Article:
Dekker, T orcid.org/0000-0003-2313-8419 and Chorus, CG (2018) Consumer surplus for random regret minimisation models. Journal of Environmental Economics and Policy, 7 (3). pp. 269-286. ISSN 2160-6544

https://doi.org/10.1080/21606544.2018.1424039

Consumer surplus for random regret minimisation models

Thijs Dekker*
Institute for Transport Studies, University of Leeds
36-40 University Road, Leeds, LS2 9JT, United Kingdom
t.dekker@leeds.ac.uk ; 0044-1133435330
Caspar G. Chorus
Transport and Logistics Group, Delft University of Technology
Jaffalaan 5, 2628BX, Delft, the Netherlands
c.g.chorus@tudelft.nl, 0031-152788546
* Corresponding author

Abstract

This paper is the first to develop a measure of consumer surplus for the Random Regret Minimisation (RRM) model. Following a not so well-known approach proposed two decades ago, we measure (changes in) consumer surplus by studying (changes in) observed behaviour, i.e. the choice probability, in response to price (changes). We interpret the choice probability as a well-behaved approximation of the probabilistic demand curve and accordingly measure the consumer surplus as the area underneath this demand curve. The developed welfare measure enables researchers to assign a measure of consumer surplus to specific alternatives in the context of a given choice set. Moreover, we are able to value changes in the non-price attributes of a specific alternative. We illustrate how differences in consumer surplus between random regret and random utility models follow directly from the differences in their behavioural premises.

Key words: Random Regret Minimisation; Consumer Surplus; welfare; probabilistic demand function; context dependency

1. Introduction

McFadden (1981), Small and Rosen (1981), and Hanemann (1984) were amongst the first to establish the theoretical connection between discrete choice modelling, specifically the Random Utility Maximisation (RUM) model, and welfare economics. Batley and Ibanez (2013a) provide a comprehensive overview of this literature, but more importantly also provide five assumptions under which the indirect utility function is consistent with economic theory. Additive Income RUM (AIRUM; McFadden 1981), for which the indirect utility function is linear in prices and income, adheres to these five assumptions and provides discrete choice modellers with its most well-known monetary measure of consumer surplus, i.e. the LogSum (e.g. Cochrane, 1975; De Jong et al. 2007).

In discrete choice models, (changes in) choice probabilities are an appropriate way to reflect (changes in) behaviour in response to price or quality (changes). When demand is restricted to unity and the Batley and Ibanez (2013a) assumptions are fulfilled, then the choice probability can be interpreted as a probabilistic demand curve. Williams (1977) and Ben-Akiva and Lerman (1985) accordingly calculate (changes in) the area underneath the demand curve to derive a Marshallian measure of consumer surplus which coincides with the Hicksian LogSum measure under AIRUM (e.g. McConnell 1995).

The five assumptions put forward by Batley and Ibanez (2013a) are, however, conflicting with many of the behavioural phenomena observed in recent empirical studies, such as compromise effects (e.g. Boeri et al. 2012), cost damping (e.g. Batley 2016), heterogeneity in cost sensitivities across goods (e.g. Hess et al. 2007) and non-linear income effects (e.g. Dagsvik and Karlström 2005) to name a few. By relaxing some of the aforementioned assumptions we may be able to better explain empirically observed behaviour. However, the resulting functional form for the choice probabilities can no longer be interpreted as probabilistic demand functions since they no longer provide a solution to what is known in the economic literature as the ‘integrability problem’ (e.g. Deaton and Muellbauer 1980). As a result, welfare analysis based on such inconsistent indirect utility functions is limited; or sometimes argued to be meaningless.

Relaxing some of the aforementioned assumptions requires giving up the notion of a fully rational consumer. This is a direct result of incorporating elements of irrationality, such as compromise effects as done by the Random Regret Minimisation (RRM) model (Chorus 2010), in the deterministic part of the 'indirect utility' function used to estimate discrete choice models. This is in line with the notion that not all irrational behaviour would be captured by the existence of an error term in the RUM model. A potential solution emerges when one follows a line of reasoning proposed by McConnell (1995), who states that "If there is a change in behaviour, there is also most likely *a change in welfare"*. In other words, if one is willing to accept that a model is viable representation of (potentially irrational) choice behaviour, this opens a door towards meaningful welfare analysis, albeit – as we will show below – in a limited number of cases.

The perspective we adopt is simple. Although for the behavioural phenomena described above choice probabilities are still well-defined and they behave consistently and in a predictable fashion with respect to price and quality changes, these choice probabilities can no longer be interpreted as probabilistic demand functions. However, if we treat them 'as if they were', we are able to develop a monetary analogue to the traditional Marshallian consumer surplus. Such an approximation will be inherently imperfect and reflects the price paid for adopting a behavioural economics approach. We will discuss its limitations in more detail in Section 5. The developed measure allows evaluating, in monetary terms, the existence value of environmental goods and welfare implications of changes in these environmental goods.

In this paper, we particularly focus on the Random Regret Minimisation (RRM) model (Chorus 2010). It is well-known for its ability to take compromise effects in individual decision-making into account (e.g. Guevara and Fukushi 2016). The compromise effect arises in the RRM since bad performance on one environmental attribute (e.g. water quality) can hardly be compensated by a very good performance on another attribute (e.g. easy access).[1] The incorporation of RRM in the NLOGIT and Latent GOLD

[1] Some readers may be familiar with Regret Theory (Loomes and Sugden 1982). The RRM model is distinctively different from Regret Theory, since it does not focus on choices under risk and uncertainty. Regret Theory is

software packages (EconometricSoftware 2012; Vermunt and Magidson 2014), and its inclusion in the second edition of the Applied Choice Analysis textbook (Hensher et al. 2015), can be considered evidence of the growing interest in RRM among scholars and practitioners, including those in the field of environmental economics (e.g., Thiene et al., 2012; Boeri et al., 2012; Adamowicz et al., 2014). This provides a context for exploring to what extent meaningful welfare measures can be derived for RRM models, something which is especially important in the field of environmental economics. Our approach extends to more recently proposed generalizations of RRM (e.g., van Cranenburgh et al., 2015), as well as to other choice models incorporating attributes of competing alternatives in an alternative's value function (e.g., Chorus and Bierlaire 2013; Leong and Hensher 2015; Guevara and Fukushi 2016).

