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The importance of regret minimization in the choice for renewable energy programmes: Evidence from a discrete choice experiment

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ABSTRACT

This study provides a methodologically rigorous attempt to disentangle the impact of various factors – unobserved heterogeneity, information and environmental attitudes – on the inclination of individuals to exhibit either a utility maximization or a regret minimization behaviour in a discrete choice experiment for renewable energy programmes described by four attributes: greenhouse gas emissions, power outages, employment in the energy sector, and electricity bill. We explore the ability of different models – multinomial logit, random parameters logit, and hybrid latent class – and of different choice paradigms – utility maximization and regret minimization – in explaining people's choices for renewable energy programmes. The "pure" random regret random parameters logit model explains the choices of our respondents better than other models, indicating that regret is an important choice paradigm, and that choices for renewable energy programmes are mostly driven by regret, rather than by rejoice. In particular, we find that our respondents' choices are driven more by changes in greenhouse gas emissions than by reductions in power outages. Finally, we find that changing the level of information to one attribute has no effect on choices, and that being a member of an environmental organization makes a respondent more likely to be associated with the utility maximization choice framework.

1. Introduction and motivation

Stated discrete choice experiments (DCE) are widely employed to analyse citizens' preferences for environmental goods and services, such as the 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). Traditionally, when analysing DCE data, researchers have relied on the Random Utility Maximization (RUM) model that assumes that respondents select the options that maximize their expected utility (McFadden, 1974; Train, 2009). However, several studies have suggested that respondents may be affected by bounded rationality when answering DCE questions (DeShazo and Fermo, 2004; Araña and León, 2009; Alemu et al., 2013). In particular, Chorus (2010), Chorus (2012a), Chorus (2012b) has indicated that a model that investigates regret minimization – the Random Regret Minimization (RRM) model – as a driver of choice, can be suitable for the analysis of DCE data (Chorus et al., 2014; van Cranenburgh et al., 2015). Differently from the RUM specification, the RRM 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.

Regret research originated in economics (Bell, 1982; Loomes and Sugden, 1982), and psychology (Gilovich and Medvec, 1995; Kahneman and Tversky, 1982; Zeelenberg and Pieters, 2007). Regret has been found to be an important determinant of choice behaviour in different domains, including purchasing (Simonson, 1992; Hensher et al., 2013), transport (Chorus et al., 2008; Guevara et al., 2014; van Cranenburgh et al., 2015), recreation (Thiene et al., 2012; Boeri et al., 2012), and health (Boeri et al., 2013; de Bekker-Grob and Chorus, 2013).

Previous studies have found that the two models – RUM and RRM – generate different elasticity values and different probabilities forecasting, implying different policy appraisals (Thiene et al., 2012; Boeri and Masiero, 2014). This study provides a methodologically rigorous attempt to disentangle the impact of various factors – unobserved heterogeneity, information and environmental attitudes – on the inclination of individuals to exhibit either a utility maximization or a regret minimization behaviour in a DCE for renewable energy programmes described by four attributes: greenhouse gas emissions, power outages, employment in the energy sector, and electricity bill. In addition, we explore the concept of regret aversion to further understand respondents' behaviour

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(van Cranenburgh et al., 2015). To our knowledge, no study has used the RRM model to investigate the choices of renewable energy programmes.

Firstly, we investigate the performance of the two choice paradigms when answering the DCE questions by running multinomial logit models (MNLs) under the RUM framework and the RRM framework. We then explore unobserved heterogeneity by estimating Random Parameters Logit (RPL) models under both choice paradigms. Next, we employ a latent class (LC) model – a hybrid model incorporating both choice paradigms, as suggested by Hess et al. (2012), Boeri et al. (2014) and van Cranenburgh et al. (2015) – to investigate how respondents' characteristics, including environmental attitudes, impact on the adoption of the two different choice behaviours, RUM or RRM. Afterwards, we explore how varying the level of information on the power outages attribute affects respondents. Specifically, we split our respondents into two sub-samples and provide additional information on the power outages attribute to one sub-sample to explore whether this treatment produces an impact on the estimated preferences structure.

