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Complexity-induced Status Quo Effects in Discrete Choice Experiments for Environmental Valuation

Abstract

In this paper we investigate the influence of choice task complexity on the propensity to choose the status quo (SQ) alternative in discrete choice experiments. Task complexity is characterized in terms of the design dimensionality systematically varying the number of choice sets, alternatives, attributes and levels as well as the level range using 16 split samples. Moreover, we use the number of level changes across alternatives and entropy to capture further complexity effects. First, we show that the frequency of choosing the SQ and the number of those respondents who always stay at the SQ varies across designs. Using a count data model and a binary logit we observe that both figures are particularly influenced by the number of alternatives. By interacting the alternative-specific constant of the SQ with our complexity measures in a conditional and random parameter logit, we then find that the probability to choose the SQ decreases with the number of alternatives and with designs having three attribute levels. The propensity to stay at the SQ, however, increases with higher values of entropy, more choice sets, and designs with a wider level range. Significant effects of socio-demographic characteristics on SQ choices are present in all our models.

Keywords*: Discrete Choice Experiment; Status Quo Effects; Task Complexity; Design of Designs; Complexity Measures*

1. Introduction

Several reasons have been put forward to include status quo (SQ) alternatives in discrete choice experiments (DCEs): First, the inclusion of a current situation ensures that choice experiments are in agreement with Hicksian welfare theory and that consistent welfare estimates can be derived (Balcombe and Fraser 2010). Second, SQ options make the choice task more realistic to respondents and similar to decision making in other market situations (Scarpa et al. 2005, Marsh et al. 2011). Third, they are included to avoid forced choice, improve model fit, increase design efficiency, and ensure unbiased estimates (Dhar 1997, Adamowicz et al. 1998, Marsh et al. 2011).

Nevertheless, the inclusion of a status quo alternative may evoke the so-called status quo bias or status quo effect which can be considered as the negative utility associated with moving away from the current situation (Adamowicz et al. 1998). Following Scarpa et al. (2005) the SQ effect can be defined as the systematic inclination of respondents to display a different attitude towards SQ alternatives from those reserved to alternatives involving some change, over and beyond what can be captured by the variation of attribute levels across alternatives. The SQ effect is a widely documented economic phenomenon (Samuelson and Zeckhausen 1988), which has also been observed in DCEs (Adamowicz et al. 1998). It may manifest itself due to multiple causes. For instance, it could be that individuals experience loss aversion or the endowment effect. Loss aversion occurs when the disutility of giving up an object is greater than the associated utility of acquiring it. This implies that individuals may stay at the SQ because the disadvantages of leaving it loom larger (Kahneman et al. 1992). The tendency to stay at the SQ may also be a result of the omission bias which is the preference for harm caused by omissions over equal or lesser harm caused by act (Ritov and Baron 1994). More specific to DCEs, the choice of the SQ option may be caused by the uncertainty of the trade-offs respondents would be willing to make (Adamowicz et al. 1998), by the description of the SQ and the survey mode (Lanz and Provins 2012) or it could be a form of protest response (Adamowicz et al. 1998, Lanz and Provins 2012). Protest responses have also been observed by Meyerhoff and Liebe (2009), who found a relationship between the perceived complexity of the choice task and the probability to choose the current situation. The propensity to choose the SQ as a response to a complex choice task has also been explored in other studies within and beyond the DCE literature (Boxall et al. 2009, Balcombe and Fraser 2010, Zhang and Adamowicz 2011).

In the following we focus on the complexity of the choice task as a possible source for the preference for the status quo. We expect that the more complex the choice task is, the higher is the probability to choose the SQ. We define choice task complexity in several different ways. First, we use the design dimensionality of the choice experiment as a measure of complexity. We follow a Design of Designs (DoD) approach which was originally introduced by Hensher (2004) in the context of transportation. Following the DoD approach, we use 16 different split samples or treatments systematically varying the number of choice sets, the number of alternatives, the number of attributes and their levels as well as the level range. Apart from the five design dimensions, secondly, we make use of further complexity measures that have been proposed in the literature. A measure which can be seen as a proxy for the number of trade-offs to be made by respondents is the number of single and multiple attribute changes or number of level changes in the choice set. Despite the dimensionality of the choice task, which captures the amount of information in the CE, the number of level changes measures the way in which the information is configured (DeShazo and Fermo 2002). Entropy and cumulative entropy, respectively,

were introduced into the DCE literature by Swait and Adamowicz (2001). Entropy, as originally defined in information theory, is a measure of information content or uncertainty. With respect to choice experiments entropy can be used as a measure for the similarity of alternatives (Zhang and Adamowicz 2011). As illustrated by Swait and Adamowicz (2001), entropy is also able to account for differences in the number of alternatives and the number of attributes.

The aim of this study is to investigate the effect of these complexity measures on the propensity to choose the status quo. We explore the complexity-induced status quo effect in two different ways.

Firstly, we relate the design dimensionality to the average frequency of choosing the status quo as well as to the number or respondents who always stayed at the current situation alternative by analyzing descriptive statistics. Moreover, we specify a negative binomial regression model for the number of SQ choices and a binary logit for the number of respondents who always chose the SQ with both models having the complexity measures as independent variables.

