The importance of information and choice paradigms when exploring preferences for renewable energy

Alberto Longo

Gibson Institute, IGFS, UKCRC Centre of Excellence for Public Health (NI), Queen's University Belfast, and BC3 Basque Centre for Climate Change, E: a.longo@qub.ac.uk

Marco Boeri

Gibson Institute, Queen's University Belfast, and RTI Health Solutions, E: mboeri@rti.org

Abstract

This study aims to assess whether additional information can affect preferences or variance in a stated discrete choice experiment on renewable energy programs. We explore the impact of additional information on one of the attributes of the choice experiment using two choice paradigms: the Random Utility Maximization (RUM) and the Random Regret minimization (RRM). When considering each choice paradigm in isolation, we find that varying the level of information has no impact on either preferences or variance. Only when considering both choice paradigms in a hybrid model, a variation in the level of information reduces the variance in people's choices, but does not affect whether respondents' preferences are more likely to be explained by either of the choice paradigms. Finally, in line with the literature, we also find that respondents with stronger attitudes towards environmental goods, and therefore with better formed preferences, are more likely to select the alternative which maximizes their utility rather than the one which minimizes the associated regret. Our results indicate that not accounting for different choice paradigms can bias not only preferences analysis, but also the interpretation of the effect of varying the level of information in discrete choice experiments.

***Keywords**:* Random Regret Minimization; Random Utility Maximization; renewable energy; greenhouse gas emissions; information.

JEL: Q42, Q51

1. Introduction and motivation

Stated discrete choice experiments (DCE) are widely employed to analyze citizens' preferences for goods and services that are either public or not yet exchanged in the market – such as the additional supply of renewable energy (see Goett et al. 2000; Roe et al. 2001; Bergmann et al. 2006, Scarpa and Willis 2010, Meyerhoff et al. 2010, Mariel et al. 2015). However, the validity of the derived welfare measures is often disputed (see Carson and Hanemann, 2005). One potentially serious problem faced by stated DCE is that respondents often have little, if any, prior experience with the proposed scenario. To alleviate this problem, it is important to provide respondents facing a stated preference questionnaire with a detailed and accurate description of the proposed scenario, so that they know what they are being asked to evaluate and can make an informed decision (Arrow et al. 1993). The possibility that different levels of information can impact on the estimation of taste and of the derived welfare changes has been widely discussed (Boyle, 1989, Bergstrom et al. 1990; Spash and Hanley 1995; Ajzen et al. 1996, Rolfe et al., 2002, Gao and Schroeder, 2009, Meyerhoff and Glenk, 2015).

This study examines whether varying the level of information has any effect on preferences' intensity or variation in a DCE on renewable energy programmes described by four attributes: greenhouse gas emissions, power outages, employment in the energy sector, and electricity bill. Furthermore, given the developing literature on Random Regret Minimization (RRM), which has shown that not considering regret may lead to biased conclusions (Chorus et al. 2014), we explore a model that combines both choice paradigms, as proposed by Boeri et al. 2014. Differently from the Random Utility Maximization (RUM) model, the RRM model is based on the assumption that, when choosing, individuals aim to minimize their anticipated regret, rather than to maximize their expected utility. In this context, regret is defined as what one experiences when a non-chosen alternative performs better than a chosen one, on one or more attributes.

The idea of regret minimization is well established theoretically and empirically as an important determinant of choice behaviour in many fields (e.g. Simonson, 1992; Zeelenberg and Pieters, 2007; Loomes and Sugden, 1982; Sarver, 2008; Zeelenberg, 1999; Connolly, 2005; Savage, 1954; Bell, 1982; Chorus et al., 2006, 2008, 2009; Boeri et al, 2012, 2013; Thiene et al, 2012; Hensher et al, 2013; Guevara et al, 2014; van Cranenburgh et al, 2015). Regret minimization has often been considered an important driver of choices under uncertainty in risky situations (Zeelenberg and Pieters, 2007), and it explains particularly well choices related to unfamiliar goods, whilst choices related to familiar goods are explained better by utility maximization (Boeri et al, 2014, Jang et al. in press).

Additional information may therefore act in two ways: it may influence whether a respondent chooses maximizing their utility or minimizing their regret and, within each choice paradigm, it may impact on the preferences' intensity and variance, as measured respectively by the estimated coefficients and scale parameter of the logit formulation. As additional information has helped respondents becoming more familiar with the goods they are evaluating (Aidt, 2000), we would expect that additional information may reduce respondents' relying on the RRM rather than on the RUM when answering DCE questions. We would also expect that respondents who are more familiar with the good, because of their attitudes towards the good itself, may be more likely to rely on the RUM than on the RRM when choosing.

To test for the effect of information on preferences' intensity and variance, we split our respondents into two sub-samples and provide additional information on the attribute describing the effects of power outages in the DCE. We then explore whether this treatment produces an impact on the estimated preferences structure, in terms of coefficient estimates and scale parameter for each choice paradigm. In addition, to overcome the limitations of a model that assumes only one choice paradigm as a driver of choice behaviour for the whole sample of respondents, we use a hybrid model incorporating both choice paradigms, as recently suggested by Hess et al. (2012) and Boeri et al. (2014).