Section 2 defines the challenges arising when measuring consumer surplus for the RRM and other non-utility theoretic models. Section 3 sets out to meet these challenges and Section 4 illustrates our approach with an empirical application. Not surprisingly, the behavioural properties of the RRM model have a direct impact on the derived welfare measures. Differences between RUM and RRM welfare measures can be substantial, and can be easily be traced back to the shape of the regret function. Section 5 discusses the interpretation and limitations of the obtained welfare measures. The proposed measure is most relevant when applied to choice situations with a well-defined set of choice alternatives, such as mode or route choice alternatives. Section 6 concludes and provides directions for future research.

2. A brief introduction into consumer surplus and random regret

2.1 Welfare effects for utility functions linear in price

For ease of exposition, we start by adopting an AIRUM indirect utility function U_i for alternative i in (1) which is linear in price p_i and income Y. Its deterministic component V_i also comprises a function

---

operationalised by means of utility differences between alternatives and it aims to capture violations of Expected Utility theory predominantly in the context of binary lotteries. The RRM model is instead concerned with differences in attributes, and aims to (non-linearly) capture choice set composition effects in multinomial and riskless choice situations. As a result, it links more closely with extremeness aversion (Simonson and Tversky, 1992) than with Regret Theory.

$f(\cdot)$ of non-price attributes X_i characterising the alternative. β is the vector of parameters relating X_i to V_i through $f(\cdot)$. Furthermore, ε_i captures the unobserved elements of the utility function independent of price, income and quality. The latter is typically defined as a random variable. We assume ε_i to be identically and independently distributed and to take the form of a Type I Extreme Value Distribution such that choice probabilities can be described in the form of the multinomial logit model (e.g. Train 2009).

$$U_i = V_i + \varepsilon_i = f(X_i, \beta) + \alpha \cdot (Y - p_i) + \varepsilon_i \qquad (1)$$

In this indirect utility function, it can be observed that α represents both the marginal disutility of price and the marginal utility of income. It can be easily verified that the above specification satisfies all five assumptions described in Batley and Ibanez (2013a). As such, the behaviour described by (1) is consistent with a consumer maximising his direct utility subject to a monetary budget constraint Y. Using the properties of duality, i.e. the possibility of rewriting the utility maximisation problem as a expenditure minimisation problem, the Slutsky equation allows separating demand responses to price (or quality changes) in so-called income and substitution effects. This separation is important in understanding the difference between Hicksian and Marshallian consumer surplus measures. Marshallian consumer surplus embodies both income and substitution effects as it is related to observed changes in demand. Because of including income effects, the Marshallian welfare measure can be subject to the issue of path dependency (e.g. Batley and Ibanez 2013b). The Hicksian compensating variation filters out the income effect by looking into how much income can be taken away from (or has to be given to) a consumer after a price or quality change has taken place to make him indifferent between the original and new situation. Following Herriges and Kling (1999) we can define the compensating variation CV in (2) where J refers to the choice set and the superscripts '0' and '1' respectively define the utility before and after the change.[2] Due to the unobserved nature of ε, the

[2] The Hicksian equivalent variation (EV) takes the new utility level as the point of departure and examines how much compensation an individual requires to forego an improvement. McFadden (1981) also denotes the CV and EV as measures of willingness to pay and willingness to accept.

compensating variation is a random variable for which typically the expected value is derived for the purpose of social welfare analysis.

$$\max_{j \in J} U_i\left(Y - p_j^0, X_j^0, \alpha, \beta, \epsilon_j\right) = \max_{j \in J} U_i\left(Y - p_j^1 - CV, X_j^1, \alpha, \beta, \epsilon_j\right) \quad (2)$$

It turns out that for the adopted AIRUM indirect utility function the CV in (3) is defined by the difference in the expected maximum utility before and after the improvement divided by α, i.e. the marginal utility of income (e.g. Small and Rosen 1981). For the multinomial logit model the expected maximum utility is defined by the 'LogSum' (e.g. Cochrane, 1975; De Jong et al. 2007). Note that the unknown constant C in (3) drops out when identifying changes in expected maximum utility.

$$CV = \frac{\mathrm{E}\left(\max_{j \in J} U_j^1\right) - \mathrm{E}\left(\max_{j \in J} U_j^0\right)}{\alpha} = \frac{\ln\left(\sum_{j=1}^{J} \exp\left(V_j^1\right)\right) + \mathrm{C} - \ln\left(\sum_{j=1}^{J} \exp\left(V_j^0\right)\right) - \mathrm{C}}{\alpha} \quad (3)$$

Williams (1977) provides an interesting perspective on obtaining the Marshallian consumer surplus, also discussed by Ben-Akiva and Lerman (1985). Here, the choice probability π_i for alternative i is viewed as the observed probabilistic demand function for alternative i. A change in environmental policy will have an impact on the vector of indirect utilities V. Accordingly, the change in consumer surplus arising from a change in environmental policy improving alternative i can be defined by (4). As described by Ben-Akiva and Lerman (1985), the integral is defined in utility terms and a common money metric, in our case α, is required to translate this utility surplus into monetary terms.[3]

$$\Delta MCS = \frac{\int_{V_i^0}^{V_i^1} \pi_i(V_i) dV_i}{\alpha} = \frac{\ln\left(\sum_{j=1}^{J} \exp\left(V_j^1\right)\right) + \mathrm{C} - \ln\left(\sum_{j=1}^{J} \exp\left(V_j^0\right)\right) - \mathrm{C}}{\alpha} \quad (4)$$

The implemented linear relationship between income (price) and utility ensures that the Marshallian consumer surplus following any order of price changes is path independent, i.e. does not exhibit income

[3] Williams' (1977) measure is already defined in monetary terms due to the use of a generalized cost approach.

effects (Batley and Ibanez 2013b).[4] As a result, the Marshallian consumer surplus, the Hicksian compensating variation and the equivalent variation measures are identical. Welfare calculations are possible for choice models with more flexible error specifications. For example, the family of Multivariate Extreme Value models have closed form solutions that are reformulations of the LogSum formula. Finally, 'translational variance' allows ignoring Y in (1) during estimation without influencing choice probabilities and welfare estimates.[5] The inclusion of Y here is illustrative as it makes explicit that consumers derive additional utility from spending their residual income on the numeraire good.