Secondly, we identify the influence of task complexity in discrete choice models by analyzing the effects of our complexity measures on the alternative-specific constant of the status quo (ASCSQ) within a conditional logit (CL) and a random parameter logit (RPL) framework. In discrete choice models the alternative-specific constant is a parameter not associated with any of the observed and measured attributes representing on average the role of all the unobserved sources of utility (Hensher et al. 2005). As a result, systematic status quo effects can be captured by the alternative-specific constants of the status quo (Scarpa et al. 2005). Thus, in the CL and RPL model we interact the ASCSQ with each of the complexity measures also controlling for socio-demographic characteristics of the respondent.

To our knowledge this is the first study which analyzes status quo effects in DCEs using a DoD approach simultaneously accounting for five design dimensions as well as other measures of choice task complexity. Furthermore, we are not aware of any study in the DCE literature which uses count data models to investigate status quo choices.

The remainder of the paper is structured as follows. Section 2 briefly reviews the literature on the status quo effect and outlines our hypothesis. Subsequently, the modeling approach (Section 3) and the design and implementation of our survey (Section 4) are described. In Section 5 we present the results of our study before providing conclusions and future research in Section 6.

2. The Status Quo Effect in the Literature and Our Hypothesis

The status quo effect is well documented in the literature with evidence coming from different areas of research such as psychology, experimental economics as well as revealed and stated preference data analysis. In an early study Samuelson and Zeckhausen (1988) showed that participants in an experiment disproportionately often chose the status quo when the number of alternatives was increased. In 1992, Tversky and Sharif argued that the presence of conflicts influences status quo choices. They found that when the complexity of the choice environment is increased in term of the similarity of alternatives, more consumers delayed their choices by opting for the default alternative. Similar findings, which were

based on revealed preference data, were presented by Dhar (1997) who showed that individuals tend to choose the status quo when they are faced with difficult trade-offs.

Turning to SQ effects in the DCE literature, Adamowicz et al. (1998) were among the first to show that not accounting for status quo effects might introduce bias into choice models and subsequent welfare estimates using stated preference data to measure passive use values. They pointed out that one reason to choose the SQ in DCEs might be the complexity of the choice experiment. Based on this result and also in an environmental valuation context, Boxall et al. (2009) analyzed the impact of single and multiple attribute changes as well as the number of choice sets on the choice of the SQ. They observed significant effects on the probability to choose the SQ in a CL and RPL model for both measures as well as for the socio-demographic variables age and gender. In a food-choice context, Balcombe and Fraser (2010) developed a model for a general treatment of the 'don't know' alternative. They concluded that the similarity between options expressed through entropy explained the tendency to choose the status quo. Zhang and Adamowicz (2011) addressed complexity-induced status quo effects in a discrete choice model simultaneously accounting for impacts on the ASCSQ as well as the preference and scale function. They tested different measures of choice task complexity finding significant impacts for entropy, the number of attribute level changes, and several socio-demographic characteristics.

Based on these findings we hypothesize that the design dimensionality as well as entropy, cumulative entropy, and the number of level changes have a significant influence on the propensity to choose the status quo. We also expect significant impacts for the socio-demographic characteristics of the respondents.

3. Modeling Approach

3.1 Complexity Measures

In this paper we investigate the relation between status quo choices and complexity. Firstly, we focus on entropy, as introduced by Swait and Adamowicz (2001). This can be seen as a measure of information provided (e.g., alternatives, attributes) or the other way round as uncertainty about a single choice set. In DCEs this may be interpreted as the similarity of alternatives or the cognitive burden of deciding about the utility-maximising option. Entropy is calculated using

$$H(\pi_x) = -\sum_{j=1}^{J} \pi(x_j) \log \pi(x_j) \qquad (1)$$

where alternatives of the DCE are characterised by $\{x_j, j = 1, \dots, J\}$ and their probability distribution is $\pi(x)$. This way the number of alternatives presented is directly included in the formula and influences the level of entropy. The more equal the probabilities of the single alternatives, the higher the entropy and, vice versa, an available dominant alternative minimizes entropy (Swait and Adamowicz 2001).

When calculating entropy, attribute levels may be coded orthogonally to ensure that no attribute level dominates expected utility (Zhang and Adamowicz 2011).

Secondly, cumulative entropy, as introduced by Swait and Adamowicz (2001) measures the uncertainty across all choice sets or the cumulative cognitive burden of choosing the best option. It is calculated by using

$$H_r = \sum_{r'=1}^{r-1} H'_r \text{ for } r = 2, \dots, R \qquad H_r = 0 \text{ for } r = 1 \tag{2}$$

where H_r stands for the cumulative entropy experienced by the respondent up to the r^{th} choice set.

Thirdly, the number of attribute level changes, as introduced by DeShazo and Fermo (2002) and Boxall et al. (2009), indicates how many trade-offs had to be made in the choice decision. More trade-offs between more different attribute levels are expected to increase the cognitive burden of trading-off alternatives against each other. Furthermore, DeShazo and Fermo (2002) showed that a higher number of attributes increases the variance of utility. If the numbers of level changes within each single option are summed up the number of level changes per alternative becomes apparent.

