must be assessed on a case-by-case basis. Final reflections and recommendations for future DCE work are provided in Section 6.

2. Conceptual framework

The concept of scope elasticity of WTP was first proposed by Amiran and Hagen (2010) to address the economic significance of scope sensitivity in CV research. Whitehead (2016) then applied the concept in simulation analyses and empirical illustrations. Existing CV studies that have subsequently reported scope elasticity estimates include Burrows *et al.* (2017), Borzykowski *et al.* (2018), and Lopes and Kipperberg (2020).

A major appeal of the scope elasticity of WTP framework is that it provides a unit-free measure of the *ceteris paribus* responsiveness of an endogenous variable of interest (in this case, WTP) to a change in an exogenous variable (in this case, environmental quality). As such, it is similar to other important elasticity measures in economics (e.g., own-price elasticity of demand; input-price elasticity of supply; income elasticity of WTP). Specifically, the scope elasticity of WTP is defined as the ratio of *percentage change in WTP to the percentage change in environmental quality*. A scope elasticity of zero signals absence of impact, or no scope effect, whereas a scope elasticity of one means proportional responsiveness. Elasticity estimates within the 0 to 1 interval imply less than proportional, i.e., inelastic, impact. Such an elasticity would be expected under neoclassical microeconomic convexity priors regarding the trade-off between market and nonmarket goods (Amiran and Hagen, 2010; Whitehead, 2016). For example, a scope elasticity of 0.4 suggests that a 10% increase in environmental quality is associated with a 4% increase in WTP. However, the scope elasticity could also be greater than one, suggesting disproportionally large, i.e., elastic, responsiveness. Elastic WTP responsiveness to a change in scope is consistent with increasing marginal utility of an economic good or increasing disutility from an economic bad. Indeed, some of the DCE studies reviewed in Section 3 report estimation results that imply scope elasticity greater than one (e.g., Layton and Brown, 2000).

2.1 Defining the scope elasticity of WTP in general

Let $WTP = WTP(q, \boldsymbol{z})$ represent a general value function for a representative consumer, where q is a scalar measure of the level of environmental quality and $\boldsymbol{z}$ is a vector of other factors influencing the consumer's valuation (including income). The scope elasticity of WTP (E_{WTP}) is then given by:

(1) $$E_{WTP} \equiv \frac{\%\Delta WTP(q,\boldsymbol{z})}{\%\Delta q} = \left(\frac{\partial WTP(q,\boldsymbol{z})}{\partial q}\right) \cdot \left(\frac{q}{WTP(q,\boldsymbol{z})}\right).$$

For a non-marginal change in environmental quality, say from q^0 to q^1, where $q^1 > q^0$, with associated change in WTP from WTP^0 to WTP^1 ($WTP^1 \geq WTP^0$), the midpoint formula can be utilized to define a scope arc elasticity ($\bar{E}_{WTP}$) as follows:

$$(2) \qquad \bar{E}_{WTP} \equiv \frac{\%\Delta WTP(q,\boldsymbol{z})}{\%\Delta q} = \left(\frac{\Delta WTP(q,\boldsymbol{z})}{\Delta q}\right) \cdot \left(\frac{\bar{q}}{\overline{WTP}}\right),$$

where $\Delta q = q^1 - q^0 > 0$, $\Delta WTP = WTP^1 - WTP^0 \geq 0$, and $\bar{q}$ and $\overline{WTP}$ are, respectively, average environmental quality ($\frac{q^0+q^1}{2}$) and average WTP ($\frac{WTP^0+WTP^1}{2}$).

2.2 Defining scope elasticities in DCE

Scope sensitivity in DCEs means that people's WTP for a specific attribute (good/bad) is (increasing/decreasing) in its level, all else held equal. However, multi-attribute discrete choice situations are typically motivated from a random utility model (RUM) framework, not via a direct valuation function, as above. Therefore, let indirect utility (*U*) be represented by $U = V + \varepsilon$, where V is the deterministic component and ε is the random component (see e.g. Hensher *et al*., 2005). For the sake of simplicity, we ignore the latter term and focus on deterministic indirect utility. Let $V = V(\boldsymbol{p}, \boldsymbol{q}, M)$ be a generalized deterministic indirect utility component, where $\boldsymbol{p}$ is an exogenous price vector, $\boldsymbol{q}$ represents nonmarket goods and amenities exogenously provided (including various environmental quantity and quality attributes), and M is exogenous consumer income. The utility an individual derives from any given policy or resource managemenet scenario, say alternative *j*, is then given by $V_j(\boldsymbol{p}, \boldsymbol{q}_j, M - B_j)$, where B_j is the fee or tax payment for that scenario. Faced with *J* mutually exclusive alternatives, the consumer prefers the alternative that yields maximum indirect utility, meaning that alternative *k* is chosen provided $V_k(\boldsymbol{p}, \boldsymbol{q}_k, M - B_k) > V_j(\boldsymbol{p}, \boldsymbol{q}_j, M - B_j), \forall\, k \neq j \in J$.

The *ceteris paribus* marginal willingness to pay (*MWTP*) for a change in the level of a specific attribute, say attribute *s* ($q_s \in \boldsymbol{q}$), is given by the marginal rate of substitution (*MRS*) between that attribute and the consumer's money income:

$$(3) \qquad MWTP(q_s) = MRS_{q_s,M} = \frac{\partial V(\cdot)/\partial q_s}{\partial V(\cdot)/\partial M}.$$

However, DCE researchers are often interested in non-marginal changes in amenity or attribute levels due to changes in public policy and management regimes. We therefore consider discrete changes in $\boldsymbol{q}$

and associated changes in WTP implied by the indirect utility given above. Let $\Delta_s^A = q_s^A - q_s^0$ and $\Delta_s^B = q_s^B - q_s^0$, $\Delta_s^B > \Delta_s^A$ represent two different discrete increases in the level of attribute s, where both these increases are considered improvements. The two associated WTP measures (WTP^A and WTP^B) are defined implicitly from the indirect utility function in the following manner:

(4) $\quad V(\boldsymbol{p}^0, \boldsymbol{q}^0, M) = V\left(\boldsymbol{p}^0, \boldsymbol{q}^A, M - WTP^j\right)$, $j = A$ or B.

Subsequently, a scope arc elasticity of WTP can be defined analogously to equation (2) as:

(5) $\quad \bar{E}_{WTP} \equiv \frac{\%\Delta WTP}{\%\Delta q_s} = \left(\frac{WTP^B - WTP^A}{(WTP^B + WTP^A)/2}\right) / \left(\frac{\Delta_s^B - \Delta_s^A}{(\Delta_s^B + \Delta_s^A)/2}\right).$

For the linear specification of the deterministic indirect utility often employed in DCE research, that is, $V_j = \alpha_j + \boldsymbol{\beta_q q}_j + \beta_M(M - \boldsymbol{B}_j)$, $MWTP(q_s) = \beta_{q_S}/\beta_M$ and $\bar{E}_{WTP} = 1$.[6] This means that the estimated scope elasticity is one provided the estimated *MWTP* is statistically significant (greater than zero). Since it would be difficult to argue that proportional responsiveness in a welfare estimate with respect to scope does not satisfy economic significance, this functional form is meaningless in terms of distinguishing between statistical and economic significance of scope effects. Researchers who wish to explore such distinction must therefore turn to more flexible functional forms.

2.3 Adequate, plausible, and economically significant scope sensitivity

Amiran and Hagen (2010) show that neoclassical utility functions with strictly convex preferences have scope elasticity bounded by zero and one (Proposition 1, p. 59). Furthermore, $\bar{E}_{WTP} = 1$ implies perfect substitution between environmental quality and market goods, whereas $\bar{E}_{WTP} = 0$ suggests a perfectly complementary relationship. Importantly, many well-behaved preference representations can imply "*arbitrarily small*" scope elasticities. These results have important implications for empirical research. First, any given application may reveal relatively moderate, but legitimate, scope effects. Second, when the underlying scope sensitivity is low in the true data-generating process, it is more challenging to statistically distinguish scope elasticity estimates from zero.