We find that the regret minimization choice paradigm explains better than the utility maximization choice paradigm about half of the choices in our sample. We also find that adding more information to the black-out attribute does not affect the probability of engagement with either choice paradigms, but it affects the scale factor, and, therefore, on the variance in the hybrid model. We also find that respondents' environmental attitude is an important determinant of the membership probability to either the RUM or the RRM class.

Previous studies found that the two models generate different elasticity values and different probability forecasting, implying different policy appraisals (Hensher et al. 2011, Thiene et al. 2012, Boeri and Masiero 2014). Therefore, we consider relevant, from both a methodological and an applied viewpoint, to introduce this approach in the field of energy economics. To our knowledge, this is the first application that employs both RUM and RRM in energy economics. Furthermore, this is the first attempt that explores whether the presence of additional information can impact on the likelihood that a choice paradigm explains better respondents' DCE answers.

The remaining of the paper is structured as follows. Section 2 describes the methodology; section 3 introduces the case study; section 4 presents the results; section 5 concludes the paper.

2. Method

2.1 Modelling Utility and Regret

We assume that, while choosing among alternative hypothetical policies for renewable energy, respondents either maximize their utility or minimize their regret. The former idea is grounded on the utility maximization theory (Thurstone, 1927; Manski, 1977), which is well established and widely used in modelling DCE data. Considering the traditional respondents' utility function:

$$U_{nit} = \beta' X_{nit} + \varepsilon_{nit}, \qquad (1)$$

where X is a vector of attributes observed for respondent *n* while choosing alternative *i* in the choice occasion *t*, β is a vector of parameters to be estimated and ε is the unobserved part of the utility assumed to be identically and independently Gumbel-distributed (i.e. Extreme Value Type I). In this context, the probability of choosing alternative *i* over any other alternative *j* in the choice set *t* is represented by a multinomial logit model (RU-MNL) as described by McFadden (1974):

$$Pr_{nit}^{RU} = \frac{e^{\mu V_{nit}}}{\sum_{j=1}^{J} e^{\mu V_{njt}}}, \qquad (2)$$

Where $V_{nit} = \beta' X_{nit}$ and μ is the scale parameter of the Gumbel error.

The second idea generates what has become known as RRM approach (Chorus, 2010), which postulates that, when choosing alternative *i* among *j* alternatives in the choice task *t*, decision-makers aim to minimize anticipated regret rather than to maximize utility. The regret function minimized by respondent *n*:

$$\Psi_{nit} = R_{nit} + \omega_{nit} \tag{3}$$

where ϑ is a vector of parameters to be estimated and ω is the unobserved part of regret Gumbel-distributed (i.e. Extreme Value Type I). Following Chorus (2010), the observed part of the regret function, $R_{nit} = \sum_{j \neq i} \sum_{m=1..,M} \ln\left(1 + e^{\theta_m \left(x_{jm} - x_{im}\right)}\right)$, represents the sum of all so-called binary regrets associated with the bilateral comparison of alternative *i* with all the other alternatives *j* in the choice set. This comparison is done for all attributes *m*. The parameter ϑ_m captures the slope of the regret-function for attribute *m*.

Recalling that minimising the random regret is mathematically equivalent to maximising the negative of the random regret,[1] the probability for individual *n* of choosing alternative *i* over any other alternative *j* in the choice set *t* is given by the multinomial logit based on RRM (RR-MNL):

$$Pr_{nit}^{RR} = \frac{e^{\lambda(-R_{nit})}}{\sum_{j=1}^{J} e^{\lambda\left(-R_{njt}\right)}}, \tag{4}$$

where λ is the scale parameter of the Gumbel-distributed error (Van Cranenburgh et al. 2015).

2.2 Hybrid choice behaviour model

[1] Note that, since $-R_i$ enters in the probability function, the negative of the RR-MNL's random error is distributed Extreme Value Type I. See Chorus (2010) for a more in-depth discussion.

In our study we gave some additional information to one subsample of respondents for one attribute. One might wonder whether this additional information provided to one subsample affected whether respondents were more likely to select their preferred alternative by either maximizing their utility or minimizing their regret.

As the RRM has been found to explain particularly well choices related to unfamiliar goods (Boeri et al, 2014), we expect that additional information may reduce respondents' relying on the RRM rather than on the RUM when answering DCE data. Therefore, for respondents that received the version of the questionnaire with a less detailed description of one attribute, we may expect that it is more likely that the regret minimization approach describes their choices better, rather than the utility maximization approach.

To understand whether a different level of information can affect the choice paradigm employed by respondents, we use a two-class latent class model (also referred to as probabilistic decision processes) with a hybrid RU-MNL, as described in Equation 2, and RR-MNL, as reported in Equation 4 specification, where class 1 consists of RUM decision makers and class 2 of RRM decision makers. Under this settings, the probability of a sequence of choices is:

$$\Pr(y_{Tn}|X_{nit}) = \prod_{t=1}^{T}\left(\pi_V \, Pr_{nit}^{RU} + (1 - \pi_V) \, Pr_{nit}^{RR}\right) \quad . \qquad (5)$$

The membership probabilities π_V for the class associated to the maximization of utility is also defined according to a logit process, we have:

$$\pi_V = \frac{\exp(\alpha_c + \gamma_c' z_n)}{\exp(\alpha_c + \gamma_c' z_n) + 1} \quad , \qquad (6)$$

where z_n is a vector of socio-economic covariates characterizing respondent n, and γ_c is the vector of associated parameters subject to estimation, while α_c is a class-specific constant.

