Information, Random Regret Minimisation, Random Utility Maximisation: Willingness to pay for Renewable Energy

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Abstract

We investigate how different levels of information affect respondents' preferences as well as choice behaviour in choice experiments by analysing respondents' choices using two choice paradigms: the Random Utility Maximisation (RUM) and the Random Regret Minimization (RRM). The RRM offers a tractable, regret-based model complementary to the dominant RUM. Analysing choice related to hypothetical programmes for the promotion of renewable energy, we find that varying the level of information does not affect preferences and scale, whilst it does affect the choice paradigm. Additional information increases the probability that a respondent's choices are better explained by the RUM than the RRM.

***Keywords**:* Random Regret Minimization; Random Utility Maximisation; renewable energy; energy security; greenhouse gases emissions.

1. Introduction and motivation

The Discrete choice experiment (DCE) method is used to investigate the trade-offs that people are prepared to make between different goods or services (Louviere et al, 2000). Although DCE has been widely employed to analyse 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 Roe et al. 2001; Goett et al. 2000; Bergmann et al. 2006, Scarpa and Willis 2010, among others), the validity of the derived welfare measures is often disputed. One potentially serious problem faced by the DCE method is that respondents often have little, if any, prior experience with the proposed scenario.

In order 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). In this paper, we consider whether varying the level of information has any effect not only on estimates of preferences and error scale, but also on the choice paradigm that drives respondents' choices. In particular, after investigating any differences across respondents assuming that they are all using the same choice paradigm, we analyse whether the provision of different levels of information affects which choice paradigm better describes respondents' answers to the DCE questions. We consider two choice paradigms: the Random Utility Maximisation Model (RUM) (McFadden, 1974) and the Random Regret Minimisation Model (RRM) (Chorus, 2010). While the Random Utility Multinomial Logit Model (RU-MNL), based on utility maximisation, has been widely used, the Random Regret Minimisation Multinomial Logit model (RR-MNL) is more recent. The RR-MNL is based on the assumption that, when choosing, individuals aim to minimize their anticipated regret, rather than to maximise their expected utility. Regret is defined as what one experiences when a non-chosen alternative performs better than a chosen one, on one or more attributes.

As regret has been found to be an important driver of choices under uncertainty (Zeelenberg and Pieters, 2007), and as additional information has been found to reduce uncertainty (Aidt, 2000), we expect that additional information may reduce respondents' relying on the RRM rather than on the RUM when answering DCE data. We expect, therefore, that additional information may provide data that better conforms to the RUM, a choice paradigm that is well suited to derive welfare estimates.

In this paper, we use both the RU-MNL and the RR-MNL to analyse DCE data to investigate individuals' preferences for the attributes of a hypothetical policy for renewable energy. We split our sample of respondents into two sub-samples and provide a treatment to one of the two in the form of additional information about one of the attributes used in the DCE: the effects of blackouts. We then explore whether the treatment produces an impact on the estimated preferences structure, in terms of coefficient estimates and error scale, and on the probability of engagement in the two choice paradigms.

To our knowledge, this is the first application that employs both RU-MNL and RR-MNL in energy economics. Furthermore, this is the first attempt to understand whether the presence of additional information can impact on the likelihood that a choice paradigm better explains 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 respondents, while choosing among alternative hypothetical policies for renewable energy, either maximise their utility or minimise their regret. The first approach is well represented by the RU-MNL model, which is grounded on the utility maximisation theory (Thurstone, 1927; Manski, 1977), and assumes that, when choosing, respondents maximise the utility function:

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

where U_{nit} is the utility function that respondent *n* maximises while choosing alternative *i* in the choice occasion *t*, $V_{nit} = \beta' X_{nit}$ is the observed indirect utility function, X is a vector of attributes, 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 for individual *n* of choosing alternative *i* over any other alternative *j* in the choice set *t* is represented by a RU-MNL model (McFadden, 1974):

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

where μ is the scale parameter of the Gumbel error.

The second approach – the RRM approach – postulates that, when choosing alternative *i* among *j* alternatives in the choice task *t*, decision-makers aim to minimise anticipated regret rather than maximise utility. The function analysed in this context is:

$$\Psi_{nit} = R(\theta, X_{nit}) + \omega_{nit} \qquad (3)$$

where Ψ_{nit} is the regret function minimised by respondent *n; θ* is a vector of parameters to be estimated and ω is the unobserved part of regret Gumbel-distributed. Following Chorus (2010), the observed part of the regret function, $R_{ni} = \sum_{j \neq i} \sum_{m=1..,M} \ln\left(1 + e^{\theta_m (x_{jm} - x_{im})}\right)$, 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 RR-MNL:

[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.