Whitehead (2016) points out that the panel of experts formed by the *National Oceanic and Atmospheric Administration* (NOAA) to assess the CV method (Arrow *et al.*, 1993) was as much

[6] The proof of this claim is provided in the Appendix.

concerned with economic significance as with statistical significance. Specifically, the NOAA panel was concerned with the *adequacy* or *plausibility* of estimated scope effects in CV studies (Arrow *et al*., 1993; Arrow *et al*., 1994). Whitehead (2016) interprets *adequatcy* as a sufficiency condition (i.e., a minimum threshold criterion). While the literature has yet to establish such a condition, it is evident from the conceptual analysis in Amiran and Hagen (2010) that it could be arbitrarily close to zero. In a follow-up to Arrow *et al.* (1993), Arrow *et al.* (1994) provide the following clarification: "*Had the panel thought that something as straightforward as statistical measurability were the proper way to define sensitivity, then we would (or should) have opted for language to that effect. A better word than 'adequate' would have been 'plausible': A survey instrument is judged unreliable if it yields estimates which are implausibly unresponsive to the scope of the insult. This, of course, is a judgment call, and cannot be tested in a context-free manner*". In line with this sentiment, Whitehead (2016) favors using a case-by-base examination of whether scope effects are "*plausible*", "*believable*" or "*within the realm of possibility*". This recommendation is supported by his Monte Carlo scope elasticity simulations, which indicate that 95% of the draws lie between 0.630 and 0.998 in the case of a simple linear WTP function and between 0.177 and 0.971 in the case of a quadratic WTP function. A re-assessment of several previously contested CV studies reveals plausible scope elasticities between 0 and 1 (Whitehead, 2016).

3. Scope elasticities in previous DCE studies

To our knowledge, no previous DCE study has explicitly analyzed the scope elasticity of WTP for attribute improvements. Nonetheless, many studies report estimation results from which it is possible to infer scope elasticities. Here, we first illustrate this by examining a purposive sample of studies from environmental economics and other fields that utilize DCE methodology (Table 1). Then we examine prior DCE studies specifically related to wind power preferences. These studies were identified from the meta-analysis of Mattmann *et al*. (2016) and supplementary Google Scholar searches (Table 2 in Section 3.3).

3.1. Examples from environmental economics

In Table 1, Adamowicz *et al*. (1994), Boxall *et al*. (1996), and Adamowicz *et al*. (1998) represent three pioneering DCE studies in environmental valuation. Adamowicz *et al.* (1994) apply DCE as a supplement to the travel cost method to analyze choice of recreational fishing site. A key attribute in the study is expected fish catch, ranging from one fish caught per four hours to one fish caught per 35 minutes. This attribute is highly significant in estimations, implying scope sensitivity. However, the linear functional form of indirect utility imposes constant marginal utility and a scope elasticity of one.

Table 1: Inferred scope elasticities of WTP in selected DCE studies from different fields

Source	Field	Scope attribute(s)	Functional form(s)	Scope discussion	Implied scope elasticity
Adamowicz *et al.* (1994)	ENV	Fish catch rate	Continuous linear	No	1
Boxall *et al.* (1996)	ENV	Moose encounters	Piecewise linear (effects code)	No	**0.51**
Adamowicz *et al.* (1998)	ENV	Caribou population	Continuous linear	No	1
			quadratic		**0.68**
		Wilderness area	Continuous linear		1
			Continuous, quadratic		1
		Forest industry jobs	Continuous linear		N/S (zero)
			Continuous quadratic		N/S (zero)
Layton & Brown (2000)	ENV	Forest loss	Piecewise linear	Yes	**1.15, 1.29**
Oehlmann *et al.* (2017)	ENV	Forest share	Continuous linear	No	1
		Land conversion	Continuous linear		1
Ando *et al.* (2020)	ENV	Flood frequency	Continuous linear	No	1
Feit *et al.* (2010)	MKT	Styling appeal	Continuous linear	No	1
Ellickson *et al.* (2019)	MKT	Fat content	Binary dummy	No	0
Hensher (2004)	TRAN	Travel time	Continuous linear	No	1
Choi *et al.* (2018)	TRAN	CO_2 emissions	Continuous linear	No	1
Bech *et al.* (2011)	HEAL	Distance to dental office	Continuous linear	No	1
Liu et. al (2017)	HEAL	Appointment delay	Piecewise linear	No	**1.11**
		In-clinic wait-time	Piecewise linear		**1.34**

<u>NOTES:</u> ENV = Environmental economics, MKT = Marketing research, TRAN = Transportation studies, HEAL = Health economics. N/S = estimated utility parameter is not statistically significant (implying $\bar{E}_{WTP} = 0$).

Boxall *et al*. (1996) apply DCE and CV to study preferences for moose-hunting sites. The main attribute is expected moose encounters per day, with four attribute levels (less than 1 encounter, 1-2, 3-4, and more than 4 encounters) entered piecewise linearly in estimations.[7] The implied scope elasticity of WTP for moose encounters is 0.51.[8] Adamowicz *et al*. (1998) use DCE methodology in combination with CV to investigate non-use values associated with habitat conservation. Their DCE design has three attributes that lend themselves to inferring scope elasticities: mountain caribou population, size of wilderness area, and number of forest industry jobs. Both linear and quadratic functional forms are explored, with only the latter permitting non-constant marginal utility and scope elasticities not equal to unity. The implied scope elasticity of WTP for improvements in the caribou population is 0.68 based on results reported for the statistically superior joint model (Table 2, p. 70), evaluated between WTP for maintaining the current level of 400 versus WTP for the conservation target of 600. For the wilderness area attribute, the quadratic term is insignificant, suggesting constant marginal utility and a scope elasticity of one. Lastly, the job attribute is insignificant, which implies zero marginal utility and a scope elasticity of zero. Common to all three of these early environmental DCE studies is the absence of a discussion of internal (construct) validity, scope sensitivity, or concepts related to economic significance.

Layton and Brown (2000), in contrast, explicitly discuss estimated scope effects in relation to economic theory. This study is the first to employ mixed logit in an environmental DCE and the first DCE to assess the nonmarket benefits of climate action. It investigates WTP to avoid adverse ecosystem impacts from climate change through mitigation and adaptation policies. A key attribute of interest is forest loss in the Rocky Mountains, with experimental levels of 0, 600, 1 200, and 2 500 feet of elevation before entering forested area. The estimated mean utility parameters in a piecewise linear specification suggest substantial WTPs and statistically significant scope effects. The implied scope elasticity of WTP from 600 feet to 2 500 is 1.15 in a 60-year time horizon and 1.29 in a 150-year time horizon.[9]

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[7] Specifically, Boxall et al. (1996) use a so-called "effects code" approach, which involves estimating utility coefficients on dummy variables for the first three levels. The implied utility coefficient for the fourth level is then the negative sum of the three estimated coefficients. The estimated coefficients reported in the article (Table 2, p. 250) are -10.238, -0.0622, and 0.444, which implies that the fourth utility coefficient is 9.86.

[8] We use Eq. (5) to compute the scope arc elasticity between WTP for going from level 1 to level 2 versus WTP for going from level 1 to level 4. For the denominator of the elasticity formula, levels of 0.5, 1.5, and 5 encounters are assumed for levels 1, 2, and 4, respectively. Marginal utility of money is identified from the estimated coefficient (-0.0056) of a travel distance attribute along with the assumption on transportation costs used by the authors ($0.27/km). Further details on how we infer this estimate and the other scope elasticities reported in Tables 1 and 2 are available upon request.

[9] These scope elasticities are indicative of increasing incremental disutility from additional forest loss and increasing incremental WTP to avoid this climate change impact.

Lastly, Oehlmann *et al*. (2017) and Ando *et al.* (2020) illustrate recent DCEs in the environmental valuation literature. These studies use sophisticated designs to explore frontier research issues. Oehlmann *et al*. (2017) report from a design-of-design study with focus on status quo effects in the empirical context of land use and biodiversity conservation in Germany. The underlying DCE includes two quantitative attributes: landscape forest share and rate of land conversion. Ando *et al.* (2020) investigate preferences for storm water management across two cities (Chicago and Portland) and across two currencies (money and time). The underlying DCE has only one quantitative non-cost attribute, namely reduced flood frequency. Unfortunately, both studies impose constant marginal utility and scope elasticity equal to unity by employing linear utility specifications. Neither study discusses DCE scope sensitivity.

3.2 Examples from other fields

The DCE methodology was originally developed from conjoint techniques utilized in marketing research (Louviere *et al.*, 2000) and is now employed in many other fields. Here, we review examples from *marketing research*, *transportation studies*, and *health economics*.

Two recent examples in the marketing literature are Feit *et al*. (2010) and Ellickson *et al*. (2019). The main contribution of Feit *et al*. (2010) is the proposal of a novel empirical method for combining DCE and market data. They exemplify this method in the context of studying preferences for minivans in the United States. A central motivation is that obtaining accurate estimates of relative attribute weights is more important for product design than market share predictions. A key attribute in their application is van appearance (*styling appeal*) coded on a five-point numeric scale. Unfortunately, this attribute is entered linearly in estimations, which imposes the constraints of constant marginal utility and scope elasticity of WTP equal to unity. These restrictions are problematic since it seems plausible that the relative importance of styling appeal could vary across the range of this attribute.