2.3 Testing for the effect of information on preferences and scale.

Both RU-MNL and RR-MNL models can be estimated on the two sub-samples created by changing the level of information on one attribute in a DCE study, and both can include scale parameters. In RRM, this is known as a measure of profundity of regret, see Van Cranenburgh et al. 2015. It is therefore possible to test, under both choice paradigms, whether increasing the level of information on one attribute of the DCE has any impact on preferences or scale by comparing the log-likelihood (LL) functions, and hence the Akaike information criterion (AIC), of the MNL models estimated for the two sub-samples. Following Swait and Louviere (1993), we do this in two steps: by first testing a null hypothesis of equality of the coefficient estimates against an alternative hypothesis that the coefficient estimates are different, and then by examining differences in scales. We perform these two steps for both the RU-MNL and the RR-MNL estimates as follows.[2]

For the RU-MNL model:

$$\text{HU0a: } \beta_1=\beta_2 \text{ against HU1a: } \beta_1\neq\beta_2 \quad , \qquad (6a)$$

where β_1 and β_2 are the coefficient estimates for the sub-sample with basic information level (β_1) and for the sub-sample with additional information level (β_2) under the RU-MNL framework. For the RR-MNL model:

$$\text{HR0a: } \theta_1=\theta_2 \text{ against HR1a: } \theta_1\neq\theta_2, \qquad (6b)$$

where θ_1 and θ_2 are the coefficient estimates for the sub-sample with basic information level (θ_1) and for the sub-sample with additional information level (θ_2) under the RR-MNL framework. If HU0a is rejected, then the two sub-samples would exhibit different preferences, under the utility maximization choice paradigm. Similarly, if the HR0a is

[2] For more details on this test see Swait and Louviere (1993).

rejected, the two sub-samples would exhibit different preferences under the regret minimization choice paradigm. If both null hypotheses are rejected, then the data show differences in preferences across sub-samples under both the utility maximization and the regret minimization choice paradigms. In each of the above situations where the null hypothesis is rejected we could stop our investigation of differences across the two sub-samples as differences in preferences would not allow us to estimate a scale parameter (Swait and Louviere, 1993). In this case, as the two sub-samples are described by different models, we would conclude that even small differences in the level of information supplied to a respondent can impact respondents' preferences.

If no differences in preferences are found – the null hypotheses (6a) and (6b) are not rejected – the next step is to test for scale differences, using the second test proposed by Swait and Louviere (1993). For the RU-MNL model:

$$HU0b: \mu_1 = \mu_2 \text{ against } HU1b: \mu_1 \neq \mu_2, \qquad (7a)$$

where μ_1 and μ_2 are the coefficient estimates for the sub-sample with basic information level (μ_1) and for the sub-sample with additional information level (μ_2) under the RU-MNL framework. For the RR-MNL model:

$$HR0b: \lambda_1 = \lambda_2 \text{ against } HR1b: \lambda_1 \neq \lambda_2, \qquad (7b)$$

where λ_1 and λ_2 are the coefficient estimates for the sub-sample with basic information level level (λ_1) and for the sub-sample with additional information level (λ_2) under the RR-MNL framework. If HU0b is rejected, then the two subsamples would exhibit different scale parameter – hence different variation of preferences – under the utility maximization choice paradigm. Similarly, if the HR0b is rejected, the two subsamples would exhibit different scale parameter under the regret minimization choice paradigm. In this latter case we would conclude that differences in the level of information supplied to a respondent can make his/her preferences more volatile (i.e. the decision is less deterministic). If both HU0b and HR0b cannot be rejected, the data would show no differences in preferences and scale, indicating that the preferences and scale have not been affected by the addition of information in one of the attributes presented to respondents.

The outcomes of the tests (6a-7b) could also identify differences across the choice paradigms. Preferences – as well as scale – could indeed result stable under one of the choice paradigms but not under the other. For example, we might find that preferences differ between the two sub-samples under utility maximization (regret minimization) but not under regret minimization (utility maximization). In this case, we would conclude that the differences in the level of information supplied had an impact on choices for people who maximize their utility (minimize their regret) but not for people who minimize their regret (maximize their utility). We could also find that scale is different among the two sub-samples when assuming that respondents used a regret minimization (utility maximization) choice paradigm, and find no differences in scale among the two sub-samples under the utility maximization (regret minimization) framework. In this case, we would conclude that the differences in the level of information supplied to respondents would increase the variability of preferences – choices are more difficult and less deterministic – for respondents more inclined to minimize their regret (maximize their utility) than for respondents who maximize their utility (minimize their regret).

3. The case study

We use the data from a DCE aimed at eliciting public preferences for hypothetical policies for the promotion of renewable energy described by four attributes: (i) annual percentage reduction in greenhouse gas emissions, (ii) duration of energy disruptions (black-outs), (iii) variation in the number of people employed in the energy sector and (iv) electricity bill increase. These attributes were chosen on the basis that current energy policies in the UK aim to reduce greenhouse gas emissions, increase energy security, maintain employment or create new jobs at affordable prices for society (DTI, 2003, DECC, 2011). The selection of attributes and their levels was finalized during the conduction of focus groups.