3.2 Count Data Analysis

The number of times respondents choose the SQ alternative has the property of count data, i.e., the response variable is a nonnegative integer (Cameron and Trivedi 2013). We use count data models to analyze whether the design dimensions and individual specific characteristics of respondents influence the number of times the SQ alternative was chosen across treatments. The basic count data model is a Poisson regression. In this model the probability of observing an individual n to choose the status quo option y times is

$$\Pr(y_n) = \frac{\mathrm{e}^{-\lambda_n t}(\lambda_n t)^{y_n}}{y_n!} . \tag{3}$$

The parameter λ is the expected number of SQ choices and is assumed to be a function of linearly independent regressors x_n that are thought to determine y_n. t is the exposure, defined as the length of time during which the events are recorded. In the present case the exposure is the number of choice sets an individual faced and thus varies across treatments. In the log-linear version of the model the mean parameter is parameterized as $\lambda = \exp(x_n'\beta)$ to ensure that $\lambda > 0$; β are the parameters.

A central assumption of the Poisson model is that the mean and the variance are equal, this is the so called equidispersion property of the Poisson. However, this property is often violated in real-life data with the variance exceeding the mean. Thus, the assumption of the Poisson may be too restrictive and less restrictive count data models such as the negative binominal may be more suitable.

3.3 Choice Models

Random utility assumes that the utility an individual n receives from choosing an alternative i (U_{ni}) consists of a systematic component (V_{ni}) and a random error component (ε_{ni}) resulting in the following utility function:

$$U_{ni} = V_{ni} + \varepsilon_{ni}. \quad (4)$$

Moreover, it is assumed that individual n selects an alternative i from the choice set C_n if the utility of alternative i is greater than the utility of any other alternative j:

$$P_{ni} = \Pr ob(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}), \forall i, j \in C, j \neq i. \quad (5)$$

Assuming that the error components are distributed independently and identically (IID) and follow the Gumbel distribution, the probability that alternative i is chosen is calculated in the conditional logit (CL) model as follows:

$$P_{ni} = \frac{\exp[V_{ni}]}{\sum_{j \in C} \exp[V_{nj}]}, \quad (6)$$

where the scale parameter of the error distribution is normalized to one, and omitted. The systematic part of utility of the i^{th} alternative is assumed to be a linear function of attributes:

$$V_{ni} = ASC + \beta_k x_{ik} + \beta_z I_n, \quad (7)$$

where β_k is the vector of preference parameters associated with attribute k, X_{ik} is attribute k of alternative i, β_z is the vector of socio-demographic variables (I), and ASC is an alternative specific constant which captures the influence of unobserved attributes on choice relative to specific alternatives.

The random parameter logit (RPL) model (Train 2009) is based on the assumption that parameters are randomly distributed in the population. Estimating the mean and variance of the random parameter distribution thus captures heterogeneity and individuals are assumed to be draws from a taste distribution. Therefore, an additional stochastic element that may be heteroskedastic and correlated across alternatives is introduced into the utility function such that

$$U_{ni} = V_{ni} + [\eta_{ni} + \varepsilon_{ni}] = U_{ij} = \beta'_n x_{ni} + [\eta_{ni} + \varepsilon_{ni}], \quad (8)$$

where η_{ni} is a random term with zero mean whose distribution over individuals and alternatives generally depends on underlying parameters and observed data relating to alternative i and individual n. The second error term ε_{ni} has zero mean, is IID over alternatives and does not depend on underlying parameters or data (Hensher and Greene 2003). The random term η_{ni} can take on different

distributional forms such as normal, lognormal, uniform, or triangular. The density of η_{ni} is denoted by $f(\eta_{ni}|\Omega)$, where Ω are the fixed parameters of the distribution. Then, for a given value of η_{ni}, the conditional probability for choosing alternative i is logit as the remaining error term is IID extreme value

$$L_{ni}(\beta_n|\eta_{ni}) = \frac{\exp(\beta'_n x_{ni} + \eta_{ni})}{\sum_j \exp(\beta'_n x_{nj} + \eta_{nj})} . \quad (9)$$

L_{ni} is the logit probability. The unconditional choice probability would be integrated over all values of η_{ni} weighted by the density of η_{ni}:

$$P_{ni}(\beta_n|\Omega) = \int_{\eta ni} P_{ni}(\beta_n|\eta_{ni}) f(\eta_{ni}|\Omega) \eta_{ni} . \quad (10)$$

In this study, we estimate both a CL and a RPL model with the estimates from the CL model serving as a baseline. In the RPL model unobserved taste heterogeneity is taken into account by specifying the non-price attribute parameters to be from a normal distribution and the price attribute to be from a lognormal distribution. Also the alternative specific constant is specified as a random parameter following a normal distribution. The mixed logit probability was simulated each time using 500 Halton draws. To capture the effect of the design dimensions and the complexity measures on the probability that the SQ alternative is chosen we interact the these variables with the alternative specific constant (Boxall et al. 2009, Zhang and Adamowicz 2011).