Ellickson *et al*. (2019) also propose and exemplify a new empirical approach for combining DCE and market data. The application context is single-cup Greek yogurt sales in the United States. All non-price attributes are qualitative/categorical (e.g., brand name, nutritional fortification indicators), which do not lend themselves easily to scope analysis. However, the authors mention one inherently quantitative attribute as potentially important to consumers, namely, "*fat level*" or "*fat content*". Unfortunately, the DCE design only makes a binary distinction between zero-fat and fat-containing varieties. In estimations, the zero-fat indicator enters positively and significantly, suggesting that consumers have a positive WTP for avoiding fat-containing yogurts. However, it is not possible to identify differences in preferences across different levels of fat content. This is effectively the same as assuming a scope elasticity of zero.

The opportunity cost of travel time is an important topic in the transportation literature, which recognizes that different types of travel time may have different scarcity values due to idiosyncratic utility/disutility elements. Hensher (2004) focuses on the impact of varying DCE design dimensions on estimates of the opportunity cost of different time usages (e.g., "*free flow time*" versus "*slowed time*"). A more recent transportation study by Choi *et al*. (2018) investigates preferences for carbon offsets (i.e., reducing one's CO_2 emissions) in air travel. While the underlying DCEs of Hensher (2004) and Choi *et al.* (2018) seem to have sufficient variation in attribute levels for the estimation of flexible functional forms, both studies settle on simple linear utility approximations, which assume constant marginal utility and a scope elasticity of unity. Neither study discusses the scope issue.

DCE methodology is also increasingly employed in the health economics field (Soekhai *et al*., 2019). Bech *et al*. (2011) study preferences for dental care services and Liu *et al*. (2017) study preferences for doctor's appointments. An important attribute in the DCE of Bech *et al*. (2011) is "*distance to the dentist*" with experimental levels of 1, 3, 7, and 15 kilometers. This attribute is entered linearly in estimations, which implies that the scope elasticity of WTP to reduce travel distance is unity. In contrast, Liu *et al*. (2017) use a piecewise linear specification for exploring the importance of two types of waiting attributes, "*appointment delay*" (ranging from zero to 14 days) and "*in-clinic wait time*" (ranging from five to 45 minutes). Based on estimation results reported in the article, we infer scope elasticities of WTP equal to 1.11 and 1.34 for reducing appointment delay and in-clinic wait time, respectively.[10]

3.3 Inferred scope elasticities in wind power DCEs

In sections 4 and 5, we present our DCE on preferences for renewable energy expansions in Norway. Table 2 below summarizes relevant comparison studies found in the intersection between environmental economics and energy economics.

As can be seen from the second column, this literature has explored a wide range of non-monetary attributes related to the renewable energy mix, characteristics of wind power expansions, landscape,

[10] Liu et al. (2017) report results from four related studies. Here, we use WTP results from Study 4 (Table 10, p. 1992). The inferred scope elasticity for appointment delay is based on the difference in WTP to avoid a 3-day versus a 14-day delay (relative to no delay). For in-clinic wait-time, the scope elasticity is based on a comparison of 30 versus 45 minutes of waiting (relative to a wait-time of 15 minutes).

ecosystem, and air pollution effects, and economic impacts. However, none of the studies explicitly discusses the scope sensitivity issue in relation to DCE validity diagnostics. Many attributes preclude scrutiny of scope elasticity because they are explored with categorical, qualitative representations (e.g., protection of cliffs in Alvarez-Farizo and Hanley, 2002). Furthermore, most quantitative attributes are estimated using linear specifications, which impose constant marginal utility and scope elasticity of WTP equal to one.

Exceptions are Drechsler *et al*. (2011), Landry *et al*. (2012), Westerberg *et al*. (2013), Vecchiato (2014), Börger *et al.* (2015), Brennan and Van Rensburg (2016), and Ladenburg and Dubgaard (2009). For example, the DCE in Drechsler *et al*. (2011) explores four quantitative attributes with piecewise linear specifications: size of wind farm, maximum turbine height, red kite population, and minimum distance to residential areas.[11] Based on results from the statistically superior error-component logit model (Table 3, p. 3849), the wind farm size and turbine height attributes do not exhibit significant scope effects (implying zero scope elasticity), while the inferred scope elasticities of WTP are 0.76 for the red kite attribute and 0.29 for the minimum distance attribute.

Several other studies also include attributes related to people's proximity to, or distance from, wind power installations. The inelastic scope sensitivity with respect to distance in Drechsler *et al.* (2011) is consistent with the inferred scope elasticities of 0.35 in Vecchiato (2014), 0.57 in Ladenburg and Dubgaard (2009), and 0.88 in Westerberg et al. (2013). In contrast, the distance attributes in Landry *et al.* (2012) do not exhibit scope effect.

[11] The same underlying DCE study is also utilized by Meyerhoff *et al.* (2010) and Mariel *et al.* (2015).

Table 2: Inferred scope elasticities of WTP in previous wind energy DCE studies

Source	Non-cost attributes	Functional form	Scope discussion	Implied scope elasticity
Álvarez-Farizo & Hanley (2002)	Protection of cliffs, fauna, flora, & landscapes	Qualitative, categorical dummies	No	N/A
Bergmann et. al. (2006)	Impact on landscape, wildlife, air pollution	Qualitative, categorical dummies	No	N/A
	Jobs	Continuous linear		1
Longo *et al*. (2008)	GHG emissions, electricity shortage, jobs	Continuous linear	No	1
Navrud & Bråten 2007)	Type of renewable energy source, size of plant	Qualitative, categorical dummies	No	N/A
Ku & Yoo (2010)	Improvements in landscape, wildlife, air quality, employment	Continuous linear	No	1
Borchers *et al*. (2007)	Source of renewable energy	Qualitative, categorical dummies	No	N/A
	Quantity of new renewable energy	Continuous linear		1
Fimereli *et al*. (2008); Fimereli & Morato (2013)	Local biodiversity	Qualitative, categorical dummies	No	N/A
	Carbon emissions, distance from home	Continuous linear		1
Kosenius & Ollikainen (2013)	Type of renewable energy, biodiversity	Qualitative, categorical dummies	No	N/A
	Jobs, CO_2 emissions	Continuous linear		1
Drechsler *et al*. (2011);	Size of wind farm	Piecewise linear	No	N/S (0)
	Max. turbine height			N/S (0)
	Red kite population			**0.79**
	Distance to residential area			**0.29**
Cicia *et al*. (2012)	Type of renewable energy	Qualitative, categorical dummies	No	N/A
Landry *et al* (2012)	Congestion	Piecewise linear	No	N/S (0)
	Ocean distance to turbines			N/S (0)
	Sound distance to turbines			N/S (0)

Table 2: Inferred scope elasticities of WTP in previous wind energy DCE studies, continued

Source	Non-cost attributes	Functional form	Scope discussion	Implied scope elasticity
Westerberg *et al.* (2013)	Distance to wind farm	Piecewise linear	No	0.88
	Artificial reefs & rec. activities	Qualitative, categorical dummies		N/A
	Coherent environmental policy			
Ek & Matti (2015)	Bird population	Binary dummy	No	N/A
	Reindeer industry			
	Jobs			
Ek & Persson (2014)	Landscape impact, ownership type, community consultation, revenue transfer	Qualitative, categorical dummies	No	N/A
Vecchiato (2014)	Wind farm placement	Qualitative, categorical dummies	No	N/A
	Turbine height	Piecewise linear		N/S (0)
	Turbine number			N/S (0)
	Minimum distance from houses			**0.35**
Börger *et al.* (2015)	Species impacted	Piecewise linear	No	**0.69**
	Turbine height/visibility			N/S (0)
	Electromagnetic impact	Binary dummy		N/A
Brennan & Van Rensburg (2016)	Number of turbines	Continuous linear	No	1
	Height of turbines	Piecewise linear		**0.68**
	Minimum distance			N/S (0)
	Community representation	Binary dummy		N/A
Ladenburg & Dubgaard (2009)	Number of wind farms/turbines	Piecewise linear	No	N/S (0)
	Distance			**0.57**
García *et al* (2016)	Number of turbines	Continuous linear	No	1
	Local sports facility	Qualitative, categorical dummies		N/A

NOTES: N/A = not available (due to use of qualitative attribute definition or insufficient information provided in the paper). N/S (0) = not statistically significant (implying $\bar{E}_{WTP} = 0$).