The first attribute, greenhouse gas emissions, indicates the percentage reduction of emission per year. Its levels, reductions by 1%, 2% and 3%, are based on the targets described by the UK Energy White Paper (DTI, 2003). The second attribute, black-outs, in the form of sudden unannounced energy shortages, takes the levels of 30, 60, 120 minutes of blackout per year, being the business as usual scenario 90 minutes per year. The third attribute describes the effects of the policy on employment. The increasing demand for renewable energy might, on the one hand, increase the number of jobs in the renewable energy sector, and, on the other hand, decrease the number of jobs in the fossil fuel energy sector. Moreover, being the private cost of renewable energy more expensive than fossil fuel energy, an increase in renewable energy might have macroeconomic consequences in the energy industry resulting in a total loss of jobs.[3] Focus groups discussions suggested to set the following levels for the attribute employment: 1000 new jobs, 1000 jobs lost, and no change in jobs in the UK energy sector. The values were calculated by assuming a hypothetical variation of about 0.5% of the total number of employees in the energy sector.[4] The final attribute is cost to the household, expressed as increases in the quarterly electricity bill. Its levels are an increase by £6, £16, £25 and £38 and they correspond to an

[3] Firms might face higher prices. This could lead to an increase in wages in such a way that the unemployment rate would need to increase to balance the effect.

[4] According to the Office for National Statistics (2005), the total number of employees in the Energy and Water Industry Sector in the UK during the second quarter of 2005 was 177,000.

increase by 10%, 25%, 40%, and 60% from the average electricity bill in the UK.[5] Table 1 summarises the attributes and their levels for the present study.

[Table 1 should be approximately here]

When describing the black-out attribute, respondents in sub-sample 2 were given the following description:

"As the demand for electricity increases, it is likely that we will experience an increase in the number and in the length of black-outs since the grid might not be able to satisfy the total demand. *Having black-outs means that there is no electricity. As a consequence, we would have no light at home, the fridge would not work, so wouldn't the lifts, etc. Also the industrial production would suffer.* Using renewable sources, we increase the number of the sources from which we can produce electricity, which lowers the risk associated with the dependence of foreign energy suppliers so that the disruption of one of the sources will have smaller effects on the total energy supply."

The difference between sub-sample 1 and 2 is that sub-sample 1 was not given the information in italics as reported in the above text. Sub-sample 2, therefore, received some additional information on the effects of black-outs compared to sub-sample 1.

In each choice task respondents were asked to indicate their preferred policy out of a choice set with three alternatives: two experimentally designed alternatives and the current situation. To create the pairs of alternative hypothetical policies, we opted for a fractional factorial design (Louviere et al, 2000), using the %MktEx SAS macro for an efficient experimental design (Kuhfeld, 2010). We then selected two of these alternatives, but discarded pairs containing dominated or identical alternatives and prepared six different

[5] The average annual electricity bill in the UK according to the National Statistics is equal to £251 (DTI, 2005a; Table 2.2.2). The electricity consumption in 2003 was equal to 337.443 billion kWh (IEA, 2003).

versions of the questionnaire with six choice tasks each.[6] An example of choice experiment is shown in Figure 1.

[Figure 1 should be approximately here]

The survey was administered in person to 300 respondents intercepted in shopping areas, public parks and other central areas of Bath, England, in July and August 2005 by professional interviewers who were instructed to interview an even number of men and women and to ensure the desired proportions of respondents in various age groups. To mitigate possible biases in the sample, interviewers were instructed to follow the common practice of stopping potential respondents every 7th person passing by. We chose to interview people through in-person interviews to guarantee a high quality in the answers. The budget constraint of this study limited our analysis to sample residents of Bath and North East Somerset. The results presented in this study should therefore be interpreted with caution: they are not representative of the UK population, but of the residents of a quite wealthy medium sized town of the South of the UK.[7]

4. Results

4.1 Descriptive statistics

Our average respondent is 35 years old, has an annual gross household income of about £37,000, and pays £70 per quarter on electricity bill. About 34% does not report how much they pay for electricity, almost 31% have electric heating, and 22% are members of an environmental organization. After the DCE questions, we investigated altruistic behaviour

[6] More efficient designing methods for DCE have been developed since the seminal work of Ferrini and Scarpa (2007), however when the survey instrument was developed, it was common practice to use fractional factorial designs, as proposed Louviere et al. (2000).
[7] For a complete description of the survey see Longo et al. (2008).

by asking respondents whether their choices were driven by what they considered be best for society or for their household. We find that 75.67% choose the options that they considered best for society, with the remaining 24.33% choosing what is better for their household. Of the 300 respondents, 132 (44%) received the version with additional information on black-outs (subsample 2), and the remaining 168 (56%) received the baseline questionnaire (subsample 1). Table 2 reports the descriptive statistics of the variables used in the econometric models.

[Table 2 should be approximately here]

4.2 Preferences and choice behaviour analysis

Table 3 reports the output of the two MNL models, the RU-MNL and the RR-MNL. By examining the log-likelihood value of the two models, we notice that the RR-MNL model fits the data better than the RU-MNL. This result appears to support our assumption that RRM is a good model for explaining choices for this type of hypothetical scenarios, based on the theoretical prediction that anticipated regret seems to drive choices perceived as important and difficult, when the decision-maker expects to receive feedback about chosen and non-chosen options in the short term, and when the decision-maker believes that he or she will be held accountable for the choices made (Zeelenberg, M., 1999). In our case, respondents make choices on behalf of their household. Therefore, it is possible that regret minimizations plays an important role in explaining their choices because respondents' decisions may affect households' wellbeing.