2.2 The restrictiveness of the economic framework

Section 2.1 illustrates that a well-defined economic framework governs the use of the LogSum as a measure of consumer welfare. The underlying assumptions significantly restrict the scope for introducing flexible indirect utility functions in estimation. Violations of the Batley and Ibanez (2013a) assumptions may arise quicker than one may expect. If such violations occur, the labelling of U as an indirect utility function, is incorrect as the connection with a rational consumer maximising his or her direct utility subject to a budget constraint no longer holds. This poses choice modellers with a trade-off between behavioural relevance and the possibility of conducting meaningful welfare analysis. Behavioural relevance allows researchers to exploit the wide range of econometrically possible formulations of the 'indirect utility function', i.e. the regression equation defining the attractiveness of a specific alternative. Batley and Dekker (2017), mathematically and graphically show that in the context of a discrete choice models, where demand is restricted to unity, non-linear income effects are not consistent with economic theory. Any additional income must be spent on the numeraire good which by definition has to be path independent, i.e. not subject to an income effect.

[4] Technically, if the absolute value of prices affect the choice probabilities, then this is an indication of an income effect (Jara-Diaz and Videla 1989).

[5] Adding αY to every alternative in the choice set does not affect choice probabilities since choice probabilities are entirely defined by utility differences.

2.3 The RRM model - attribute level differences and non-linearity

We set out to develop an approximation of the Marshallian consumer surplus for the Random Regret Minimisation (RRM) model as presented in equation (5). A detailed description of the RRM model is provided in Chorus (2010), and a review of the model's core properties and empirical comparisons between RRM and RUM models can be found in Chorus et al. (2014).

$$R_i = \sum_{j\neq 1}^{J} \sum_{m=1}^{M-1} \ln\left(1+\exp\left(\theta_m\left(x_{jm}-x_{im}\right)\right)\right) + \ln\left(1+\exp\left(\theta_M\left(p_j-p_i\right)\right)\right) + \varepsilon_i \qquad (5)$$

The RRM model in (5) is particularly interested in differences in attribute levels across alternatives. That is, regret R (alternatively interpretable as the negative of (decision) utility) arises when alternative i is outperformed by alternative j on attribute m. The consumer is assumed to select the alternative with the lowest level of regret and θ_m is a parameter to be estimated for attribute m. The RRM treats attribute level differences in a non-linear fashion such that the marginal regret of being outperformed by another alternative on attribute m is increasing in the level of the attribute level difference. The behavioural justification for this non-linearity can be found in extremeness aversion (Simonson and Tversky 1992) where people are argued to dislike extremely 'bad' attribute level performance and in loss aversion in riskless choice contexts (Tversky and Kahneman 1991) where losses with respect to a reference point (in this case: another alternative's attribute level) weigh heavier than gains. As a result of this model specification, the RRM model is able to account for choice set composition effects and tends to predict higher market shares for so-called compromise alternatives with an intermediate performance on every attribute (e.g. Chorus and Bierlaire 2013, Guevara and Fukushi 2016).[6] The RRM model clearly represents a decision model based in behavioural decision theory (Edwards 1961; Slovic et al. 1977; Einhorn and Hogarth 1981) rather than economics.

[6] The non-linear specification of the RRM model enables estimation of a dispersion parameter in the logit framework (van Cranenburgh et al. 2015). The researcher can ensure that regret equals zero when all alternatives in the choice set are equivalent by subtracting a constant of size (J *-1)· M · ln(2)*, but this constant is obsolete.

Unlike the AIRUM model, the RRM model does not exhibit a connection between income and utility. It is not a valid indirect utility function as it offers no opportunity to reflect a reduction in regret achieved by spending residual income on the numeraire good. In effect, it lacks a common money metric to transform changes in regret into monetary welfare measures. Formally, if we assume $\theta_I = -\theta_M$ then for any income level the binary regret function reduces to

$\ln\left(1+\exp\left(\theta_I\left(\left(Y-p_j\right)-\left(Y-p_i\right)\right)\right)\right)=\ln\left(1+\exp\left(\theta_M\left(p_j-p_i\right)\right)\right)$. Regret arising from differences in disposable income between any pair of alternatives remains solely determined by the underlying price differences between these two alternatives. A lump-sum increase in income will therefore have no impact on regret.

Note that the specification of the regret function in terms of non-linear attribute level differences is significantly different from the non-linear in price utility functions considered in e.g. Dagsvik and Karlström (2005); Herriges and Kling (1999); Karlström and Morey (2001); McFadden (1995). The referred papers have explored methods to derive the (Hicksian) compensating variation in the presence of income effects. Typically, simulation methods are required, but Dagsvik and Karlström (2005) and de Palma and Kalani (2011) provide analytical formulae. These Hicksian measures, however, appear not to be utility theoretic per the work of Batley and Dekker (2017) and Batley and Ibanez (2013a, 2013b).

A distinguishing feature of the RRM model which poses challenges for the derivation of consumer surplus, is that a deterioration in attribute x_{im} increases the regret of alternative i, but simultaneously decreases the regret of all other alternatives $j \neq i$. Hence, not only the current users of (or those who switch to) alternative i are affected by the change in x_{im}.

In the next section, we use the regret function in (5) to develop three specific cases of the RRM-based analogue of the Marshallian consumer surplus. First, it defines the welfare effects of changing the price of alternative i. Second, we use McConnell (1995) to value the presence of an alternative in the choice set. Third, based on McConnell's method we are able to value changes in non-price attributes. The approach allows researchers to extract additional welfare information from RRM models that have already been estimated.

3. Consumer surplus in the RRM model

3.1 Changing the price of a single alternative

As mentioned in the introduction section, we acknowledge that RRM-based choice probabilities are not consistent with the economic definition of a Marshallian (i.e. observed) probabilistic demand function. We only interpret it as such since choice probabilities provide the best information available on changes in behaviour in response to price and quality changes. We initially focus on the welfare effect of a change in the price of alternative i. By focusing on a price change, our approximation of the Marshallian consumer surplus is directly expressed in monetary terms. Where Ben-Akiva and Lerman (1985) take the integral over changes in indirect utility resulting from the price change, we take the integral with respect to the change in prices. Please note the resemblance with standard micro-economics (Neuberger 1971; Harris and Tanner 1974) which also measures the Marshallian consumer surplus as the area underneath the uncompensated demand curve with respect to price. In line with the law of demand choice probabilities $\pi_i(p_i)$ are expected to fall in prices. Equation (6) describes the change in consumer surplus as a result of the change in p_i.

$$\Delta CS_{p_i} = \int_{p_i^0}^{p_i^1} \pi_i(p_i) dp_i \tag{6}$$

Choice probabilities are well-defined in the RRM model and typically take the multinomial logit form (e.g. Chorus 2010; Chorus et al. 2014), but do not comply with the Independence of Irrelevant Alternatives axiom even when random errors are i.i.d. Appendix A confirms that RRM-based choice probabilities are monotonically decreasing in p_i such that the probabilistic demand function for alternative i is well-behaved. This result does not depend on the assumptions regarding the error term.