A key attribute in our application below is the number of new wind turbines in Norway. The turbine attribute enters significantly, with functional form-restricted scope elasticity of unity in both Brennan and Van Rensburg (2016) and Garcia et al. (2016), whereas it is insignificant in Vecchiato (2014) and Ladenburg and Dubgaard (2009). In Drechsler *et al*. (2011), the wind farm size attribute is highly correlated with turbine count.[12] However, as noted above, there are no statistical differences in preferences across wind farm sizes.

4. Case study: preferences for renewable energy in Norway

We analyze data from a recent DCE study of preferences relating to expansion of renewable energy production in Norway, that had a specific focus on wind power externalities. The study was motivated by the Norwegian Government's 2018 call for a long-term National Plan for the expansion of wind power production on land. The Ministry of Petroleum and Energy assigned to the Norwegian Water Resources and Energy Directorate (NVE) the tasks of providing an update of the scientific knowledge base and identifying the geographical areas of Norway that would be the most suitable for new wind farms.

The interest in expanding wind power production is two-fold. First, even though Norway is self-sufficient when it comes to *renewable electricity*, less than 2/3 of domestic *energy consumption* is met from renewable sources.[13] Second, the Norwegian Government is seeking to expand renewable production in order to meet its international commitments in connection with transforming the global energy system and reducing carbon emissions.

By 2018, the wind power industry generated 3-4 TWh per year on 30 sites with 610 wind turbines. An additional 30 projects with 600-700 new turbines had also been approved and were under planning or construction. With some of Europe's best wind resources, the Government envisages that wind power production could reach 25 TWh per year by 2030, depending on production costs and prospective electricity prices (NVE, 2019).

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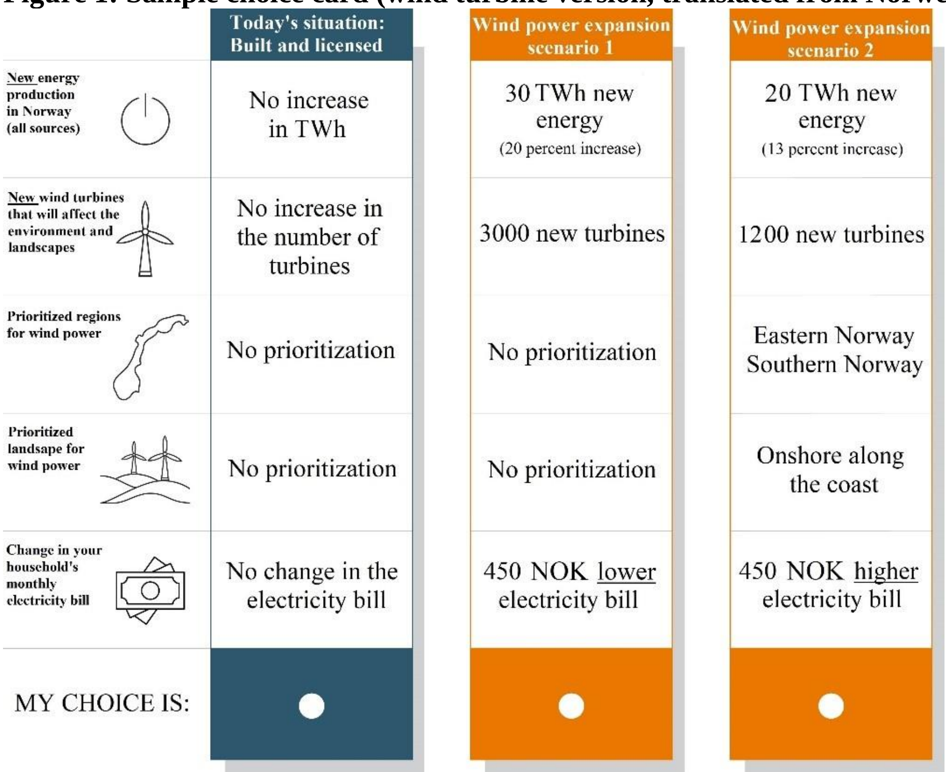
[12] Small farm = 4-6 wind turbines, medium farm = 10-12 wind turbines, large = 16-18 wind turbines.

[13] In a typical year, Norway is a net exporter of renewable electricity, with a production portfolio comprising 95% hydropower and 5% thermal and wind power. For more information, see the following electricity and energy reports from Statistics Norway:
https://www.ssb.no/energi-og-industri/statistikker/elektrisitet/aar
https://www.ssb.no/energi-og-industri/statistikker/energibalanse

NVE’s work on the National Plan started with the mapping of 43 areas distributed across different regions of Norway that were deemed to have high potential and meet basic eligibility criteria for new wind power deployment. NVE then examined each of these areas with respect to production and transmission capacity, stakeholder interests, and environmental impact. During its work, NVE commissioned multiple technical/scientific reports from external consultants, collaborated with the Norwegian Environment Agency, and solicited input from local and regional stakeholders in both the private and the public sector. This process led to the identification of a sub-set of 13 geographical areas proposed for future prioritization. The priority areas are located throughout Norway, with concentrations in Central and Western Norway, and comprise mostly coastal and mountain landscapes.

Despite the deliberate planning process, the final report (NVE, 2019) met widespread criticism leading to intense debate in social and public media. Citizens expressed concern about the impact of wind power installations on Norway’s increasingly reduced pristine nature. Various environmental groups and outdoor recreation and tourism organizations protested. Local politicians objected on the basis that the plan would limit their local autonomy. Finally, the wind power industry itself opposed the plan because of the spatial constraints it placed on future expansions of production. Our study was conducted concurrently with NVEs planning process. Hence, we argue that our DCE study exhibits an unusually high degree of relevance and consequentiality.

Figure 1: Sample choice card (wind turbine version, translated from Norwegian)



4. The DCE design

The DCE survey was designed over a 15-month period starting in January 2018, with implementation in April 2019. An overarching design consideration was the objective of making the study relevant for national policy decisions. The selection and configuration of attributes and other elements of the choice architecture was the combined outcome of a careful review of the existing literature, input from a workshop with experts on valuation of wind power externalities, and feedback from two focus groups and several pilot tests, and following general SP guidance (e.g., Johnston *et al*., 2017).

The final survey started with questions that elicited general opinions, awareness, and knowledge before guiding the respondents through information about Norway's renewable energy production and potential plans for future expansions. Next, the respondents were provided details on the structure of the DCE, including careful descriptions of alternatives and attributes. At the core of the DCE, the respondents were asked to express their preferences on eight choice cards. Standard debriefing, attitudinal, and socio-economic questions followed at the end of the survey.[14]

Figure 1 provides an illustrative choice card. Each choice card contained three alternatives, status quo and two scenarios with expansion of energy production, varying in five attributes. The first attribute, *new renewable energy production from all sources*, had experimental levels of zero (no change), 10, 20, and 30 TWh per year. The second attribute, *new wind turbines*, had experimental levels of zero (no change), 600, 1200, and 3000 turbines. The third attribute designated *prioritized region for new wind power production* (no prioritization, Northern Norway and Central Norway, Western Norway, or Eastern Norway and Southern Norway). The fourth attribute was *prioritized landscape type for new wind power production* (no prioritization, coastal land, lowland and forest land, or mountain land). Finally, the fifth attribute, *change in household's monthly electricity bill (NOK)*, had experimental levels of -450, -150, zero (no change) +150, and +450. Attribute configurations and the resulting choice cards were generated by means of SAS software using the ChoicEff-macro[15] and subject to the restriction that new wind turbines imply new renewable energy production, but not vice versa. In total, the survey utilized 3 x 8 = 24 different choice cards.

The two quantitative non-cost attributes are of particular interest for the scope elasticity analysis in this paper. The first attribute is intended to broadly capture the nonmarket benefits of expanding

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[14] Dugstad et al. (2020) provide further details. A translated version of the DCE part of the survey is available as supplementary material. A copy of the full survey in Norwegian is available upon request.

[15] http://support.sas.com/techsup/technote/mr2010choiceff.pdf

Norway's production of renewable energy. Both prior research and our focus group results indicate that people are positive to such expansion for reasons related to concern over energy security, support of carbon emission reduction, and a desire to stimulate economic activity. The second attribute is intended to capture specific preferences for wind power, holding constant the level of renewable energy production. As documented by prior research summarized in Mattman *et al.* (2016) and Zerrahn (2017), wind turbines and accompanying infrastructure (e.g. roads and power lines) have multiple adverse impacts. These impacts include habitat displacement, ecosystem fragmentation, negative effects on recreational experiences and visual landscape amenities, and issues related to noise and light-, shadow- and ice-casting. In total, these externalities can reduce the well-being of local residents (e.g., Gibbons, 2015; Krekel and Zerrahn, 2017), lower the growth potential of other regional industries such as tourism and recreation (e.g., Broekel and Alfken, 2015), and generally threaten non-use values associated with the protection of pristine nature (Krutilla, 1967).