[Table 3 about here.]

The output shows that for both models all parameters are highly statistically significant and have the expected signs. However, the interpretation of the coefficients from the two models is not directly comparable. In fact, a positive and significant coefficient in the RR-MNL, such as the one for the reduction of greenhouse gas emissions and the number of jobs, suggests that regret increases as the level of those attributes increases in a non-chosen hypothetical policy, compared to the level of the attributes characterizing the chosen alternative. Similarly, the negative coefficients for price and for the minutes of unexpected black-outs suggest that regret decreases as the differences in levels for price and for minutes of black-out between the chosen and the non-chosen alternative increase. When these differences increase, non-chosen alternatives would become less attractive as they would be more expensive and entail longer periods of energy disruptions.

[Table 4 about here.]

It is also of interest to understand whether small changes in the description of one attribute can impact on preferences or scale. We show in Table 4 the results from the test proposed by Swait and Louviere (1993) under both RUM and RRM specifications. We firstly show the results from the MNL models specified under both assumptions of RRM and RUM: RU-MNL and RR-MNL. We then specify a hybrid modelling approach in which RRM and RUM are specified in the same LC model – Hybrid RU-RR – and we finally add covariates to check whether information and other socio-economic characteristics impact on the membership probability.

For each specification, we estimate four models: (a) only sub-sample 1, respondents with no additional information on black-outs; (b) only sub-sample 2, respondents with additional information on black-outs; (c) pooled dataset with both sub-samples, not controlling for differences in scale between the two sub-samples; (d) pooled dataset with both sub-samples, controlling for differences in scale between the two subsamples.

Models (a), (b) and (c) are used to test the null hypothesis H0a of no differences in preferences between sub-samples 1 and 2, while Models (c) and (d) are used to test the null hypothesis H0b of no differences in scale parameters between the two sub-samples.

Table 4 shows that, In both tests based on MNL models, the values estimated are smaller than the critical values of the χ^2 distribution (TEST 1 and 2). Therefore, since we cannot reject the null hypothesis in Equation 5 and 6, we would conclude that the additional information on the attribute black-out has no impact on either preferences or the scale factor in our data.

However, estimating hybrid models which can take into account for both RUM and RRM choice paradigms, we find that the additional information impacts on scale (TEST 3 and 4). In others words, when estimating only RUM or RRM alone it is assumed that all respondents have adopted the same choice paradigm. This assumption could bias not only preferences analysis, welfare analysis and probability forecasting, but also our conclusions on the effect of information. Indeed, the small changes in the level of information in our questionnaire impacted on the scale factor, and, therefore, on the variance.

In table 5 we report the full output of the results from the pooled hybrid RU-RR model with scale parameter estimated for subsample 2 to inspect whether the additional level of information on the black-out attribute and respondents' socio-economic characteristics and attitudes towards the environment affect which choice paradigm explains better respondents' choice behaviour.

[Table 5 about here.]

The results show that respondents' choices are almost equally well described by either the RUM or the RRM, as no choice paradigm strongly dominates the class membership probability. The coefficient for the additional information on black-out is estimated with a positive but not statistically significant sign, indicating that increasing the amount of information on one attribute has a positive, but not statistically significant effect on the probability of using a utility maximization choice paradigm. When we look at individuals' socio-economic characteristics and attitudes, we find that being member of an environmental organization is the only element that increases the probability that a respondent uses the utility maximization framework when choosing. These results provide evidence that, even though a small change in the level of information has little effect on the choice paradigm, having a strong preference towards the environment makes a respondent more likely to choose the utility maximization framework. This result is consistent with previous work that found that the RUM is particularly suitable to analyse data of respondents who have a good knowledge of the topic, whilst the RRM is well suited when respondents are unfamiliar with the good being evaluated (Boeri et al, 2014).

5. Conclusions

In this paper we consider the effects of information and environmental attitudes in a DCE for investigating the willingness to pay for renewable energy. Firstly, we explore whether varying the level of information of one of the attributes in the DCE has any effect on preferences, scale, as well as on the choice paradigm that drives respondents' choices. We analyze the data from the DCE using two choice paradigms: the RUM and the RRM. We find that additional information does not affect preferences and has a negligible effect on the choice paradigm, but it does affect the scale parameter, and therefore the variance, in a hybrid model that accommodates both RUM and RRM choice paradigms. This result indicates that small changes in information in one attribute may have an effect in choice experiments data that may not be easily detected if a researcher focuses only on using one choice paradigm when analysing the data. The results from Table 5 further show that respondents equally randomize between the RUM and the RRM and only those who have strong environmental attitudes are more likely to adopt the RUM framework when choosing. This result is important for policy analysis. As welfare estimates from DCE data are computed assuming that respondents use a RUM choice paradigm, it is important that researchers try to design questionnaires aimed at increasing the likelihood that a respondent uses the utility maximization framework when choosing. We found that, whilst respondents who have strong attitudes towards environmental goods are more likely to choose using a RUM choice paradigm, a small change to the level of information in one attribute does not affect a respondent's choice paradigm. Further research should investigate whether a larger change in the level of information on one attribute produces any effect on choice behaviour. This research could also be expanded by looking at whether varying the level of information on more than one attribute maintains the preferences of the respondents stable across the choice paradigms and increases the probability of respondents using the RUM choice paradigm.