Figure 1 illustrates the reduction in monetary consumer surplus arising from an increase in p_i. Note that in the RRM model the change in choice probability is not only caused by an increase in the regret of alternative i, but also by a simultaneous reduction in regret of all other alternatives $j \neq i$. Changes in p_i might have a minor impact on R_i, but the change in R_j may be large such that π_i is still affected. By focusing on changes in probability rather than compensating for changes in regret our approach significantly differs from the indifference based approach to marginal welfare measurement in the RRM model discussed by Dekker (2014).

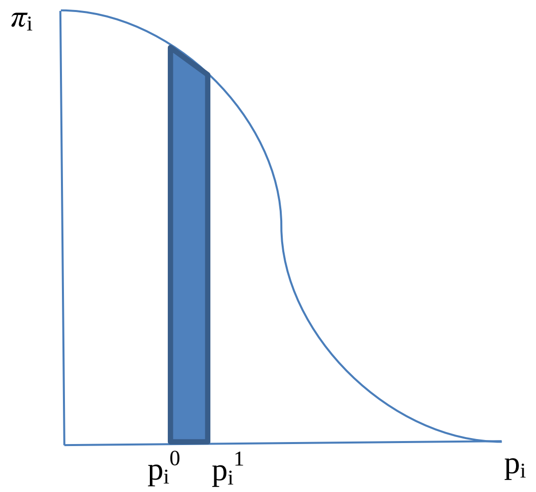

Figure 1: Reduction in consumer surplus as a result of a price increase in p_i

3.2 Value of having an alternative in the choice set

McConnell (1995) points out that the preceding logic can also be used to determine the value of having (access to) a particular alternative in the choice set (up to a constant). Namely, by increasing the price of an alternative (by means of introducing a hypothetical tax t_i or alternative price levy) the associated choice probability π_i reduces to zero. The consumer surplus C_i of having alternative i in the choice set (within either a RUM or RRM model) is then defined by the integral over all possible positive values of t_i , i.e. the price increase, and denotes the amount of money that can be collected from the individual before demand reduces to zero.

$$C_i = \int_0^{\infty} \pi_i(t_i) dt_i \tag{7}$$

McConnell (1995) showed that for the AIRUM model the integral in (7) has a closed form solution equal to $C_i = \frac{\ln(1-\pi_i^0)}{\alpha}$, where α again represents the marginal utility of income and π_{i}^{0} the probability of selecting alternative i in the original situation 0. In practice, this is an alternative mathematical formulation of the LogSum. Integrating down to zero demand as McConnell (1995) suggests, assumes that the estimated model is valid at extremely low choice probabilities. The corresponding price levels, however, may lie outside the normal range over which models are estimated. The inclusion of a choke price (e.g. Morkbak et al. 2010) might address this problem in order to avoid making assumptions about model behaviour in unobserved areas. The latter is an empirical rather than a theoretical matter and is not restricted to the RRM model.

The differences between the linear-in-all-attributes RUM and the RRM model manifest themselves when J > 2.[7] First, they provide a different starting point, i.e. choice probability, to (7). Second, the shape of the probabilistic demand function varies between the two models. The marginal change in the RUM-based choice probability due to levying a tax is given by (8). This change in $\pi_{\mathrm{i}}^{\mathrm{RUM}}$ is largest when $\pi_{\mathrm{i}}^{\mathrm{RUM}} = 0.5$ due to entropy. For the RRM model, the corresponding derivative is given by (9). For large $\mathrm{t_i}$, the derivative approaches $\lim_{\mathrm{t_i}\to\infty} \frac{\partial \pi_{\mathrm{i}}^{\mathrm{RRM}}}{\partial \mathrm{t_i}} = \pi_{\mathrm{i}}^{\mathrm{RRM}}\left(1-\pi_{\mathrm{i}}^{\mathrm{RRM}}\right)\left(\mathrm{J}-1\right)\theta_{\mathrm{M}}$ from below since $\lim_{\mathrm{t_i}\to\infty} \frac{\partial \mathrm{R_j}}{\partial \mathrm{t_i}} = 0$ and $\lim_{\mathrm{t_i}\to\infty} \frac{\partial \mathrm{R_i}}{\partial \mathrm{t_i}} = -\theta_{\mathrm{M}}$. The size difference between $-\alpha$ and (J-1) θ_{M} then determines whether the choice probability in the linear-in-attributes RUM or RRM has a fatter tail. Faster convergence to a zero choice probability reduces the consumer surplus of an alternative.

$$\frac{\partial \pi_{\mathrm{i}}^{\mathrm{RUM}}}{\partial \mathrm{t_i}} = -\pi_{\mathrm{i}}^{\mathrm{RUM}}\left(1-\pi_{\mathrm{i}}^{\mathrm{RUM}}\right)\alpha < 0 \text{ for } \alpha > 0 \tag{8}$$

$$\frac{\partial \pi_{\mathrm{i}}^{\mathrm{RRM}}}{\partial \mathrm{t_i}} = \pi_{\mathrm{i}}^{\mathrm{RRM}}\left(\sum_{\mathrm{j}\neq\mathrm{i}} \pi_{\mathrm{j}}^{\mathrm{RRM}} \frac{\partial \mathrm{R_j}}{\partial \mathrm{t_i}} - \left(1-\pi_{\mathrm{i}}^{\mathrm{RRM}}\right)\frac{\partial \mathrm{R_i}}{\partial \mathrm{t_i}}\right) < 0 \tag{9}$$

[7] RUM and RRM are behaviourally equivalent for binary choices, including welfare implications (Chorus 2010).