4.2 Sampling scheme, experimental design variation and implementation

During the survey development stages, previous experience and the likelihood of future exposure were identified as potentially important determinants of preferences. For this reason, it was decided to conduct the survey in two geographic regions with differential experiences and exposure. Specifically, we sampled Rogaland County in Western Norway and Oslo County in Eastern Norway with population sizes (shares) of approximately 476 000 (9%) and 681 000 (13%), respectively. Rogaland is the county that currently has most wind power production and could have substantially more in the future. In contrast, Oslo does not have wind power production and is also unlikely to have any in the future.

In our analysis, we investigate potential differences in scope elasticities across the two subsamples. The tentative *a priori* expectation is that wind power experience/exposure could affect both WTP and scope elasticity estimates. Previous research indicates that WTP to avoid adverse impacts from industrial development may be higher or lower as result of experience/exposure, depending on the mechanisms in play (Zerrahn, 2017; Dugstad *et al*., 2020). However, this research is silent with respect to how experience/exposure might affect scope sensitivity. Consequently, we do not hypothesize a specific sign on expected difference in scope elasticities between the two counties.

In addition to the dual-region sampling scheme, we also implement experimental variation in the unit of measurement of the wind power attribute. Half the respondents were given choice cards with *new wind turbines* (as in Figure 1), while the other half received cards with *new production sites*. The two survey versions were otherwise identical. Moreover, these two measurement units were perfectly correlated (1 production site = 30 wind turbines). The motivation for this experimental treatment is an emerging literature on attribute translations, choice architecture, and signposting/nudging (e.g., Hertwig and Grüne-Yanoff, 2017; Ungemach *et al*., 2018), which suggests that how an attribute is presented in a choice context, including its unit of measurement, is not arbitrary. Specifically, different measurement units can invoke different motivational associations or activate different objectives/goals (e.g., Dellaert *et al.*, 2018; Schlüter *et al.*, 2017). Consequently, the representation of an attribute may cause people to weight the attribute differently in the decision-making process. A change in unit of measurement could also potentially shift the weight of the attribute in question relative to other choice dimensions. Here, we investigate whether a seemingly innocuous change in unit of measurement, from number of wind turbines to number of production sites, alters scope elasticity estimates. This is particularly interesting since elasticities are unit free. Our tentative *a priori* expectation is that the unit of measurement will not have an impact on the scope elasticity estimates.

The data collection was implemented as an online survey using the pre-recruited household panel of *NORSTAT*,[16] one of the leading survey companies in Norway. In total, 4 404 households were invited to participate in the survey. The topic of the survey was not revealed in the survey invitation. The response rate was 24% and the dropout rate was 12%. Table A1 in the appendix provides basic descriptive statistics for the full dataset, the geographic subsamples, and the unit of measurement subsamples. For additional details, see Dugstad et al. (2020).

[16] www.norstat.no

Table 3: Variables used in the estimation of deterministic indirect utility

Name	Description
COST	Change in household monthly electricity price
TWH	New renewable energy production in Norway, TWh (per year)
TWH2	Squared term for TWH
TURB	Number of new wind turbines built in Norway
TURB2	Squared term for TURB
TWH10	Dummy for 10 TWh of new renewable energy production in Norway (per year)
TWH20	Dummy for 20 TWh of new renewable energy production in Norway (per year)
TWH30	Dummy for 30 TWh of new renewable energy production in Norway (per year)
TURB600	Dummy for 600 new wind turbines built in Norway
TURB1200	Dummy for 1200 new wind turbines built in Norway
TURB3000	Dummy for 3000 new wind turbines built in Norway
MOUNT	Dummy for mountain landscapes being prioritized for new wind power
LOW	Dummy for lowland & forest landscapes being prioritized for new wind power
COAST	Dummy for coastal landscapes being prioritized for new wind power
NORTHMID	Dummy for prioritizing Northern & Central Norway for new wind power
WEST	Dummy for prioritizing Western Norway for new wind power
EASTSOUTH	Dummy for prioritizing Eastern & Southern Norway for new wind power

5. Empirical results and analysis

We estimate panel mixed logit models with jointly normally distributed parameters on the non-cost attributes to account for multiple observations per respondent and preference heterogeneity and to relax the IIA assumption associated with fixed parameter logit models (Train, 2009). The joint probability for the sequence of preference expressions (i_n) for individual *n* over *J* alternatives (*j* = 1, 2, 3) for the *T* choice cards (*t* = 1, 2, …,8) presented in the DCE is given by:

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

where $f(\beta|\theta)$ represents the parameter distribution.[17]

[17] The probability in (6) does not have a closed-form solution and must be approximated by simulation procedures (Train, 2009). The mixed logit results presented in this paper were produced in R-Studio using 1000 Halton draws.

We estimate three different specifications for deterministic indirect utility (V_{int}), a linear specification (LINEAR) implying constant marginal utilities and restricting the scope elasticities to unity, a quadratic specification (QUADRATIC), and a piecewise linear specification (PIECEWISE). Relating the most flexible specification, PIECEWISE, to the attributes described in Section 4, yields the following indirect utility function:

$$V_{int} = \alpha_{SQ} + \beta_1 COST_{it} + \beta_{2,n} TWH10_{it} + \beta_{3,n} TWH20_{it} + \beta_{4,n} TWH30_{it} + \beta_{5,n} TURB600_{it} + \beta_{6,n} TURB1200_{it} + \beta_{7,n} TURB3000_{it} + \beta_{8,n} MOUNT_{it} + \beta_{9,n} LOW_{it} + \beta_{10,n} COAST_{it} + \beta_{11,n} NORTHMID_{it} + \beta_{12,n} WEST_{it} + \beta_{13,n} EASTSOUTH_{it}. \tag{7}$$

The variables used in the estimation are described in Table 3. The term α_{SQ} is an alternative-specific constant that captures the effect of the status quo alternative on the choice cards (no additional renewable energy production, no regional/landscape prioritization for wind power production, and an unchanged electricity bill). The variable COST represents change in electricity bill. The variables TWH10, TWH20, and TWH30 are indicators for the levels of *new renewable energy production*, TURB600, TURB1200, and TURB3000 are indicators for numbers of *new wind turbines*, NORTHMID, WEST, and EASTSOUTH are regional prioritization indicators, and MOUNT, LOW, and COAST are landscape prioritization indicators.

5.1 Baseline results and comparison across functional forms

Estimation results for the full dataset are reported in Table 4. Overall, the different model specifications yield consistent patterns for key utility parameters. The estimated COST parameter is negative and highly significant, as expected. The average respondent obtains positive utility from expansion of renewable energy production and disutility from increasing the number of turbines, as indicated by the signs of the mean coefficients of the linear terms (TWH and TURB). The signs of the coefficients of the quadratic terms (THW2 and TURB2) in the QUADRATIC model indicate diminishing marginal utility from new renewable energy production and diminishing marginal disutility from new wind turbines. These preference patterns are also reflected in the PIECEWISE estimation. For example, the difference between the mean coefficients of TURB600 and TURB1200 is larger than the difference between the mean coefficients of TURB1200 and TURB3000. The results for prioritized regions and landscapes, which are of second-order interest for the research focus of this article, are mixed. The estimated standard-deviation coefficients are generally large and significant suggesting substantial preference heterogeneity. Lastly, the overall model-fit statistics indicate that the PIECEWISE model is statistically superior.