4. Study Design and Samples

The non-price attributes used in the stated DCE are all related to environmental aspects associated with land use changes. The list of attributes comprises Share of Forest, Land Conversion, several attributes regarding biodiversity conservation as well as the price attribute Cost. This is presented as an annual contribution to a landscape fund. All attributes except those concerning biodiversity conservation were presented in all designs. In order to be able to adjust the number of attributes according to the design plan, the attribute Biodiversity was based on an indicator using stocks of bird populations used in Germany (BMU 2010). This indicator can be segregated and aggregated into various bird populations in different landscapes (e.g., birds in the whole landscape can be split up into birds in agrarian landscape plus birds in other landscape). Table 1 illustrates this. Moreover, according to the Design of Designs plan numbers of alternatives and choice sets presented are varied across designs. Also, numbers of levels and range of levels are varied. However, this does not refer to the Cost attribute – cost levels remained unchanged throughout the CE.

Table 1: Attributes used in the Choice Experiment

Attribute	Description
Share of Forest	Percentage changes in the share of forest (positive and negative)
Land Conversion	Percentage changes in land conversion for housing development and traffic (positive and negative)
Bio_whole	Biodiversity in the whole landscape including all landscape types
Bio_agrar	Agricultural landscape biodiversity
Bio_forest	Forest landscape biodiversity
Bio_urban	Urban area biodiversity
Bio_other1	Biodiversity in other landscape types: Forests, urban areas, mountains, waters
Bio_other2	Biodiversity in other landscape types: Urban areas, mountains, waters
Bio_other3	Biodiversity in other landscape types: Mountains, waters
Cost	Contribution to a landscape fund in € per year

Following the design master plan by Hensher (2004), 16 different designs were created using NGENE software. The dimensions covered by Hensher (2004) were slightly changed. Numbers of choice sets presented are increased (6, 12, 18, 24 choice sets), also the number of attributes included (four to seven). All other dimensions remained unchanged. These were number (two to four) and range (base, +20%, -20%) of levels and available alternatives (three to five incl. status quo option). From these dimensions 16 C-efficient designs were created which combine characteristics of dimensions (see Table 2). C-efficient designs allow minimizing the sum of the variance of WTP (Scarpa and Rose 2008).

Table 2: Design overview

Design	Sets	Alternatives	Attributes	Levels	Range
1	24	4	5	3	Base
2	18	4	5	4	+20%
3	24	3	6	2	+20%
4	12	3	6	4	Base
5	6	3	4	3	+20%
6	24	3	4	4	-20%
7	6	4	7	2	-20%
8	12	5	4	4	+20%
9	24	5	4	4	Base
10	6	5	7	3	+20%
11	6	4	6	4	-20%
12	12	5	5	2	-20%
13	18	4	7	2	Base
14	18	3	4	3	-20%
15	12	3	5	2	Base
16	18	5	6	3	-20%

All choice tasks included a status quo-alternative, i.e., a zero price option with no environmental changes ('as today'), plus two or more alternatives depending on the Design of Designs plan. Choices in this generic CE regarding landscape changes had to be made considering landscape within a radius of about 15 kilometres around the respondents' place of residence.

Figure 1 presents an example choice set with seven attributes and four alternatives (Design 7). Attribute levels for the different options are presented according to the Design of Designs plan and for the status quo option 'as today' is inserted. The SQ option was part of each design and always was presented in the last column. The attribute levels of Share of Forest and Land Conversion are defined as relative changes from the current state of the landscape. As we did not know the current state of these attributes for each individual respondent, no current value was stated. For the biodiversity attributes we informed respondents about the current state of the indicator ('today 65 scores') in each choice set, informing them also about possible regional differences. For the Cost attribute '0 €' was presented as current state. For further details on our study design see also Oehlmann et al. (2013).

Figure 1: Example choice set with four alternatives and seven attributes

If only the following options were available for the future development of the landscape within a radius of up to 15 kilometres around your place of residence, which one would you choose?

If you live in a large city, please consider the surrounding area of the city.

	Option 1	**Option 2**	**Option 3**	**Option 4**
Share of forest in the landscape	20% more	20% less	20% more	as today
Land conversion	40% more	40% more	40% more	as today
Biodiversity in agricultural landscapes (Today 65 scores)	76 scores	89 scores	89 scores	as today
Biodiversity in forest landscapes (Today 80 scores)	95 scores	95 scores	95 scores	as today
Biodiversity in other landscapes (Today 65 scores)	89 scores	89 scores	89 scores	as today
Biodiversity in urban areas (Today 60 scores)	90 scores	90 scores	70 scores	as today
Financial contribution to the landscape fund per year	80 €	50 €	80 €	0 €
I choose	○	○	○	○

The Germany-wide online survey was run in December 2012. Respondents were recruited from a panel of a survey company. Each respondent was randomly allocated to one of the 16 designs. Before the respondents started to answer the choice sets, which were presented to them in a randomized order, they were asked to evaluate the current situation regarding the attributes presented to them in the DCE. At the end of the questionnaire standard socio-demographics were requested from respondents.

Each of the 16 treatments was presented to an average number of around 133 participants with a total of 2133 interviews, of which 1684 interviews were fully completed. The average interview length was 23 minutes and the response rate was 29.5%.

Table 3 reports basic socio-demographics as well as the number of interviews realized for all 16 designs. The relative shares of education refer to the highest educational level achieved.