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

where λ is the scale parameter of the Gumbel-distributed error.

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

Both RU-MNL and RR-MNL models can be estimated on different sub-samples and both can include scale parameters. It is possible to test, under both choice paradigms, whether the added information on the attribute "black-out" has any impact on preferences or scale by comparing the log-likelihood (LL) functions of the MNL models estimated for the two subsamples: subsample 1, which received the baseline questionnaire, and subsample 2, which received the questionnaire with the additional information on the effects of black-outs. As proposed in Swait and Louviere (1993) it is possible to test this information effect 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.

2.3 Identifying the drivers of choice behaviour

Even if the preference and scale estimates are stable between subsamples under both the regret minimisation and the utility maximisation choice paradigms, one might wonder whether the additional information provided to one subsample of respondents affected which choice paradigm better describes the answers to the DCE question. Regret has been found to be an important driver of choices under situations of uncertainty (Zeelenberg and Pieters, 2007), and additional information has been shown to reduce uncertainty (Aidt, 2000). So, for respondents that received the version of the questionnaire with a less detailed description of the attributes, we may expect that it is more likely that the regret minimisation approach describes better their choices, rather than the utility maximisation approach.

To understand whether a different level of information can affect the choice paradigm employed by respondents, we therefore compute the contribution to the value of the Log-likelihood function for each respondent's sequence of choices under both the RU-MNL and the RR-MNL. We then create a dummy variable equal to one when the respondent's sequence of choices is better described by the regret minimisation approach – i.e. when the sample Log-likelihood fitted according to the RR-MNL estimates is higher than that fitted according to the RU-MNL estimates – and zero otherwise. Next, we run a logit regression on this variable where the characteristics of the respondents and a dummy variable equal to one if a respondent received the version of the questionnaire with additional information on the black-out attribute and zero otherwise are used as explanatory variables:

$$P(d|y_n) = 1/(1+\exp(-\alpha+\tau*\text{Info}+\gamma'\mathbf{Z}_n)) \; . \tag{7}$$

In Equation 7, d is a dummy variable equal to 1 when the sequence of choices, y_n, faced by respondent n is better described in terms of Log-likelihood function by a regret minimisation approach and 0 otherwise, *Info* is a dummy variable equal to 1 for the respondents who received additional information on the attribute black-out, α, τ and γ are parameters of the logit regression on this variable and $\boldsymbol{Z}$ is a vector representing the characteristics of respondent n. A negative and statistically significant coefficient estimate for τ would suggest that respondents that received the version of the questionnaire with additional information were more likely to have used a utility maximisation approach to choice.

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.[2] 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.[3] 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 increase by 10%, 25%, 40%, and 60% from the average electricity bill in the UK.[4] Table 1 summarises the attributes and their levels for the present study.

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

[2] 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.

[3] 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.

[4] 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).

When describing the black-out attribute, respondents in subsample 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 subsample 1 and 2 is that subsample 1 was not given the information in italics as reported in the above text. Subsample 2, therefore, received some additional information on the effects of black-outs compared to subsample 1.

In each choice task respondents are 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). We then selected two of these alternatives, but discarded pairs containing dominated or identical alternatives and prepared six different versions of the questionnaire with six choice tasks each.[5] 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.[6]

4. Results

4.1 Descriptive statistics

Table 2 reports descriptive statistics for our sample. Our average respondent is 35 years old, has an annual gross household income of about £37,000, pays £70 per quarter on electricity bill. About 34% does not report how much they pay for electricity, 12% uses green electricity, almost 31% have electric heating, and 22% are members of an environmental organisation. After the DCE questions, we investigated altruistic behaviour 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 survey (subsample 1).

[5] 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).

[6] For a complete description of the survey see Longo et al. (2008).

Table 2. Descriptive statistics

Variable (acronym used in regressions)	Observations	Sample average/ percent (Standard deviation)
Age	300	35.75 (12.52)
Annual Income in £	300	37,687.29 (26528.63)
Electricity bill in £ (BILL)	197	70.86 (38.78)
Dummy variables		
Male	300	51.33%
Have a college degree (UNIVERSITY)	300	22.66%
Married (MARRIED)	300	28.67%
Have children	300	25.66%
Member of environmental organizations (ENV_ORG)	300	22.00%
Use green electricity (GREEN_ELECTRICITY)	300	12.00%
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%
Electric heating	300	30.33%

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 the theoretical prediction that regret-minimisation is a good model for explaining choices that are 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. In our case respondents make choices on behalf of their household. So, it is possible that regret minimisations plays an important role in explaining their choices because respondents' decisions may affect their households' wellbeing.