Table 4: Full sample panel mixed logit parameter estimates for different functional forms (linear, quadratic, and piecewise linear) of deterministic indirect utility

MODEL:	**LINEAR**		**QUADRATIC**		**PIECEWISE**	
Attribute	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
ASC	0.0585		0.1150**		0.088	
COST	-0.0035***		-0.0038***		-0.0040***	
TWH	0.0247***	0.0793***	0.0878***	0.1652***		
TWH2			-0.0019***	0.0028***		
TURB	-0.2414 ***	0.8830***	-1.4920***	3.9245***		
TURB2			0.3474***	1.1034***		
TWH10					0.8640***	1.4921***
TWH20					1.0346***	2.2837***
TWH30					1.1447***	2.4985***
TURB600					-1.0822***	2.4324***
TURB1200					-1.4410***	3.2451***
TURB3000					-1.4758***	3.0170***
MOUNT	-0.5617***	1.6608***	0.1625	2.1366***	0.3782	2.1685***
LOW	-0.5474***	1.8033***	0.1779	1.6997***	0.3949	1.6706***
COAST	-0.4554***	2.0590***	0.1751	1.8426***	0.3595	2.0671***
NORTHMID	-0.0663	1.9498***	-0.2973	1.9703***	-0.4128*	2.2133***
WEST	-0.2712*	2.7642***	-0.5454**	3.1065***	-0.5773**	3.2677***
EASTSOUTH	-0.0177	1.3767***	-0.2857	1.9040***	-0.3991*	2.1664***
Log likelihood	-5342.2		-5225.8		-5187.3	
Pseudo-R^2	0.2600		0.2760		0.2811	
No. of obs.	6568		6568		6568	

Note: ***p<0.01, **p<0.05, *p<0.1.

Figure 2: Full sample WTP per household per month (mean and 95% CI) for different functional forms for the attributes TURB (number of turbines) and TWH (renewable electricity production in TWh) based on piecewise linear specification

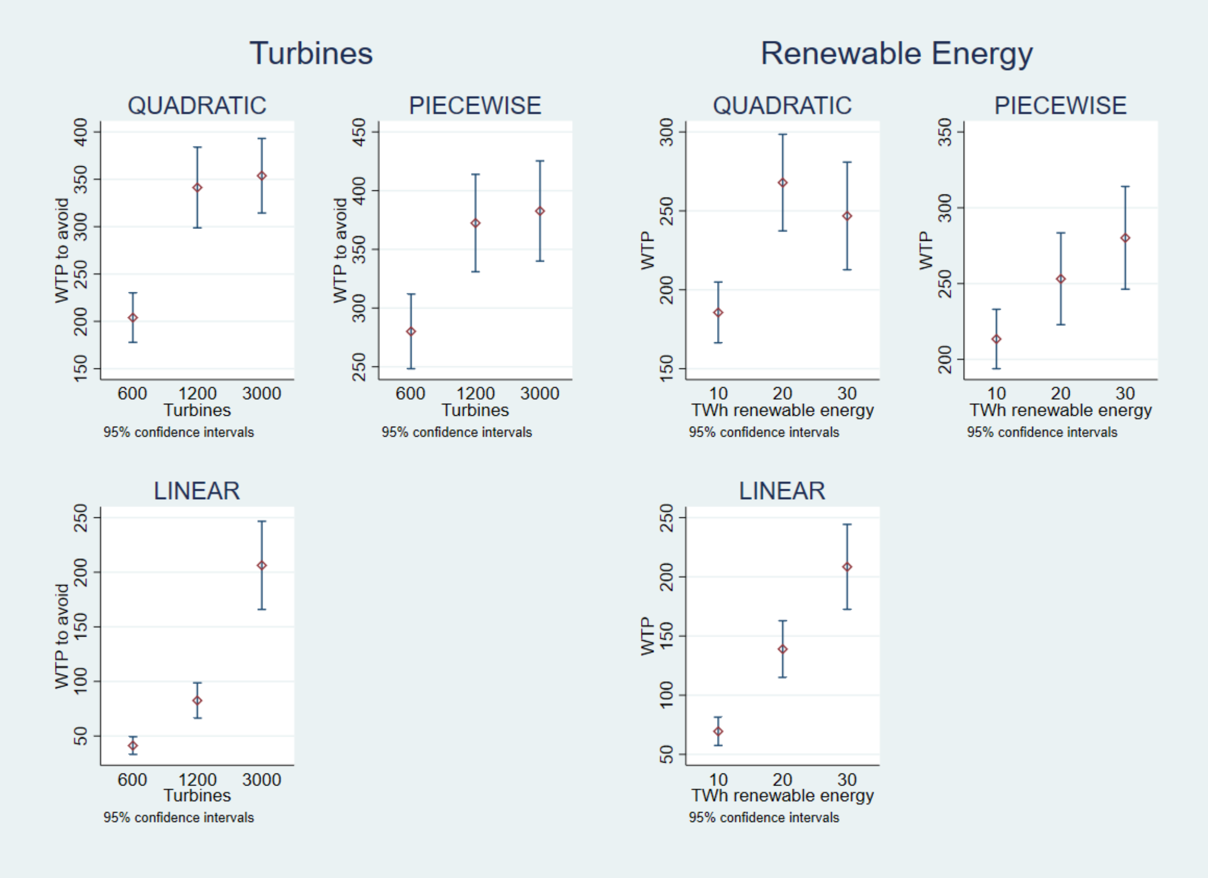


Figure 2 summarizes welfare estimates for the two quantitative attributes in terms of WTP for 10, 20, and 30 TWh of new renewable energy production and WTP to avoid 600, 1200, and 3000 new wind turbines, respectively. The welfare estimates are reported in Norwegian Kroner (NOK) on a per household per month basis.[18] The LINEAR model has the lowest welfare (WTP) estimates, which increase monotonically due to the constant marginal utility restriction. The QUADRATIC and PIECEWISE specifications generate somewhat higher WTP estimates. For example, the mean estimates of WTP to avoid 600, 1200 and 3000 turbines are NOK 200, NOK 340, and NOK 360 in the QUADRATIC model and NOK 270, 360, and 380 in the PIECEWISE model. In contrast, these estimates are NOK 40, NOK 80, and NOK 200 in the LINEAR model.

[18] Given the specific nature of our DCE design, welfare estimates for the wind power attribute can be interpreted either as "WTP to avoid new wind turbines" or "WTA compensation for new wind turbines". We use the phrase WTP for the sake of simplicity and consistency with the scope elasticity of WTP concept.

The estimated utility coefficients in Table 4 together with the corresponding welfare measures in Figure 2 establish the presence of scope impact. Furthermore, these estimated effects are statistically significant. For the LINEAR model, statistical significance follows directly from the significance of the estimated mean coefficients of THW and TURB. In the QUADRATIC and PIECEWISE cases, statistical scope significance can be inferred from the fact that the WTP estimates for the lowest and highest attribute levels for both attributes have non-overlapping confidence intervals.

Table 5: Full sample scope elasticity of WTP estimates (mean and 95% CI) for different functional forms for the attributes TURB (no. of turbines) and TWH (renewable electricity production in TWh)

Model	Attribute	Mean	Lower bound	Upper bound
LINEAR	TURB	1	1	1
	TWH	1	1	1
QUADRATIC	TURB	0.4028	0.3431	0.4617
	TWH	0.2827	0.2133	0.3516
PIECEWISE	TURB	0.2320	0.1864	0.2762
	TWH	0.2703	0.2066	0.3341

Note: The bootstrap *t*-percentile method with 10 000 replications was used to estimate the CI.

Table 5 summarizes scope elasticity of WTP. The LINEAR model assumes unitary elastic scope sensitivities for all increases in a good. In the QUADRATIC and PIECEWISE models, the scope elasticities of WTP for new renewable energy production evaluated between 10 and 30 TWh are 0.28 and 0.27, respectively. The scope elasticities of WTP to avoid new wind turbines evaluated from 600 to 3000 turbines are 0.40 in the QUADRATIC model and 0.23 in the PIECEWISE model. Interestingly, while the confidence intervals indicate that both estimates are statistically greater than zero and less than one (i.e., inelastic), they are also statistically different at the 0.01 significance level. This suggests that choice of functional form may have an impact on scope inferences in DCE studies. In the following we limit the subsample analyses to comparing results for the more flexible and statistically superior PIECEWISE specification.