Table 3: Socio-demographics across designs

Design	Number of Interviews	Age	Females	Middle-school degree	High-school degree	University degree	Income	Income question not answered (%)
1	85	41.98	0.45	0.29	0.22	0.44	2701.97	5.62
2	82	44.32	0.41	0.24	0.21	0.49	2850.71	7.77
3	124	43.81	0.43	0.25	0.28	0.40	2583.50	8.00
4	80	42.50	0.50	0.33	0.30	0.31	2720.63	10.03
5	104	43.30	0.55	0.24	0.25	0.46	2962.50	7.26
6	82	42.32	0.46	0.29	0.18	0.45	2572.46	7.49
7	222	42.49	0.47	0.31	0.27	0.36	2679.26	8.14
8	79	42.54	0.57	0.25	0.29	0.35	2803.62	7.15
9	81	43.47	0.37	0.28	0.31	0.36	2527.34	11.59
10	151	42.02	0.50	0.21	0.30	0.39	2882.09	6.38
11	88	41.44	0.57	0.36	0.22	0.38	2696.48	10.26
12	81	39.47	0.40	0.22	0.38	0.36	2685.62	5.51
13	113	42.09	0.56	0.26	0.27	0.43	2847.89	8.46
14	84	43.40	0.50	0.24	0.24	0.37	2513.19	6.75
15	144	40.44	0.50	0.30	0.26	0.36	2791.53	6.56
16	84	42.15	0.49	0.24	0.29	0.42	2742.67	6.06
Total	1684	42.46	0.47	0.27	0.27	0.40	2705.11	7.71

5. Results

5.1 Descriptive Statistics of Status Quo Choices

In order to better understand the relationship between the design dimensionality of the DCE and to analyze possible correlation structures, we first ran an ordinary least-squares (OLS) regression of the five design dimensions on entropy, which was summed up over choice sets for each design. The results are presented in Table 4. As previously expected and illustrated by Adamowicz et al. (2001), the number of alternatives as well as the number of attributes influences entropy, but with opposite signs. A positive relationship on the summed entropy can also be observed for the number of attribute levels, and, apparently, for the number of choice sets. Since we did not include the level range in the orthogonal level coding, this design dimension could not have any effect on entropy (see also Section 3).

Table 4: OLS regression between summed entropy and design dimensions

Design dimension	Coefficient	|T-value|
Number of choice sets	0.6864	8.79
Number of alternatives	1.5505	2.52
Number of attributes	-1.2154	2.27
Number of levels	1.6539	2.44
Level range	-0.0058	0.19

Note: N =16; R-square =0.9295

We start our analysis of the relationship between the complexity of the choice task and the propensity to choose the status quo by analyzing descriptive statistics. Table 5 depicts the five design dimensions of the DoD approach, the minimum (min), maximum (max), mean, and sum for entropy as well as the number of level changes (total and mean) of each design. In terms of both, entropy and number of level changes, there is a high degree of variation across the 16 treatments. Table 4 also shows the number of interviews realized for each design. Furthermore, the average number of times the status quo alternative is chosen and the number of respondents who stayed at the SQ option across all choice tasks are indicated. For instance, a respondent presented with Design 1 had to choose the SQ 24 times in order to be assigned to this category. For both SQ figures there is a high variation across designs ranging from 17.13% (3.02 times, Design 16) to 54.30% (13.02 times, Design 3) and 7.14% (Design 16, 6 respondents) to 25.69% (Design 15, 37 respondents), respectively. Regarding the average frequency of choosing the SQ, the three designs with the lowest percentage all have five alternatives while the three designs with the highest status quo frequency all have three alternatives. For these designs no clear pattern can be observed for the other design dimensions, so there might be suggestive evidence that the number of alternatives influences the average frequency of choosing the status quo. Although less clear, there might be also some indication that the number of alternatives also negatively influences the number of respondents who always stayed at the SQ. However, to more formally test both relationships, we present two regression analyses in the next section.

Table 5: Descriptive statistics on the choice of the status quo alternative

Design	Number of ...				Level range	Entropy			Cum. Entropy	Level change		N	SQ choices (n/%)	Always SQ (n/%)
	Sets	Alt.	Attr.	Level		Min	Max	Mean		Mean	Total			
1	24	4	5	3	Base	0.06	1.30	0.56	13.37	9.33	896.00	85	7.59 (31.62)	10 (11.76)
2	18	4	5	4	+20%	0.17	1.35	0.83	14.75	12.44	896.00	82	7.20 (39.97)	12 (14.63)
3	24	3	6	2	+20%	0.09	0.88	0.56	13.35	10.33	744.00	124	13.02 (54.30)	29 (23.39)
4	12	3	6	4	Base	0.08	0.92	0.45	5.29	9.33	336.00	80	5.30 (44.12)	16 (20.00)
5	6	3	4	3	+20%	0.43	0.88	0.69	3.73	6.00	108.00	104	3.11 (51.76)	20 (19.23)
6	24	3	4	4	-20%	0.18	1.09	0.79	18.76	7.29	525.00	82	12.76 (53.15)	12 (14.63)
7	6	4	7	2	-20%	0.07	1.07	0.51	3.54	13.04	320.00	222	1.74 (28.98)	34 (15.32)
8	12	5	4	4	+20%	0.31	1.49	0.90	10.52	11.50	690.00	79	4.00 (33.33)	9 (11.39)
9	24	5	4	4	Base	0.34	1.56	0.96	22.77	10.79	1295.00	81	8.27 (34.47)	13 (16.05)
10	6	5	7	3	+20%	0.17	1.17	0.68	3.91	17.83	535.00	151	1.45 (24.17)	21 (13.91)
11	6	4	6	4	-20%	0.31	1.16	0.77	4.31	13.00	312.00	88	2.42 (40.34)	17 (19.32)
12	12	5	5	2	-20%	0.20	1.48	0.63	7.42	10.83	650.00	81	3.00 (25.00)	11 (13.58)
13	18	4	7	2	Base	0.01	1.13	0.40	7.20	9.89	712.00	113	6.29 (34.96)	23 (20.35)
14	18	3	4	3	-20%	0.15	1.06	0.73	12.90	6.39	345.00	84	8.39 (46.63)	13 (15.48)
15	12	3	5	2	Base	0.03	0.83	0.39	4.62	6.58	237.00	144	6.06 (50.46)	37 (25.69)
16	18	5	6	3	-20%	0.09	1.19	0.70	12.46	14.56	1310.00	84	3.08 (17.13)	6 (7.14)
Total						∅0.17	∅1.16	∅0.66	∅9.93	∅10.70	∅619.44	1684	37.78 %	283 (16.81)