References

Aidt, T.S., 2000. Economic voting and information. *Electoral Studies* 19, 349–362.

Ajzen, I., Brown, T., Rosenthal, L.H., 1996. Information Bias in Contingent Valuation: Effects of Personal Relevance, Quality of Information, and Motivational Orientation. Journal of Environmental Economics and Management 30, 43-57.

Alberini, A., Longo, A., 2009. Valuing the Cultural Monuments of Armenia: Bayesian Updating of Prior Beliefs in Contingent Valuation. Environment and Planning A. 41(2), 441-460.

Araña, J.E., León, C.J., 2009. Understanding the use of non-compensatory decision rules in discrete choice experiments: The role of emotions. Ecological Economics.68 (8-9), 2316-2326.

Arrow, K., Solow, R., Portney, P., Leamer, E., Radner, R., Schuman, H., 1993. Report of the NOAA panel on contingent valuation, Federal Register 58: 4602–4614.

Bell, D.E., 1982. Regret in decision making under uncertainty. Operations Research, 30(5), 961-981.

Bergmann, A., Hanley, N., Wright, R., 2006. Valuing the Attributes of Renewable Energy Investments. Energy Policy. 34(9), 1004-1014.

Bergstrom, J.C., Stoll, J.R., Randall, A., 1990. The Impact of Information on Environmental Commodity Valuation Decisions. American Journal of Agricultural Economics. 72 (3), 614-621.

Boeri, M., Longo, A., Doherty, E., Hynes, S., 2012. Site choices in recreational demand: a matter of utility maximization or regret minimization? Journal of Environmental Economics and Policy. 1, 32-47

Boeri, M., Longo, A., Grisolía, J.M., Hutchinson, W.G., Kee, F., 2013. The role of regret minimization in lifestyle choices affecting the risk of coronary heart disease. Journal of Health Economics. 32(1), 253-260

Boeri, M., & Masiero, L. (2014). Regret minimisation and utility maximisation in a freight transport context. Transportmetrica A: Transport Science, 10(6), 548-560

Boeri, M., Scarpa, R. and Chorus, C.G., 2014. Stated choices and benefit estimates in the context of traffic calming schemes: Utility maximization, regret minimization, or both?. *Transportation research part A: policy and practice*, *61*, pp.121-135.

Boyle, K.J., 1989. Commodity Specification and the Framing of Contingent-Valuation Questions, Land Economics. 65(1), 57-63.

Carson, R.T. and Hanemann, W.M., 2005. Contingent valuation. *Handbook of environmental economics*, *2*, pp.821-936.

Chorus, C.G., 2010. A new model of Random Regret Minimization. European Journal of Transport and Infrastructure Research. 10(2), 181-196.

Chorus, C.G., 2012. Random Regret-based discrete choice modeling: A tutorial. Springer Science & Business Media.

Chorus, C.G., 2012. Regret theory-based route choices and traffic equilibria. Transportmetrica. 8(4), 291-305.

Chorus, C.G., Annema, J., Mouter, N. van Wee, G.P., 2011. Modelling politicians' preferences for road pricing policies: A regret-based and utilitarian perspective. Transport Policy, 18(6) 856-861.

Chorus, C.G., Arentze, T.A., Timmermans, H.J.P., 2008. A Random Regret Minimization model of travel choice. Transportation Research Part B. 42(1), 1-18.

Chorus, C.G., Arentze, T.A., Timmermans, H.J.P., 2009. Spatial choice: A matter of utility or regret? Environment and Planning Part B. 36(3), 538-551.

Chorus, C.G., van Cranenburgh, S., Dekker, T., 2014. Random regret minimization for consumer choice research: Assessment of empirical evidence. Journal of Business Research, 67, 2428-2436

Chorus, C.G., de Jong, G.C., 2011. Modelling experienced accessibility for utility maximizers and regret-minimizers. Journal of Transport Geography. 19, 1155-1162.

Chorus, C.G., Molin, E.J.E., van Wee, G.P., Arentze, T.A., Timmermans, H.J.P., 2006. Responses to transit information among car-drivers: Regret-based models and simulations. Transportation Planning and Technology, 29(4), 249-271.

Chorus, C.G., Rose, J.M., 2011. Selecting a date: A matter of regret and compromises. Paper presented at the 2nd International Choice Modelling Conference, Leeds, UK.

Daly, A., Hess, S., Train, K. E., 2009. Assuring finite moments for willingness to DECC 2011 "The Carbon Plan: Delivering our low carbon future" Department of Energy and Climate Change, London.

DTI 2003 "Our energy future - creating a low carbon economy", Energy White Paper, Department of Trade and Industry, London.

Ferrini, S., Scarpa, R., 2007. Designs with a-priori information for nonmarket valuation with choice-experiments: a Monte Carlo study. Journal of Environmental Economics and Management. 53(3), 342-363.