5.2 Comparing across geographic subsamples

Figure 3 and Table 6 summarize WTP and scope elasticity estimates for the two geographic subsamples. The underlying panel mixed logit estimation results are provided in Table A2. As seen from Figure 3,

Figure 3: WTP per household per month (mean and 95% CI) by geographic subsample (Oslo and Rogaland counties) for the attributes TURB (number of turbines) and TWH (renewable electricity production in TWh) based on piecewise linear specification

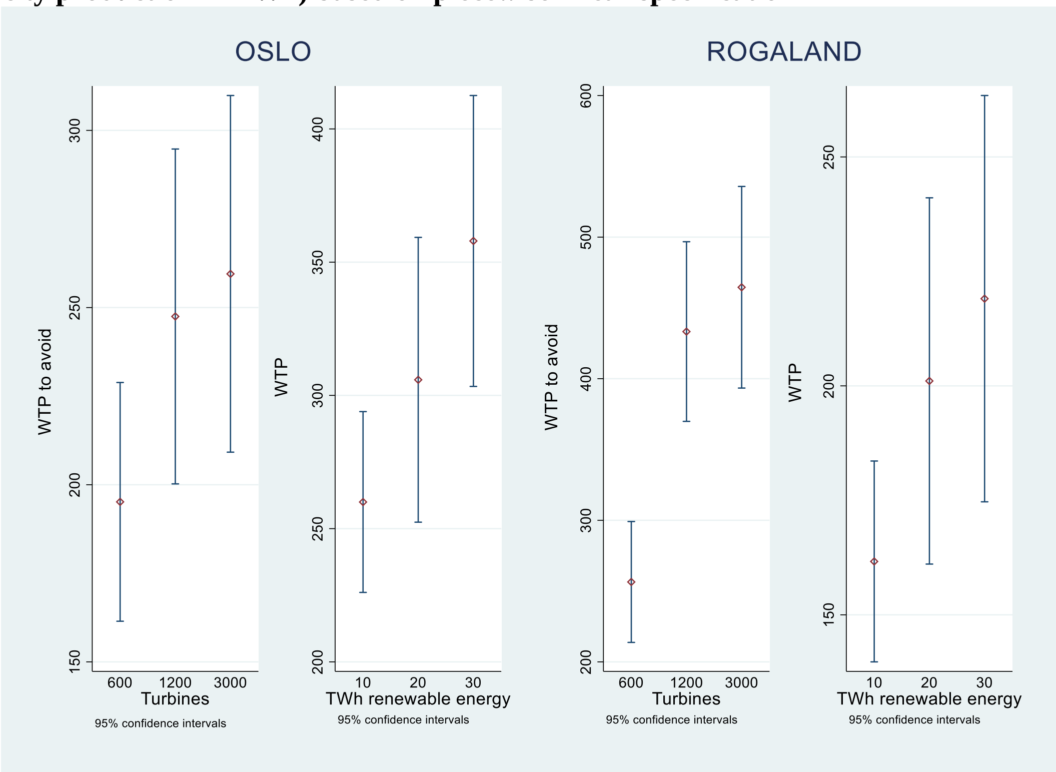


Table 6: Scope elasticity of WTP estimates (mean and 95% CI) by geographic subsample (Oslo and Rogaland counties) for the attributes TURB (no. of turbines) and TWH (renewable electricity production in TWh) based on piecewise linear specification

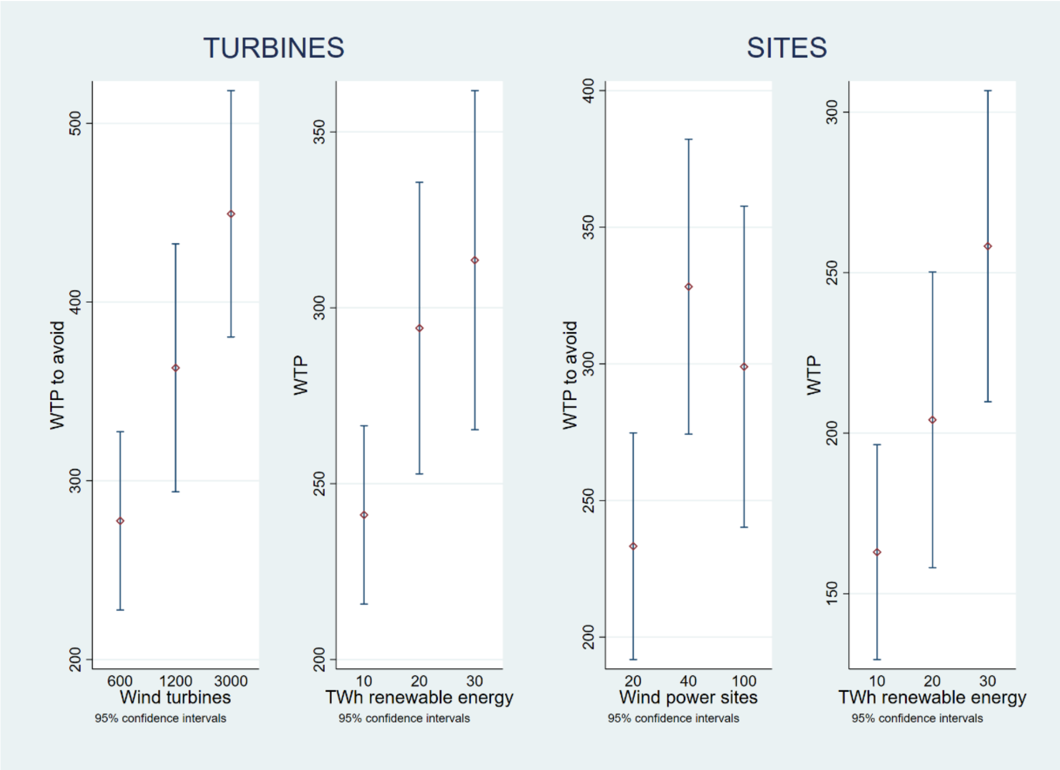
Model	Attribute	Mean	Lower bound	Upper bound
OSLO	TURB	0.2123	0.0756	0.3457
	TWH	0.3171	0.2372	0.3960
ROGALAND	TURB	0.4330	0.3679	0.4978
	TWH	0.3015	0.1750	0.4366

Note: The bootstrap *t*-percentile method with 10 000 replications was used to estimate the 95% CI.

the ROGALAND model implies lower WTPs for new renewable energy production and higher WTPs for avoiding wind turbines than the OSLO model. The differences in WTP between the two subsamples are significantly different for all attribute levels, except for the case of 600 turbines, as assessed by the bootstrap t-percentile method with 10 000 replications to construct 95% confidence intervals (Cameron and Trivedi, 2005). Nonetheless, as seen in Table 6, the scope elasticities for new renewable energy production are statistically and substantively indistinguishable, at 0.30 for Rogaland

and 0.32 for Oslo. In contrast, the estimated scope elasticity of WTP to avoid turbines is twice as high in ROGALAND as in OSLO (0.43 versus 0.21). This difference is also statistically significant (see Table 8). In combination, the higher WTPs and scope sensitivity associated with the turbine attribute in the Rogaland subsample suggest that experience/familiarity may adversely affect wind power acceptance in Norway.[19]

Figure 4: WTP per household per month (mean and 95% CI) by unit of measurement subsample (1 site = 30 turbines) for the attributes TURB (no. of turbines) and TWH (renewable electricity production in TWh) based on piecewise linear specification



[19] These differences may be attributable to factors other than experience/exposure (Dugstad *et al.*, 2020). The two geographic subsamples have slightly different socioeconomic profiles (Table A1). For this reason, we performed a robustness check using propensity score matching techniques (Liebe et al., 2015). The differences in WTPs and scope elasticity between the two subsamples were retained in these estimations. Results are available upon request.

Table 7: Scope elasticity of WTP estimates (mean and 95% CI) by unit of measurement subsample (1 site = 30 turbines) for the attributes TURB (no. of turbines) and TWH (renewable electricity production in TWh) based on piecewise linear specification

Model	Attribute	Mean	Lower bound	Upper bound
TURBINES	TURB	0.3544	0.2739	0.4318
	TWH	0.2611	0.1619	0.3608
SITES	TURB	0.1851	0.1026	0.2633
	TWH	0.4526	0.3575	0.5481

Note: The bootstrap *t*-percentile method with 10 000 replications was used to estimate the 95% CI.

5.3 Comparing across units of measurement

Figure 4 and Table 7 summarize WTP and scope elasticity estimates for the two unit of measurement subsamples (see Table A2 for the underlying panel mixed logit results). The estimated models are referred to as TURBINES and SITES, respectively. Bear in mind that the only difference between the two DCE versions was the unit of measurement for the wind power attribute, specifically, the number of wind turbines versus the number of production sites, with one production site described as comprising thirty wind turbines. The WTP estimates are reported on a per turbine basis for comparison.

Contrary to our tentative *a priori* expectation, the two measurement units are associated with different welfare estimates and scope sensitivities. Specifically, the TURBINES model has higher WTPs (Figure 4) and scope elasticity (Table 7) for the wind power attribute than the SITES model. For example, estimated WTP to avoid 1200 turbines is NOK 450 in the former versus NOK 330 in the latter. Furthermore, the scope elasticity is different in the two subsamples, at 0.35 versus 0.19. These differences are statistically significant (Table 8).