5.2 Frequency of Choosing the Status Quo and Always Choosing the Status Quo

In Table 6 we present the results of a negative binomial regression with the dependent variable being the number of times a respondent chose the status quo alternative. Since the length of the DCE varied due to the design respondents were assigned to, we adjusted the model to account for the different number of choice sets. As we expected non-linear complexity and interaction effects to be present, we specified a series of models using quadratic terms, dummy variables as well as interactions between the complexity measures. However, none of the interactions and quadratic effects became significant at the five percent level. We found a high correlation (0.559) between the number of level changes and the number of alternatives and, therefore, excluded the former measure from the negative binomial model. Turning now to the model results, designs with four and five alternatives have a significant and negative influence on the expected number of times the status quo is chosen compared to designs with three alternatives. This relationship has already been indicated in Table 5. However, this finding is not consistent with the hypothesis that more alternatives lead to a more complex choice task which in turn increases the number of times the status quo alternative is chosen. By contrast, our result lends some evidence to the preference matching effect (Zhang and Adamowicz 2011). With respect to the other design dimensions as well as the summed entropy no significant effect can be observed. Within the socio-demographic variables it is found that only the parameter for being male is significant at the five percent level. So, compared to female respondents being male has a negative impact on the expected number of times the status quo alternative is chosen.

Table 6: Negative binomial regression: Count data results for the number of times the SQ is chosen

Variable	Coefficient	|T-value|
Summed entropy	-0.0015	0.19
3 alternatives (base)		
4 alternatives	-0.2636	2.14
5 alternatives	-0.6131	5.80
4 attributes (base)		
5 attributes	-0.1799	1.27
6 attributes	-0.2155	1.92
7 attributes	-0.2885	1.52
2 levels (base)		
3 levels	-0.1820	1.86
4 levels	0.0161	0.13
Base level range (base)		
Narrow level range	-0.1156	1.29
Wide level range	0.1021	1.11
Age	0.0025	0.99
Gender female (base)		
Gender male	-0.2255	3.34
9 or less years of schooling (base)		
Middle-school degree	-0.0137	0.10
High-school degree	-0.1209	0.81
University degree	-0.2390	1.69
Constant	-0.3857	1.52

Note: N =1684; Log-likelihood =-4319.7917; Pseudo R-squared =0.0113

Table 7 shows the results of a binary logit model with the dependent variable being zero if a respondent chooses at least once an alternative different from the status quo, and one if the respondent chooses the current situation across all choice tasks. Similar to the count data model we omitted the number of level changes due to multicollinearity. Table 7, again, provides us with some indication of a preference matching effect. Compared to respondents who were asked to choose among three alternatives, respondents who were given five alternatives had a lower probability to stay at the status quo across all choice tasks presented to them. An impact in the same direction is observed for the dummy variable narrow level range (see next section for further discussion on impacts resulting from the level range). A negative effect on the probability to always choose the current situation is also suggested by the parameter for gender (male) and education (university degree).

Table 7: Binary logit results for the number of respondents who always chose the SQ

Variable	Coefficient	|T-value|
Summed entropy	0.0379	0.71
Number of choice sets	-0.0358	0.93
3 alternatives (base)		
4 alternatives	-0.3369	1.64
5 alternatives	-0.6710	2.76
Number of attributes	0.0629	0.64
Number of levels	-0.1282	1.08
Base level range (base)		
Narrow level range	-0.4352	2.08
Wide level range	-0.1800	0.99
Age	0.0090	1.77
Gender female (base)		
Gender male	-0.4001	2.96
9 or less years of schooling (base)		
Middle-school degree	-0.0488	0.19
High-school degree	-0.0583	0.22
University degree	-0.5495	2.12
Constant	-0.8940	1.21

Note: N =1684; Log-likelihood =-740.05176; Pseudo R-squared =0.0294

5.3 Including Status Quo Effects into Choice Models

In this section we now investigate within discrete choice models the influence of our complexity measures on the propensity to choose the SQ. We specified two different models. First, we used the standard conditional logit with interactions between the alternative-specific constant of the status quo and the design dimensionality of the DCE as well as entropy, cumulative entropy, and number of level changes. However, the coefficients in this model including the parameter for the ASCSQ are forced to be the same for all respondents. As a consequence, we also estimated a random parameter logit again interacting the complexity measures with the mean of the ASCSQ. On the one hand, this allowed us to account for unobserved taste heterogeneity across respondents with respect to the attributes used in our study. As the survey was conducted nation-wide and respondents lived in quite different landscapes

it is likely that participants prefer different changes and thus accounting for unobserved heterogeneity will probably have an impact on the results. On the other hand, the RPL specification also enables us to account for the panel character of our data, and for heterogeneity of the status quo effect.