We find that bounded rationality plays an important role in the choices for renewable energy programmes, as the RRM explains respondents' behaviour well. Our results are robust: adding more information to the power outages attribute does not affect either the preference structure or the probability of adopting a particular choice paradigm. On a final note, we also find little evidence that personal characteristics, except membership to an environmental organization, make a respondent less likely to exhibit a rational decision making process.

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 DCE data: utility and regret

We assume that, whilst 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:

$$U_{nit} = \beta' X_{nit} + \varepsilon_{nit,} \tag{1}$$

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):

$$Pr^{RU}_{nit} = \frac{e^{\mu V_{nit}}}{\sum_{j=1}^{J} e^{\mu V_{njt}}}' \tag{2}$$

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

The psychological notion that regret can be an important determinant of choice behaviour (Loomes and Sugden, 1982) originated 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. The regret function minimized by respondent n is:

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

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). The observed part of the regret function, $R_{nit} = \sum_{j\neq i} \sum_{m=1\ldots,M} \lambda_m \ \ln\left(1 + e^{\frac{\theta_m}{\lambda_m}(x_{jm} - x_{im})}\right)$ 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 and the parameter λ_m captures regret aversion for the attribute m. Recalling that minimizing the random regret is mathematically equivalent to maximizing the negative of the random regret, 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):

$$Pr^{RR}_{nit} = \frac{e^{\mu(-R_{nit})}}{\sum_{j=1}^{J} e^{\mu(-R_{njt})}}' \tag{4}$$

The classical RRM model, originally proposed by Chorus (2010), assumes that the error-variances λ in the logsum transformation presented above are normalized to $\pi^2/6$. More recently, van Cranenburgh et al. (2015) relaxed this assumption and allowed the variance of implicit errors in the regret logsum to be estimated along with the preference weights θ_m to explore regret aversion. This model is the λRRM (λRR-MNL). In this context, λ determines the "smoothness", or linearity, of the regret function. A value of this parameter larger (smaller) than one implies that the degree of regret aversion is smaller (larger) than implicitly imposed by the classical RRM model. If the parameter is statistically indistinguishable from one, the classical RRM model is the best representation of the choice behaviours underlying the data, while if the parameter is large, the regret function is linear and the model generates the same choice probabilities as the RUM model. Finally, if the parameter is not different from zero, the regret function is similar to the original formulation: only regret matters and rejoice is irrelevant. The obtained model is the 'pure-RRM' (van Cranenburgh et al., 2015).[1]

2.2. Unobserved heterogeneity

The MNL models are quite restrictive, as they assume that all respondents have the same preferences. A more flexible model, the RPL, can be used to explore how respondents' heterogeneity affects choices. As highlighted by C. Chorus (2012), C.G. Chorus (2012), and described in Boeri and Masiero (2014), the extension of RRM models to RPL is straightforward. In the case of RUM, the RPL is derived by integrating the product of logit probabilities over the distribution of β:

$$Pr\left(y_n^t \mid \beta_n, X_n\right) = \int \prod_{t=1}^{T} \frac{e^{\mu V_{int}}}{\sum_{j=1}^{J} e^{\mu V_{jnt}}} f(\beta) d\beta. \tag{5}$$

In the case of RRM, the RPL is derived by integrating the product of logit probabilities over the distribution of θ:

$$Pr\left(y_n^t \mid \theta_n, X_n\right) = \int \prod_{t=1}^{T} \frac{e^{\mu(-R_{int})}}{\sum_{j=1}^{J} e^{\mu(-R_{jnt})}} f(\theta) d\theta. \tag{6}$$

We will estimate the RPL in Eq. (6) and explore regret aversion.

2.3. Hybrid choice behaviour model

Both the MNL and the RPL models treat all choices as either utility or regret. However, it is reasonable to assume that some choices may be

[1] As the parameter λ could be confused with the scale parameter in the logit model (μ), it is important to highlight that the two parameters are originated from two different concepts. We note, on a side, that the scale parameter μ remains an additional parameter which is confounded and, therefore, fixed to one in most occasions, but that can be estimated under both choice paradigms. To avoid confusion between μ and λ we changed the name adopted by Van Cranenburgh et al. (2015) from μRRM to λRRM model.