3.3 Valuing changes in the attributes of a single alternative

Now moving to our third type of consumer surplus: changes in consumer surplus (i.e., the change in existence value of the alternative) as a result of changing the attribute levels of alternative i. When introducing changes in the non-price attributes of alternative i, the probabilistic demand curve in Figure 1 shifts rather than that a change along the probabilistic demand curve is made. Accordingly, the change in consumer surplus cannot be simply obtained by integrating over the change in price. McConnell (1995) shows that the probabilistic demand function can, however, still be applied to derive this particular change in value. Equation (10) then measures the difference in existence value between the new and original situation as denoted by the superscripts '1'and '0' respectively. This formulation can be applied to RUM, RRM and other well-behaved specifications of the choice model.

$$\Delta \mathrm{CS}_{\mathrm{i}} = \int_{0}^{\infty} \pi_{\mathrm{i}}^{1}\left(\mathrm{t}_{\mathrm{i}}\right) \mathrm{dt}_{\mathrm{i}} - \int_{0}^{\infty} \pi_{\mathrm{i}}^{0}\left(\mathrm{t}_{\mathrm{i}}\right) \mathrm{dt}_{\mathrm{i}} \tag{10}$$

McConnell shows that for the AIRUM model, the change in consumer surplus is then given by $\Delta \mathrm{CS}_{\mathrm{i}} = \mathrm{C}_{\mathrm{i}}^{1} - \mathrm{C}_{\mathrm{i}}^{0} = \dfrac{\ln\left(1-\pi_{\mathrm{i}}^{1}\right) - \ln\left(1-\pi_{\mathrm{i}}^{0}\right)}{\alpha}$, where the 0 and 1 refer to respectively the value before and after the change in attribute levels of alternative i. Not surprisingly, this is a simple reformulation of the difference in the LogSum between the two situations.

4. Empirical illustration

To illustrate our concepts of consumer surplus in the RRM model, we use a dataset on route choice as discussed in Chorus and Bierlaire (2013). Section 4.1 discusses the dataset and estimates a linear-in-parameters and attributes RUM and an RRM model. Section 4.2 derives the value of having access to a particular route. Section 4.3 derives the welfare implications of improving or deteriorating the travel time on a particular route. The welfare calculations for the RUM model have a closed form solution as discussed in Section 3. For the RRM model this is also the case, but we prefer to numerically approximate the integrals reported in (7) and (10). Its analytical derivation is overly complex and leaves too much scope for programming error. MATLAB's built in integral() function is used for the purpose of numerical approximation.

4.1 The Chorus and Bierlaire (2013) route choice dataset

The Chorus and Bierlaire (2013) datasets comprises 390 respondents, all members of a Dutch internet panel maintained by IntoMart. All respondents owned a car, were employed and over 18 years old. The sampling strategy was designed to ensure that the sample was representative for the Dutch commuter in terms of gender, age and education level. The response rate was approximately 71 % and the data were collected in April 2011.

Each respondent was presented with nine choice tasks in which they were requested to choose between three different routes for their commute that differed in terms of the following four attributes, with three levels each: average door-to-door travel time (45, 60, 75 min), percentage of travel time spent in traffic jams (10, 25, 40 %), travel time variability (5,15, ± 25 min), and total costs (5.5, 9, €12.5).
The choice tasks were then generated using a 'optimal orthogonal in the differences' design (Street et al. 2005).

Table 1 provides an overview of the estimated model parameters for a linear-in-parameters RUM model and the RRM model. All parameters are of the expected sign and it can be observed that $\alpha > 2\theta_M$ such that for very expensive alternatives the choice probability in the RRM model is decreasing more rapidly than in the RUM model, in the context of this dataset. In Sections 4.2 and 4.3 we will focus on two specific choice tasks (see Table 2), one with and one without a clear compromise alternative. We expect that in the case of the former differences between the welfare effects between the RUM and RRM model are larger due RRM's possibility to capture compromise effects.

Table 1: Estimation results for a basic RUM and RRM MNL model

	Linear RUM model		RRM model	
	Parameter estimate	t-value	Parameter estimate	t-value
Average travel time	-0.0673	-35.02	-0.0468	-33.31
Percentage of travel time in congestion	-0.0273	-17.17	-0.0181	-16.68
Travel time variability	-0.0316	-12.04	-0.0210	-12.00
Travel costs	-0.173	-20.64	-0.1128	-19.79
Observations	3,510		3,510	
Loglikelihood	-2,613		-2,605	

Table 2: Examples of choice-tasks featuring a compromise alternative and one without

Task: Alternative B acts as a compromise alternative	Route A	Route B	Route C
Average travel time (minutes)	45	60	75
Percentage of travel time in congestion (%)	10%	25%	40%
Travel time variability (minutes)	±5	±15	±25
Travel costs (€)	€12.5	€9	€5.5
YOUR CHOICE	☐	☐	☐

Task: no clear compromise alternative	Route A	Route B	Route C
Average travel time (minutes)	60	75	45
Percentage of travel time in congestion (%)	10%	25%	40%
Travel time variability (minutes)	±15	±25	±5
Travel costs (€)	€5.5	€12.5	€9
YOUR CHOICE	☐	☐	☐

4.2 Existence value of particular route

The model parameters and attribute levels are combined to derive the model specific choice probabilities (see Table 3), which serve as starting points for (7). The compromise alternative, Route B in the first choice set, as expected receives a market share bonus in the RRM model compared to the RUM model. Consequently, the other alternatives comprising more extreme attribute levels are assigned a lower choice probability in the RRM model. Choice probabilities are more comparable between RUM and RRM in the second choice set, in the absence of a clear compromise alternative. These differences in starting points are also reflected in the alternative specific CS measures presented in Table 3. In the first choice set, Routes A and C are valued higher in the RUM model than in the RRM model as a result of their higher choice probabilities. Since alternative A is the most expensive alternative in the choice set, its RRM-based CS is particularly low due to the high level of marginal regret caused by price increases (i.e. the tax levy). As expected Route B is valued higher by the RRM model than by the RUM model due to being a compromise alternative. The additional popularity of Route B results in a €0.14 increase in consumer surplus (existence value). Despite being cheap, alternative C is not very popular in both the RUM and RRM model and is therefore assigned a rather low consumer surplus in both models.