In Table 8 one can find the results of the CL and the RPL. Since we focus on complexity effects with respect to the ASCSQ, we do not report the parameters for the attributes. All attributes including means and standard deviations (SD) for the RPL were found to be significant at the one percent level and had all the expected signs in both models. Their coefficients and T-values are in the appendix of this paper. A likelihood-ratio (LR) test indicates that the CL with ASCSQ-interactions is preferred to the CL estimated without accounting for choice task complexity (LR =701.85, critical Chi-squared value for 18 degrees of freedom =28.8693). We also reject the null hypothesis at the one percent level of significance that the RPL is not better than the CL (LR =18165.004, critical Chi-squared value for 11 degrees of freedom =19.6751).

The results presented in Table 8 reveal that a positive status quo effect is apparent in the CL since the coefficient for the ASCSQ is highly significant and positive. However, when accounting for unobserved taste heterogeneity the mean of the ASCSQ, which was specified random, is not significantly different from zero. The size and T-value of the parameter estimated for the standard deviation of the status quo parameter indicates that a high degree of heterogeneity exists towards the preference for the status quo which can be either negative or positive. Turning now to the complexity measures, the ASCSQ-interaction with entropy became highly significant in the CL and RPL. So, the more similar the alternatives are, the higher the preference for the status quo. This finding is in line with Swait and Adamowicz (2001), Balcombe and Fraser (2010), and Zhang and Adamowicz (2011) who made similar observations. Cumulative entropy, which is used to capture the cumulative burden induced by the similarity of alternatives across choice sets, has, unexpectedly, a negative and significant sign. Yet, no significant effect is found in the RPL specification. Furthermore, it has to be noted that the cumulative entropy is highly correlated with the sequence of choice tasks, whose parameters became positive and significant in both models. When we estimated both models without accounting for the sequence of choice tasks, cumulative entropy had a positive and significant impact. This lends some support to the hypothesis that the cognitive burden caused by an increasing number of choice situations makes respondents more likely to choose the current situation. This result is in agreement with Boxall et al. (2009). Like in the models presented in Section 5.2, the number of alternatives significantly decreases the probability to choose the status quo in both models again suggesting preference matching effects. For the number of attributes only two dummy parameters became significant. Yet, this effect disappears when we account for unobserved taste heterogeneity.

Concerning the number of attribute levels a significant impact can be found for designs with three levels compared to those having only two in the CL and RPL. However, no significant effect can be shown for designs with four levels. We speculate that this non-linear relationship might be due to the fact that in designs with three levels the attributes Share of Forest and Land Conversion could adopt the level ‘as today’ in hypothetical alternatives, which was also shown in all SQ alternatives. By contrast, in designs with two and four levels, level values could only adopt negative and positive percentage changes, not ‘as today’. This might have motivated respondents to move away from the current situation since it is more likely to ’buy’ a positive change for Land Conversion or Share of Forest without having to accept a negative change for one of these attributes.

The significant parameters for both level range dummies in both models suggest that the higher the level range, the higher the probability to choose the SQ. It may be argued that this is a result of loss aversion. Respondents seem to be inclined to choose the current situation when attribute levels are less extreme. In this context, again, the attributes Share of Forest and Land Conversion may have played an important role as, for example, the disutility of a negative change (-30%), loom larger than the utility of a positive change (+30%).

All socio-demographic parameters influence status quo choices in both models. The older a respondent, the higher is the probability to choose the SQ. Furthermore, holding a university degree decreases the probability to stay at the current situation. Similar phenomena are well-documented in the literature (see Boxall et al. 2009 for an example within the DCE literature). Male respondents, moreover, were less likely to stay at the SQ than females. For the number of level changes we cannot find any statistically significant effect in all of our specified models. Boxall et al. (2009), and Zhang and Adamowicz (2011), however, have observed significant influences on the choice of the status quo for this complexity measure.