Gao, Z., Schroeder, T.C. 2009. Effects of Label Information on Consumer Willingness-to-pay for Food Attributes. American Journal of Agriculture Economics. 91(3), 795-809.

Goett, A.A., Hudson, K., Train, K.E., 2000. Customers' Choice Among Retail Energy Suppliers: The Willingness-To-Pay For Service Attributes. Energy Journal. 21(4): 1-28.

Guevara, C.A., Chorus, C.G. and Ben-Akiva, M.E., 2014. Sampling of alternatives in random regret minimization models. *Transportation Science*.

Hensher, D.A., Greene, W.H. and Chorus, C.G., 2013. Random regret minimization or random utility maximization: an exploratory analysis in the context of automobile fuel choice. *Journal of Advanced Transportation*, *47*(7), pp.667-678.

Hess, S., Stathopoulos, A. and Daly, A., 2012. Allowing for heterogeneous decision rules in discrete choice models: an approach and four case studies. *Transportation*, *39*(3), pp.565-591.

Jang, S., Rasouli, S. Timmermans, H. In press. Incorporating Psycho-Physical Mapping into Random Regret Choice Models: Model Specifications and Empirical Performance Assessments. Transportation

Kuhfeld, W.K, 2010. Experimental Design: Efficiency, Coding, and Choice Designs. SAS.

Longo, A., Markandya, A. Petrucci, M., 2008. The Internalization of Externalities in the Production of Electricity: Willingness to pay for the attributes of a policy for renewable energy. Ecological Economics. 67(1): 140-152.

Louviere, J. J., Hensher, D.A., Swait, J.D., 2000. Stated choice methods: Analysis and applications. Cambridge University Press, Cambridge.

Manski, C.F., 1977. The structure of random utility models. Theory and Decision. 8(3), 229-254.

Mariel, P. Meyerhoff, J. Hess, S. 2015. Heterogeneous preferences toward landscape externalities of wind turbines - combining choices and attitudes in a hybrid model. Renewable & Sustainable Energy Reviews 41, 647-657

McFadden, D., 1974. Conditional logit analysis of qualitative choice-behaviour. In Zarembka, P., (Ed.) Frontiers in econometrics, Academic Press, New York.

Meyerhoff, J., Ohl, C., Hartje, V. (2010) Landscape externalities from onshore wind power. Energy Policy 38(1) 82-92

Meyerhoff, J. Glenk, K. (2015) Learning how to choose - effects of instructional choice sets in discrete choice experiments. Resource and Energy Economics 41, 122-142

Roe, B., Teisl, M.F., Levy, A., Russell, M., 2001. US consumers' willingness to pay for green electricity. Energy Policy. 29(11): 917-925.

Rolfe, J., Bennett, J. Louviere, J. 2002. Stated values and reminders of substitute goods: Testing for framing effects with choice modelling. Australian Journal of Agricultural and Resource Economics. 46: 1–20.

Simonson, I., 1992. The influence of anticipating regret and responsibility on purchasing decisions. Journal of Consumer Research. 19(1), 105-119.

Scarpa, R., Willis, K.G., 2010. Willingness-to-pay for renewable energy: Primary and discretionary choice of British households’ for micro-generation technologies. Energy Economics. 32(1), 129-136.

Spash, C., Hanley, N., 1995. Preferences, information and biodiversity preservation. Ecological Economics. 12, 191-208.

Swait, J., Louviere, J. 1993. The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models. Journal of Marketing Research. 30, 305-314.

Thiene, M., Boeri, M., Chorus, C.G., 2012. Random Regret Minimization: Exploration of a New Choice Model for Environmental and Resource Economics. Environmental and Resource Economics. 51(3), 413-429.

Thurstone, L.L., 1927. A law of comparative judgment. Psychological Review. 34, 273-286.

Van Cranenburgh, S., Guevara, C.A. and Chorus, C.G., 2015. New insights on random regret minimization models. *Transportation Research Part A: Policy and Practice*, *74*, pp.91-109.

Zeelenberg, M., Pieters, R., 2007. A theory of regret regulation 1.0. Journal of Consumer Psychology. 17(1), 3-18.

Zeelenberg, M., 1999. The use of crying over spilled milk: A note on the rationality and functionality of regret. Philosophical Psychology. 12(3), 325-340.

Table 1. Attributes and their levels for the choice experiments

Attribute	Level 1	Level 2	Level 3	Level 4	Status quo
Annual reduction in greenhouse gases emissions due to renewable energy increase (3 levels)	1%	2%	3%	-	no additional greenhouse gases emissions reduction
Annual length of electricity shortages in minutes (3 levels)	30	60	120	-	90
Change in number of employees in the electricity sector (3 levels)	+1000	-1000	0	-	no employment change in the energy sector
Increase in electricity bill in £ (4 levels)	6	16	25	38	no price increase in the electricity bill

Table 2. Descriptive statistics

Variable (acronym used in regressions)	Observations	Sample average or percent (Standard deviation)
Age	300	35.75 (12.52)
Electricity bill in £ (BILL)	197	70.86 (38.78)
Dummy variables		
Married (MARRIED)	300	28.67%
Member of environmental organizations (ENV_ORG)	300	22.00%
Did not state the electricity bill (NOBILL)	300	34.33%
Answered DCE questions as best for society (SOCIETY_ CHOICE)	300	75.67%
Answered DCE questions as best for the individual	300	24.33%
Received the additional information on black-outs (BLACKOUT_INFO)	300	44.00%
BLACKOUT_INFO	300	44.00%