Table 3: Value of the alternatives in the two choice sets presented in Table 1 (in euros)

Choice set 1	Observed	RUM					RRM				
	Choice share	π_i	E(CS)	Std.	2.5%	97,5%	π_i	E(CS)	Std.	2.5%	97,5%
Route A	68%	70%	7.00	0.49	6.09	8.03	67%	5.51	0.43	4.72	6.42
Route B	27%	23%	1.49	0.08	1.35	1.65	27%	1.63	0.07	1.49	1.78
Route C	5%	7%	0.44	0.04	0.37	0.52	6%	0.38	0.03	0.32	0.45
Choice set 2		RUM					RRM				
	Choice share	π_i	E(CS)	Std.	2.5%	97,5%	π_i	E(CS)	Std.	2.5%	97,5%
Route A	54%	51%	4.14	0.22	3.73	4.59	53%	4.49	0.22	4.08	4.94
Route B	2%	3%	0.16	0.02	0.12	0.20	2%	0.12	0.02	0.09	0.16
Route C	44%	46%	3.61	0.27	3.12	4.16	45%	3.36	0.24	2.92	3.88

* Standard deviations and confidence intervals obtained using the Krinsky and Robb (1986,1990) method with 10,000 draws from the original variance covariance matrix of parameter estimates.

Also for the second choice set the consumer surplus measures differ across alternatives and behavioural models. For example, having access to Route A is valued €4.14 by the RUM model and €4.49 by the RRM model. The higher value of Route A in the RRM model can be explained by its higher choice probability and good performance in terms of price (implying a low marginal regret for marginal price increases caused by the tax levy). Again, this results in lower choice probabilities, and hence access values, for the other two routes relative to the RUM model.

4.3 Changes in the travel time on a route

We illustrate the use of (10) by respectively improving and deteriorating (see Tables 4 and 5) the average travel time of the routes presented in Table 2 by five minutes.[8] The non-linearity of (10) with respect to average travel time implies that the obtained welfare effects are alternative and choice set specific

[8] We treat changes in travel time in isolation. That is, we reduce (or increase) the travel time of alternative A by five minutes and evaluate the change in consumer surplus for alternative A. We then go back to the initial situation and repeat the same process for alternatives B and C.

irrespective of the selected model. We start by comparing the size of welfare gains and losses within the RUM, respectively the RRM model. Then differences between the size of welfare gains predicted by the two models are discussed, and we conclude by making the same comparison for welfare losses which result from deteriorations in travel time.

As expected, strict welfare gains and losses are observed as a result of improving, respectively deteriorating the average travel time of the considered alternative. Tables 4 and 5 also confirm the theoretical expectation that for the RUM model welfare gains are larger than welfare losses associated with respectively an improvement and equivalent deterioration in average travel time. In general and for all cases presented in Tables 4 and 5, our data also display this size difference for the RRM model. The latter is, however, not theoretically guaranteed but after evaluating the entire design we only find two out of twenty-seven cases where the predicted welfare loss is larger than the predicted welfare gain in the RRM model.[9] In those two cases the altered alternative is already fast, cheap and also performs top notch on the other attributes. Improvements then only induce an incremental change in choice probability, while the RRM model starts putting more weight on deteriorations in attribute performance due to increasing levels of marginal regret.

The convexity of the regret function explains why differences between the welfare gains predicted by the RUM and RRM model are largest when alternatives are improved on attributes on which they are already well performing. For example, the welfare gain for alternative A in choice set 1 predicted the RUM model is about 49% larger than its RRM model counterpart (see Table 4). Similarly, Route C obtains a 32% higher welfare gain in the RUM model in the second choice set (see Table 5). Note that the 95% confidence intervals for the RUM and RRM model are non-overlapping in these two examples. The RRM model tempers these welfare gains, because performing extremely well is not valued much higher than performing well, i.e. marginal regret approaches zero for good performing attributes. These

[9] In the design nine unique choice cards are included. Each of the choice cards includes three alternatives which can be improved or deteriorated in terms of average travel time. This provides a total of twenty-seven cases to evaluate.

differences between the RUM and RRM model are amplified even further when the altered alternative already has a high choice probability in the original situation, as the other alternatives in the choice set will then turn out to be somewhat irrelevant in defining welfare impacts.

The differences in welfare gains between the RUM and RRM model reduce in magnitude when an alternative other than the fastest one is improved in terms of travel time. It can even be the case that RRM predicts a higher welfare gain than the RUM model, although such differences are non-significant in our data, when the slowest alternative is improved. Route C in the first choice set is an example of such an alternative. Again, this is a direct result of the convexity of the regret function, which puts much emphasis on not performing worse than competing alternatives, on a given attribute.

Table 4: Change in CS for choice set 1 after reducing/increasing travel time by 5 minutes (in €)

Δt=-5	RUM				RRM				
Differences in CS	Mean	Std.	2.5%	97.5%	Mean	Std.	2.5%	97.5%	Ratio RUM-RRM
Route A	1,43	0,09	1,27	1,61	0,96	0,06	0,85	1,09	1.49
Route B	0,50	0,02	0,47	0,54	0,48	0,02	0,45	0,52	1.04
Route C	0,17	0,01	0,15	0,19	0,17	0,01	0,15	0,20	0.97

Δt=+5	RUM				RRM				
Differences in CS	Mean	Std.	2.5%	97.5%	Mean	Std.	2.5%	97.5%	Ratio RUM-RRM
Route A	-1,30	0,08	-1,46	-1,14	-0,91	0,06	-1,04	-0,80	1.42
Route B	-0,39	0,01	-0,42	-0,36	-0,40	0,01	-0,43	-0,37	0.97
Route C	-0,12	0,01	-0,14	-0,11	-0,12	0,01	-0,14	-0,11	1.00

* Standard deviations and confidence intervals obtained using the Krinsky and Robb (1986,1990) method with 10,000 draws from the original variance covariance matrix of parameter estimates.

Table 5: Change in CS for choice set 2 after reducing/increasing travel time by 5 minutes (in €)

Δt=-5	RUM				RRM				
Differences in CS	Mean	Std.	2.5%	97.5%	Mean	Std.	2.5%	97.5%	Ratio RUM-RRM
Route A	1,08	0,04	0,99	1,17	1,02	0,04	0,94	1,11	1.05
Route B	0,06	0,01	0,05	0,08	0,06	0,01	0,05	0,07	1.05
Route C	0,99	0,07	0,86	1,12	0,74	0,05	0,65	0,85	1.32

Δt=+5	RUM				RRM				
Differences in CS	Mean	Std.	2.5%	97.5%	Mean	Std.	2.5%	97.5%	Ratio RUM-RRM
Route A	-0,91	0,04	-0,99	-0,84	-0,92	0,04	-1,00	-0,85	0.99
Route B	-0,04	0,00	-0,06	-0,04	-0,04	0,01	-0,05	-0,03	1.10
Route C	-0,82	0,06	-0,94	-0,72	-0,66	0,04	-0,76	-0,58	1.25

* Standard deviations and confidence intervals obtained using the Krinsky and Robb (1986,1990) method with 10,000 draws from the original variance covariance matrix of parameter estimates.