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	
Observations	1,800		1,800	

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 characterising 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: testing differences in preferences and scale for additional information under both RU-MNL and RR-MNL models

	RU-MNL		RR-MNL	
Specification	**LL**	**Observations**	**LL**	**Observations**
Subsample 1 (no additional information on black-out)	-871.174	1008	-856.985	1008
Subsample 2 (additional information on black-out)	-661.825	792	-654.891	792
Pooled model with scale parameter fixed to one in both subsamples	-1535.497	1800	-1512.959	1800
Pooled model with scale parameter estimated for subsample 2 scaled model	-1534.634	1800	-1511.926	1800
TEST under RU-MNL model	**TEST**	**χ^2 at P = 0.05**	**χ^2 at P = 0.01**	**χ^2 at P = 0.001**
HU0a vs. HU1a (dgf* = 9)	3.27	11.07	15.09	20.52
HU0b vs. HU1b (dgf* = 1)	1.726	3.84	6.64	10.83
TEST under RR-MNL model	**TEST**	**χ^2 at P = 0.05**	**χ^2 at P = 0.01**	**χ^2 at P = 0.001**
HR0a vs. HR1a (dgf* = 9)	0.10	11.07	15.09	20.52
HR0b vs. HR1b (dgf* = 1)	2.066	3.84	6.64	10.83

*dgf = Degrees of Freedom

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 utility maximisation and regret minimisation specifications. The upper part of the table reports the values of the sample log-likelihood functions at a maximum for four specifications for each choice paradigm, utility and regret. The four models are: (a) only subsample 1, respondents with no additional information on black-outs; (b) only subsample 2, respondents with additional information on black-outs; (c) pooled dataset with both subsamples, not controlling for differences in scale between the two subsamples; (d) pooled dataset with both subsamples, 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 subsamples 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 subsamples.

The lower part of the table reports the results of the Swait and Louviere (1993) tests. In all tests the values estimated are smaller than the critical values of the χ^2 distribution. Therefore, since we cannot reject the null hypothesis in Equation 5 and 6, we conclude that the small amount of additional information on the attribute black-out has no impact on either preferences or the scale factor in our data.

Next, we investigate whether the additional information on the black-out attribute has affected the choice behaviour of the respondents using the binary logit model of equation 7. Table 5 reports the results for two models specifications. Both models use as dependent variable a proxi that captures whether a respondent is more likely to adopt a regret minimisation approach rather than a utility maximisation choice paradigm.

The first model specification only uses the intercept and a dummy variable (BLACKOUT_INFO) which is set equal to one if the respondent received additional information on unexpected black-outs and zero otherwise. The positive and significant sign of the intercept suggests that, on average, respondents' choices are mostly driven by a regret minimisation approach. This choice behaviour, however, changes for respondents that receive additional information on black-outs: the negative and significant coefficient for BLACKOUT_INFO indicates that when a respondent receives additional information he/she is more likely to use a utility maximisation choice paradigm. This result suggests that the additional information on black-outs helps respondents to make better informed choices, hence reducing the uncertainty in the choices. This result conforms to the previous literature that finds that regret is important when uncertainty affects choices (Zeelenberg and Pieters, 2007).

Table 5: Logit model to explain determinants of RR-MNL outperforming RU-MNL for each person (300 observations).[a]

	Model 1		**Model 2**	
	AIC	**2366.9**	**AIC**	**2313.0**
	Coeff.	**|t-stat|**	**Coeff.**	**|t-stat|**
INTERCEPT	0.693	10.37	2.120	4.01
BLACKOUT_INFO	-0.388	3.95	-0.395	3.88
SOCIETY_CHOICE	-	-	0.579	4.96
MARRIED	-	-	0.261	2.10
BILL[b]	-	-	0.003	1.81
NOBILL	-	-	0.099	0.61
AGE	-	-	-0.076	3.04
AGE_SQUARED	-	-	0.0007	2.24
ENV_ORG	-	-	-0.590	4.82
GREEN_ELECTRICITY	-	-	0.299	1.84
UNIVERSITY	-	-	-0.359	3.22

[a] The dependent variable is equal to 1 if RR-MNL outperforms RU-MNL in describing the choice behaviour of that particular respondent and 0 otherwise.

[b] 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).