Table 8: Results from the CL and RPL model

Variable interacted with the ASCSQ	Conditional logit		Random parameter logit (Mean)	
	Coefficient	|T-value|	Coefficient	|T-value|
ASCSQ (mean)	0.8547	7.45	-0.2458	0.41
ASCSQ (SD)			4.4529	30.08
Entropy	0.1031	2.31	0.3391	3.89
Cumulative entropy	-0.0330	2.84	-0.0401	1.58
Number of level changes	-0.0029	0.29	-0.0005	0.03
Sequence of choice tasks	0.3665	4.46	0.0725	4.04
3 alternatives (base)				
4 alternatives	-0.1299	2.22	-0.7618	2.18
5 alternatives	-0.2232	3.63	-1.7658	6.65
4 attributes (base)				
5 attributes	-0.2206	2.88	0.4458	1.23
6 attributes	-0.2746	3.58	-0.4480	1.49
7 attributes	-0.0905	0.76	-0.6440	1.21
2 levels (base)				
3 levels	-0.3516	7.44	-1.2642	4.31
4 levels	-0.0584	1.00	-0.1771	0.49
Base level range (base)				
Narrow level range	-0.1950	4.80	-0.5009	2.28
Wide level range	0.2351	5.26	1.2824	5.55
Age	0.0032	2.97	0.0194	2.78
Gender female (base)				
Gender male	-0.3306	11.58	-0.8467	4.33
9 or less years of schooling (base)				
Middle-school degree	0.0747	1.25	0.1816	0.48
High-school degree	-0.1173	1.89	-0.2541	0.68
University degree	-0.3412	5.84	-1.0463	2.97
Log-likelihood	-27094.947		-18012.445	

Note: N =90354; Parameter estimates for attributes are not reported here (see text and appendix)

6. Conclusions

The aim of this study was to investigate complexity-induces status quo effects in discrete choice experiments. In total, we specified four models to account for possible complexity effects on the probability to choose the status quo alternative: A count data negative binomial regression for the number of times the SQ is chosen, a binary logit with the dependent variable indicating whether a respondent chooses the current situation across all choice tasks, as well as a CL and a RPL to study SQ effects in discrete choice models. In all models we have found evidence for a complexity-induced SQ effect. Within the dimensionality of the choice task particularly the number of alternatives has been found to significantly decrease the probability to choose the current situation. This indicates that by adding alternatives respondents may have easier found an option that matches their preferences (Zhang and Adamowicz 2009). At the same time this finding suggests that researchers should not worry too much about increasing the number of alternatives when they want to avoid the status quo bias evoked by a high number of alternatives. Nevertheless, this may lead to a trade-off to be made since only the binary choice question is known to be incentive compatible (Carson and Groves 2007). Unlike our approach, Zhang and Adamowicz, for instance, included a two alternative choice experiment in their study.

The estimates regarding the relation between SQ choices and the sequences of the choice tasks supports the hypothesis that as the number of choice tasks increases, the more likely the choice of the SQ. This may be a result of fatigue effects. We speculate that our findings concerning the number of levels and level range might be a result of the level specification for the attributes Share of Forest and Land Conversion.

No systematic effect has been found for the number of attributes in all the model specification we have tried. Within the additional complexity measures, there is clear evidence that the more similar the alternatives are, the higher the probability to choose the status quo. This is at least apparent in the choice models. In agreement with other studies investigating the SQ effect, all models also indicate that the respondent's characteristics gender (male), and education (university degree) made respondents less likely to stay at the current situation. The same is true, although with opposite sign, for age.

Our findings suggest that accounting for complexity impacts on SQ choices in discrete choice models can significantly improve model results. Knowing which complexity effect impacts SQ choices may help researchers in the design and modeling stage of the discrete choice experiment when status quo effects are of interest. However, our results have to be interpreted with a degree of caution. We cannot draw any conclusions on the underlying motivation respondents might have to stay at the current situation. It may result from different phenomena like loss aversion, unwillingness to make trade-offs, fatigue, etc.

As pointed out by Boxall et al. (2009), for instance, effects of fatigue could be also accounted for in the error term of the choice model. So, further research could start by estimating choice models simultaneously including complexity effects in the status quo parameter and the error term. Additionally, future estimations could even account for complexity effects in the preference structure (see Zhang and Adamowicz 2011). A further extension might be the inclusion of other complexity variables. For instance, DeShazo and Fermo (2002) defined the mean standard deviation of attribute levels within each

alternative (S.D. of Attributes), and the dispersion of the S.D. of attribute levels across alternatives as possible sources of complexity. As we asked respondent about their perceived status quo before they started answering the DCEs, we may include these statements into the choice models to explain status quo effects. Furthermore, future research should also analyze the influence of complexity-induces status quo effects on welfare estimates.

Appendix A

Table 9: CL and RPL parameter results for the attributes of our study

Attribute	Conditional Logit		Random Parameter logit (Mean)		Random Parameter logit (SD)	
	Coefficient	|T-value|	Coefficient	|T-value|	Coefficient	|T-value|
Share of Forest	0.0171	35.85	0.0313	26.97	0.0347	28.58
Land Conversion	-0.0085	36.47	-0.0145	21.27	0.0213	33.20
Bio_whole	0.0112	8.50	0.0158	5.54	0.0341	11.20
Bio_agrar	0.0052	8.24	0.0086	8.15	0.0130	8.08
Bio_forest	0.0067	7.07	0.0152	9.37	0.0137	4.97
Bio_urban	0.0060	4.96	0.0094	5.51	0.0010	2.84
Bio_other1	0.0070	5.29	0.0102	4.13	0.0224	8.19
Bio_other2	0.0041	4.78	0.0103	6.87	0.0127	5.74
Bio_other3	0.0056	5.51	0.0078	5.50	0.0066	2.29
Cost	-0.0059	25.33	-5.5122	43.80	2.6386	15.91

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