The tendency of the RRM model to put more weight on (relatively) bad attribute performances also explains why we typically observe that the ratio of welfare effects of the RUM over the RRM model decreases when switching from welfare gains to welfare losses. Route C in choice set one and Route B in the second choice set are exceptions where we observe an increase in the ratio after deteriorating the performance of the slowest alternative.

Route C in choice set one and Route B in the second choice set are already associated with a low choice probability, where the RRM provides an additional `penalty' for bad attribute performance (see Table 3). Further deteriorating the performance of these two routes does not affect choice probabilities that much, since both routes remain very unpopular in both RUM and RRM. However, the higher initial choice probability for RUM allows for a larger welfare effect.

It can be considered remarkable that differences in welfare predictions between the RUM and RRM model particularly arise in extreme scenarios. That is, RUM predicts larger welfare effects than RRM when improving popular alternatives on attributes which are already outperforming those of the other alternatives; RRM shows larger (negative) welfare effects when relatively popular alternatives are deteriorated in the one or few attribute(s) on which they are already performing poorly. Despite the subtleness – especially when applied in the context of RRM models – of the consumer surplus measure, these patterns can be traced back to the properties (i.e. convexity) of the regret function and the implied preference for middle-of-the-road, as opposed to extreme, attribute performance. Noteworthy is that welfare implications of small changes in the attributes of compromise alternatives, which receive a higher choice share in RRM models (and have been shown in the previous section to have a higher existence value for regret minimisers), are comparable between the RUM and RRM model. This is a result of the fact that the implications of the asymmetric regret function are less pronounced at intermediate attribute levels.

As a final note, and before we discuss limitations of the proposed approach, it is worth emphasizing here that the differences between RUM and RRM in terms of the value of alternatives and in the welfare effects of changes in attribute values, are larger than what might be expected given the small difference in model fit between the two models. This finding is in line with the more general observation (e.g., Chorus et al. 2014) that despite the fact that RRM and RUM often differ hardly in terms of model fit, application of the two models can lead to markedly different policy implications[10].

[10] The recently proposed muRRM model (van Cranenburgh et al. 2015) does potentially lead to larger differences in model fit. This is due to its ability to capture a wide range of levels of regret aversion.

5. Limitations of RRM-based consumer surplus

Section 4 illustrated that the proposed method can be successfully applied to derive a measure of (changes in) the consumer surplus (existence value) of specific alternatives within a specific choice context. A direct result of using a different behavioural model is that the differences in welfare and welfare effects between the linear-in-parameters-and-attributes RUM and RRM model can be substantial. These differences can be traced back to differences in the core behavioural properties of the RRM and RUM model. Despite these promising results, there are, however, issues regarding the interpretation of the obtained RRM welfare measures, and limitations regarding the applicability of the proposed method. Both will be discussed in this section.

5.1 Total surplus and aggregation bias

The proposed measure for changes in consumer surplus (following changes in attribute levels of an alternative) that was put forward in Section 3.3 entirely focus on the existence value of alternative i. For the RUM model this is inconsequential, since only the utility of alternative i is affected by changes in its attribute levels. Therefore, (10) also represents the change in total consumer surplus (i.e., at the choice set level) for the RUM model. In the RRM model, the attribute levels of alternative i, however, also enter the regret function of the other alternatives in the choice set. Accordingly, (10) does not capture changes in the existence value of the other alternatives in the choice set. Without looking into the relevant equations, we already know that changes in x_{im} by definition have an opposite effect on R_i and R_j. Improvements in x_{im} translate into a reduction in R_i and an increase in R_j. Hence, when $\Delta CS_i > 0$ (i.e., when a single attribute of alternative i is improved) the proposed measure of the (change in) consumer surplus for the altered alternative represents an upper bound on the change in the total surplus in the choice set, since the decrease in existence value of the other alternatives is not taken into account Similarly, when $\Delta CS_i < 0$ (i.e., when a single attribute is deteriorated) a lower bound on the total welfare effects in the choice set is attained. Note that the change in consumer surplus of alternative i in (10) provides the largest possible effect on the total surplus. Namely, the lower bound on attribute deteriorations implies that in absolute terms the welfare loss in the choice set will be smaller than the obtained bound, i.e. closer to zero.[11]

McConnell (1995) derives the total surplus associated with a choice set by sequentially eliminating all alternatives from the set, by means of repeatedly levying taxes in the way described before. After having established the value for alternative i the price of a second (arbitrary) alternative can be gradually raised to derive the consumer surplus of this particular alternative.[12] The process can be repeated until all but one arbitrarily selected alternatives are removed from the choice set. The inability of McConnell's method to value the only remaining alternative in the choice set introduces an aggregation bias to both the RUM and RRM model. In the linear-in-income RUM model, the size of the aggregation bias can be calculated using the utility of the remaining alternative divided by the marginal utility of income. This is, however, impossible in the RRM model in the absence of a marginal regret of income.

5.2 Path dependency

Even if the value of the remaining alternative could be established in the RRM model, application of McConnell's method for total surplus in the context of RRM models remains hampered by the issue of path dependency (e.g. Batley and Ibanez 2013b). For the linear-in-income RUM model the order in which the alternatives are eliminated from the choice set does not affect the level of total surplus. The order of elimination, however, matters for the RRM model, since increases in the price of alternative i change the relative popularity of the remaining alternatives in an asymmetric fashion. This violation of IIA – which, it should be noted here, is a property of the RRM model by design – induces path dependency in the RRM model, i.e. a non-unique measure of the consumer surplus.

[11] Note that when some attributes of alternative i are improved and others deteriorated it is impossible to set bounds on changes in total surplus.

[12] Alternative i has a zero choice probability in deriving this subsequent consumer surplus, since it has been made very unpopular, but is not removed from the choice set.