Table 8: Simulated subsample differences in estimated scope elasticities (mean and 95% CI) based on piecewise linear specification

Sub-sample comparisons	Attribute	Mean difference	Lower bound	Upper bound
OSLO vs ROGALAND	TURB	-0.1953	-0.3946	-0.0491
	TWH	0.0224	-0.1308	0.1698
TURBINES vs SITES	TURB	0.1721	0.0653	0.2759
	TWH	-0.1937	-0.3279	-0.0607

Note: The bootstrap *t*-percentile method with 10 000 replications was used to estimate the 95% CI.

Interestingly, the unit of measurement also seems to have an impact on the new renewable energy production attribute. Here, the scope elasticity of WTP is lower in the TURBINES model (0.26) than in the SITES model (0.45). In combination, these findings suggest that choice of attribute representation may influence scope inferences in DCE studies, even when the difference in the available metrics seems innocuous from a design perspective.

6. Concluding remarks

Investigating the significance of scope sensitivity remains an important validity check in SP research. However, it is important to distinguish between statistical and economic significance (Amiran and Hagen, 2010; Whitehead, 2016; Lopes and Kipperberg, 2020). This paper is the first to study the significance of scope effects in DCEs using the scope elasticity of WTP concept.

Based on our literature analysis, we make the following observations: 1) Investigation of sensitivity to scope as an SP validity check (or for any other reason) seems uncommon in the applied DCE literature. 2) The majority of studies assume unitary elastic scope sensitivities by employing a linear functional form for the deterministic utility component. 3) When more flexible specifications are employed, such as quadratic or piecewise linear, there is a tendency towards inelastic scope sensitivity (e.g., Boxall *et al.*, 1996; Adamowicz *et al.*, 1998; Drechsler *et al*, 2011; Ladenburg and Dubgaard, 2009), though some authors report estimates that are indicative of elastic relationships (e.g., Layton and Brown, 2000; Liu *et al*., 2017).

The scarcity of scope sensitivity testing in DCE research seems to coincide with a general lack of attention to functional form and the theoretical properties of utility functions (e.g., positive and diminishing marginal utility associated with attributes conceptualized as *economic goods*) in the DCE literature. This deficiency, in turn, has implications for the ability to differentiate between statistical and economic significance in estimated effects. This observation is consistent with observations made by Johnston et al. (2017): "*Many published SP studies facilitate estimation by assuming a utility function that is linear and additively separable (with constant marginal utilities). Although such functions may serve as a useful local first approximation, these implicit assumptions will not always hold. Among the concerns in this area is the likelihood that preferences will exhibit nonlinearity (e.g., diminishing marginal utility or nonconstant marginal rates of substitution between attributes). Such possibilities can be accommodated using richer specifications for preference or welfare functions*."

In our analysis of renewable energy preferences in Norway, we find positive WTP for new renewable energy production combined with positive WTP for avoiding the negative externalities associated with new wind turbines. Furthermore, there are substantial differences in WTP across attribute levels. All scope elasticity of WTP estimates are statistically significant and vary between 0.18 and 0.46, depending on the attribute analyzed, model specification, geographic subsample, and unit of measurement chosen for the wind power attribute. While there is no strict and universally applicable benchmark for determining the economic significance of scope impacts, we deem these elasticity estimates to be of an adequate and plausible order of magnitude. Thus, they can provide valid inputs to cost-benefit analyses and optimization models for the sizing and siting of wind power.

Finally, we advise DCE researchers to include explicit assessments of scope sensitivity and economic significance as part of validation diagnostics. Specifically, we recommend that it become routine practice to report scope elasticity estimates alongside welfare estimates for the attributes that are explored quantitatively in DCE studies. This also means that *ex ante* design considerations should be made to facilitate such analysis. DCE researchers should seek experimental designs that permit estimation of flexible functional forms and identification of scope elasticities. Related to this, a fruitful direction for future research would be systematic exploration of scope sensitivity determinants. As indicated by our analysis, scope elasticities are influenced by conceptual, methodological, and empirical dimensions. We believe that it is likely that scope sensitivity will vary across individuals, sub-groups and study contexts, as well as be dependent on overall choice architectures. Hence, the adequacy, plausibility and economic significance of DCE findings must be assessed on a case-by-case basis.

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APPENDIX

Proof: $\overline{E}_{WTP} = 1$ for linear indirect utility specification

Let $V_j = \alpha_j + \boldsymbol{\beta_q q}_j + \beta_M(M - \boldsymbol{B}_j)$. Then marginal willingness to pay for a change in the level of q-vector elements s is: $WTP(q_s) = \frac{\beta_{q_S}}{\beta_M}$, which is constant.

WTPs for two discrete changes, $\Delta_s^A = q_s^A - q_s^0$ and $\Delta_s^B = q_s^B - q_s^0$, are therefore: $WTP^A = \frac{\beta_{q_S}}{\beta_M} \cdot \Delta_s^A$ and $WTP^B = \frac{\beta_{q_S}}{\beta_M} \cdot \Delta_s^B$, respectively.

Hence, the arc-scope elasticity between the two WTPs is:

$\overline{E}_{WTP} \equiv \frac{\%\Delta WTP}{\%\Delta q_s} = \left(\frac{\frac{\beta_{q_S}}{\beta_M} \cdot \Delta_s^B - \frac{\beta_{q_S}}{\beta_M} \cdot \Delta_s^A}{\frac{\beta_{q_S}}{\beta_M} \cdot \Delta_s^B + \frac{\beta_{q_S}}{\beta_M} \cdot \Delta_s^A)/2}\right) / \left(\frac{\Delta_s^B - \Delta_s^A}{(\Delta_s^B + \Delta_s^A)/2}\right)$, which reduces to 1.

Table A1: Basic descriptive statistics for full sample, Oslo subsample versus Oslo population, Rogaland subsample versus Rogaland population, and turbine subsample versus sites subsample

SOCIODEMOGRAPHIC PROFILE		FULL SAMPLE	OSLO	OSLO POPULA-TION	ROGA-LAND	ROGA-LAND POPULA-TION	TUR-BINES	SITES
Gender	Male	49 %	46 %	50 %	51 %	51 %	48 %	49 %
	Female	51 %	54 %	50 %	49 %	49 %	52 %	51 %
Income	Mean household income (1000 NOK)	576	564	624	588	735	567	585
Education	Higher education, (Bachelor or more)	59 %	70 %	31 %	47 %	23 %	62 %	53 %
Age	Mean age	43	41	44	44	38	42	43
Region	Oslo	51 %	100 %	100%	0 %	0%	51 %	51 %
	Rogaland	49 %	0 %	0%	100 %	100%	49 %	49 %

Table A2: Subsample panel mixed logit parameter estimates (Oslo versus Rogaland counties; turbines versus sites unit of measurement)

ATTRIBUTE	OSLO		ROGALAND		TURBINES		SITES	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ASC	0.1241		0.1673*		0.1540*		0.1681*	
COST	-0.0038***		-0.0046***		-0.0045***		-0.0043***	
THW10	1.0147***	1.7507***	0.6937***	1.3601***	1.0712***	1.5058***	0.6898***	2.0012***
THW20	1.2163***	2.6229***	0.8445***	2.4962***	1.3198***	2.4672***	0.8356***	2.6553***
THW30	1.4094***	2.5820***	0.9079***	2.6166***	1.3877***	2.8032***	1.0811***	2.7162***
TURB600	-0.6935**	1.6236***	-1.2832***	2.3709***	-1.2222***	3.1267***	-0.9985***	2.2681***
TURB1200	-0.8721***	2.3222***	-2.1278***	3.8167***	-1.5968***	3.9916***	-1.4029***	3.1223***
TURB3000	-0.9304***	2.4276***	-2.2999***	3.9642***	-2.0321***	3.8975***	-1.2464***	3.2486***
MOUNT	-0.0922	1.7476***	0.484	2.7228***	-0.0789	1.5018***	0.3953	2.7577***
LOW	0.2088	1.5914***	0.2389	2.4598***	0.1929	1.9583***	0.2747	2.6160***
COAST	-0.2373	2.1047***	0.685	2.3854***	0.1032	1.6772***	0.4582	2.2040***
NORTHMID	-0.363	2.0535***	-0.2734	3.0474***	-0.6259*	2.7704***	-0.2496	2.6013***
WEST	-0.4361*	3.2056***	-1.0364***	3.7531***	-0.6317**	3.7770***	-0.6954*	3.7142***
EASTSOUTH	-0.5282*	1.6731***	-0.4213	3.6087***	-0.7133*	2.3974***	-0.4241	2.9662***
Log likelihood	-2687.8		-2445.6		-2561		2571.9	
Pseudo-R^2	0.2719		0.3061		0.2893		0.2880	
No of obs.	3360		3208		3280		3288	

Note: ***p<0.01, **p<0.05, *p<0.1.