Table 3: Model estimates for RU-MNL and RR-MNL (1,800 observations)

	RU-MNL		RR-MNL	
Attribute	**Coeff**	**|t-stat|**	**Coeff**	**|t-stat|**
BLACK-OUT	-0.0099	9.17	-0.0066	9.71
GREENHOUSE GASES REDUCTION	0.9280	13.00	0.7510	14.76
JOBS	0.0007	9.79	0.0005	11.61
PRICE	-0.0133	2.42	-0.0145	4.36
Log-likelihood (LL)	-1535.497		-1512.959	
parameters	4		4	

Table 4: testing differences in preferences and scale for additional information under both RU-MNL, RR-MNL models, Hybrid RU-RR and Hybrid RU-RR with covariates.

specification	**RU-MNL**		**RR-MNL**	
	LL	**Observations**	**LL**	**Observations**
(a) Subsample 1 (no additional information on black-out)	-871.174	1008	-856.985	1008
(b) Subsample 2 (additional information on black-out)	-661.825	792	-654.891	792
(c) Pooled model with scale parameter fixed to one in both subsamples	-1535.497	1800	-1512.959	1800
(d) Pooled model with scale parameter estimated for subsample 2	-1534.634	1800	-1511.926	1800
TEST under RU-MNL model	**TEST 1**	**χ at 90% c.l.**	**95% c.l.**	**99% c.l.**
H1a (D.G.F. = 9)	3.27	14.68	16.92	21.67
H1b (D.G.F. = 1)	1.73	2.71	3.84	6.63
TEST under RR-MNL model	**TEST 2**	**χ at 90% c.l.**	**95% c.l.**	**99% c.l.**
H1a (D.G.F. = 9)	0.10	14.68	16.92	21.67
H1b (D.G.F. = 1)	2.07	2.71	3.84	6.63
specification	**Hybrid RU-RR**		**Hybrid RU-RR with covariates**	
	LL	**Observations**	**LL**	**Observations**
(a) Subsample 1 (no additional information on black-out)	-819.594	1008	-805.701	1008
(b) Subsample 2 (additional information on black-out)	-598.374	792	-589.691	792
(c) Pooled model with scale parameter fixed to one in both subsamples	-1422.20	1800	-1412.970	1800
(d) Pooled model with scale parameter estimated for subsample 2	-1418.459	1800	-1410.400	1800
TEST under Hybrid model	**TEST 3**	**χ at 90% c.l.**	**95% c.l.**	**99% c.l.**
H1a (D.G.F. = 20)	0.98	28.41	31.41	37.57
H1b (D.G.F. = 2)	7.48	4.61	5.99	9.21
TEST under Hybrid model (socioec)	**Test 4**	**χ at 90% c.l.**	**95% c.l.**	**99% c.l.**
H1a (D.G.F. = 38)	27.55	49.51	53.38	61.16
H1b (D.G.F. = 2)	7.61	4.61	5.99	9.21

*dgf = Degrees of Freedom; c.l. = confidence level

Table 5: Latent Class model estimates with one class for RU-MNL and one for RR-MNL and socio-economic and attitudinal variables to explain membership probability

	RU-MNL-class		RR-MNL-class	
Attribute	**Coeff**	**|t-stat|**	**Coeff**	**|t-stat|**
BLACK-OUT	-0.0182	6.28	-0.00901	7.46
GREENHOUSE GASES REDUCTION	1.95	6.84	0.838	9.53
JOBS*1,000	0.315	1.56	1.10	10.71
PRICE	-0.02	1.47	-0.0334	6.01
Scale BLACKOUT INFO	1	-	1	-
no Scale BLACKOUT INFO	-0.191	1.54	-0.201	2.28
Membership probability model	46.7%		53.3%	
INTERCEPT	-2.52	1.60		
BLACKOUT_INFO	0.134	0.44		
SOCIETY_CHOICE	0.0565	0.17		
BILL[a]	-0.00263	0.57		
NOBILL	-0.304	0.67		
AGE	0.101	1.38		
AGE_SQUARED	-0.000897	1.03		
MARRIED	-0.21	0.61		
ENV_ORG	0.854	2.49		
Log-likelihood (LL)	-1410.400			
Observations	1800			

[a] To avoid losing observations, we set the value of BILL equal to zero when there was a missing observation for that variable. By introducing the dummy variable NOBILL equal to one when there was a missing observation for BILL and zero otherwise in the model allows us to capture any statistical difference between respondents that reported and those that did not report their energy bill (see Alberini and Longo, 2009).

Figure 1. A choice experiment question used in the questionnaire.

Choice set 1:

Characteristics	**Policy A**	**Policy B**	**Neither**
Greenhouse Gasses emissions	2% reduction	3% reduction	no greenhouse gasses emissions reduction
Black-outs	120 min/per year	30 min/per year	no new actions to prevent future black-outs
Employment	0 new jobs	-1,000 jobs	no employment change in the sector
Price	£6.5 per quarter	£16 per quarter	no price increase in the electric bills
Which policy would you choose?	☐	☐	☐