The second model specification of Table 5 adds socio-economic and attitudinal variables to the first model specification to explore the marginal effects of respondents' characteristics and attitudes on choice behaviour.

Results from this estimation show that the intercept is positive and significant, suggesting that, all else being equal, respondents approach the choice of hypothetical policies for the promotion of renewable energy mainly by minimising their anticipated regret. Also the coefficient estimate for BLACKOUT_INFO maintains the same negative sign as in Model 1, suggesting that the added information on the black-out attribute did not change respondents' preferences or variance in choices, but increased the probability for the respondent to adopt a regret minimisation approach to his/her choices. The positive coefficient for

SOCIETY_CHOICE indicates that when a respondent's choices are made considering what is best for society, the respondent is more likely to follow a regret minimisation choice paradigm. Similarly, the positive and significant coefficient for MARRIED shows that married respondents are more likely to follow a regret minimisation choice paradigm. These two results would conform to the findings by Zeelenberg and Pieters (2007) that claim that regret is important when choices are perceived to impact on other people and the decision-maker expects to receive feedback about chosen and non-chosen options.

The explanatory variables capturing the age of the respondent (AGE) and its squared value (AGE_SQUARED) show that the likelihood to be regret minimisers decreases the older a respondent becomes, suggesting that respondents are generally less concerned about the regret consequences of wrong choices. This result conforms to Araña and León (2009), who also find that older respondents are more likely to use a utility maximisation paradigm in choice experiments.

We also find that having higher electricity bill positively affect the likelihood of being regret minimisers. We interpret this result in terms of the relative importance that respondents attach to electricity consumption: the more households pay for electricity, the more likely they are to consider a policy related to energy production important to their welfare and, therefore, the more likely they are to approach the choice between policies by minimising their anticipated regret. The coefficient estimate for NOBILL is not statistically significant, indicating that respondents that did not report their electricity bill are not different from those that reported their electricity bill in terms of choice paradigm used when answering the DCE questions.

We also find that respondents purchasing green electricity are more likely to be associated with the regret minimisation choice behaviour, whilst respondents who are members of an environmental organisation are less likely to use the regret minimisation choice paradigm. We further find that respondents who have a university degree are more likely to use a utility maximisation choice paradigm. We believe that this latter finding reinforces the result that additional information, in this case in the form of higher education, makes choices less difficult and less uncertain to respondents, thus reducing the likelihood of using a regret minimisation choice paradigm (Zeelenberg and Pieters, 2007).

5. Discussion and conclusions

In this paper we consider whether varying the level of information of one of the attributes in a DCE for renewable energy programmes has any effect on preferences, scale, as well as on the choice paradigm that drives respondents' choices. We analyse the data from the DCE using two choice paradigms: the RUM and the RRM. We find that additional information does not affect preferences and scale, whilst it has an effect on the choice paradigm. The results from Table 4 show that adding some information about one attribute makes our respondents more likely to choose using the utility maximisation choice paradigm. The Akaike Information Criterion (AIC) shows that Model 2 of Table 4 outperforms Model 1. Therefore, using the output from Model 2, we can calculate the effect of additional information on the probability that the utility maximisation choice paradigm better describes the choices than the regret minimisation approach. For example, considering a respondent who is not married, is 35 years old, has an electricity bill equal to £70 per quarter, is a member of an environmental organisation, does not buy green electricity, has a university degree, answers the DCE questions considering what is best for society, and does not receive additional information on the black-out attribute, the probability that his/her choices are better described by the regret minimisation choice paradigm is equal to 53.93%. When the same respondent receives the questionnaire with the additional information on black-outs, the probability that his/her choices are better described by the regret minimisation choice paradigm decreases to 44.09%. This result shows that when additional information is given for one of the attributes, the probability that the utility maximisation choice paradigm better describes a respondent's choices increases of about 10%. This result is important for policy analysis. Whilst in the past the attention of the literature has focussed on the effects that information has on preferences and scale, we claim that this debate should also consider how information affects the choice behaviour.

As welfare estimates from DCE data are computed assuming that respondents use a RUM choice paradigm, it is useful to design a questionnaire that helps respondents to use the utility maximisation choice paradigm. Not considering the effect that information has on choice behaviour would have led us to conclude that the two subsamples are not different, hence that it makes no difference which version of the questionnaire to use. However, when considering the effects of information on the choice paradigm, we find that the additional information increases the probability of being a utility maximiser. We conclude that a questionnaire designed to increase the probability that respondents use a utility maximisation choice paradigm should be preferred, especially when the results of the DCE study are to be used for welfare analysis.

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