Path dependency thereby also precludes the identification of welfare effects of simultaneous changes in the attribute levels of multiple alternatives in the choice set. Indeed, the value of alternative i changes due to changes in its own attributes as well as in those of a competing alternative z. We can define a change in value for the distinct alternatives i and z using (10). The implications on the joint surplus for i and z, however, varies with the adopted tax path from (0,0) to (∞,∞). Furthermore, the opposite directional effect of changes in i (or z) on the regret of the other alternatives in the choice sets precludes setting bounds on the overall implications of the change on the total surplus of the choice set.

Despite the limitations discussed in this section, we believe that the proposed measure constitutes a step forward for RRM-based welfare analysis as it allows researchers to compute the existence value of specific alternatives and the impact of changes in the alternative's attributes on its existence value. Furthermore, the proposed measure provides insight into the impact on total consumer surplus (i.e., the value of the full choice set) of changes in the attributes of a specific alternative. Although the latter measure only provides a bound on the maximum welfare implications of such a change, this is much more informative than having no information at all regarding the resulting welfare implications.

6. Conclusions and future research

Since its introduction, the Random Regret Minimisation model has received significant attention in the field of choice modelling and has been applied to a broad range of stated choice and revealed preference datasets (see Chorus et al. 2014 for an overview). Due to its empirical nature and its behavioural, rather than axiomatic underpinning, the model's capacity to conduct welfare analysis is yet to be determined, but very likely to be considerably more limited than that of conventional AIRUM models. At first sight, the absence of a marginal regret of income even precludes a meaningful RRM-based welfare analysis. In this paper however, we show that observed behavioural responses to price changes can be applied to approximate certain specific Marshallian measures of consumer surplus.

The proposed method interprets the RRM-based choice probability ‘as if’ it represents a probabilistic demand function. It should, however, be noted that in contrast to RUM models, the RRM-based indirect utility function has no direct utility function counterpart which adheres to the principles as set out by Batley and Ibanez (2013a). Nevertheless, the choice probability is the best and most well-behaved approximation available of how consumers respond to price and quality changes in a discrete choice context. Following the tradition in microeconomics, measuring the area underneath the probabilistic demand function up to a choke price assigns an existence value to an alternative in the context of a particular choice set. The capability of the RRM model to account for choice set composition effects is clearly reflected in the predicted consumer surplus measures and their differences from RUM-counterparts. For example, the RRM model assigns a higher value to so-called compromise alternatives as it favours intermediate – as opposed to extreme – performance on the different attributes characterizing an alternative, relative to the attributes of competing alternatives. Changes in the value of an alternative as a result of changes in its attribute levels can also be valued using the same method, where the method becomes simpler when a price change is considered. We find that differences between the welfare effects predicted by the RUM and RRM model are largest when alternatives are improved on attributes on which they are already performing well. These findings are again in line with differences in behavioural premises underlying RUM and RRM models, in the sense that the convexity of the RRM model tempers such welfare gains, compared to the RUM model. In most other cases, the differences between the RUM and RRM welfare effects are more comparable, but also these more subtle differences can still be traced back to the core properties of the RRM model.

We discuss in what ways the developed welfare measure is incomplete. Indeed, it only focuses on the change in surplus for the altered alternative and not the change in total surplus; aggregation bias and path dependency prevent the quantification of these overall welfare implications for the entire choice set, i.e. the net welfare effect. When unidirectional changes in the attribute levels are introduced, we are however able to set an upper bound on the resulting welfare gains and losses in the entire choice set. Note that these bounds differ from the theoretical bounds discussed by Batley and Dekker (2017); Morey (1994); and McFadden (1995) which are related to the possibility of switching across alternatives; here these bounds arise because the actual regret of unaltered alternatives is affected by improving a particular environmental alternative. The latter could potentially prevent a priori knowledge on the direction of the net welfare effect. The issue is closely related to the non-monotonicity of the expected minimum regret in the RRM model (Chorus 2012). A second limitation of the method is the impossibility to value changes in the attributes of multiple alternatives as non-unique welfare estimates will in that case be obtained due to path dependency. Nevertheless, this paper provides researchers a tool to quantify certain welfare implications based on the RRM model. These limitations, however, significantly limit the application of the RRM model in combination with social welfare measurement, leaving the researcher with the inevitable trade-off between behavioural relevance and economic theory based social welfare analysis.

Naturally, these limitations call for future research and ultimately a movement towards Hicksian (or compensated) welfare measures which are not hampered by path dependency. The simple solution is to adhere to the AIRUM specification and only allow for context dependency in the non-price attributes. We provide a little thought experiment here when one wishes to keep treating prices in a RRM fashion. Hicksian measures require an individual to be indifferent before and after a change in attribute levels. Section 2 already established that income compensation is not feasible in the context of the RRM model. Price compensation may, however, be an alternative measure of compensation. One could ask the question, what is the minimum amount of price compensation required to bring the individual back to his old regret (utility) level? Essential in the context of random regret (utility) are the implications of switching behaviour (e.g. Karlström and Morey 2001). As such it may not matter of which alternative the regret is reduced to the minimum level of regret experienced in the original choice set. Particularly the non-linearity of regret with respect to price (and attributes) may cause that price changes in other alternatives are more effective to bring regret back to its original level at a lower cost. The relevant question therefore becomes: what is the minimum amount of price compensation required and on which alternative to bring the minimum regret in the choice set back to its original level? This requires either extending the method proposed by Karlström and Morey (2001) or applying McFadden’s (1995) simulation method to obtain a measure of expected compensating variation. Naturally, the economic properties of such a measure of compensating variation would need to be established. Violations of the conditions specified in Batley and Ibanez (2013a) are foreseen, such as symmetry, but some of these also extend to the framework of utility functions which are non-linear in income.

Finally, our analysis has been at the level of the individual, not the representative consumer. A particular reason for this is that the described preference relations do not take the well-known Gorman polar form. This requires judgements with respect to aggregation of individual welfare effects for the purpose of economic appraisal. Our empirical examples assume preferences are constant across individuals, but it is not uncommon that preferences vary across income groups (or other socio-economic characteristics). In both the RUM and RRM model, heterogeneity in preferences has implications for the implemented social welfare function. The welfare function may be corrected for such effects by means of income adjusted weights (e.g. UK Treasury 2011).

Acknowledgements

The authors gratefully acknowledge support from the Netherlands Organisation for Scientific Research (NWO), in the form of VIDI-grant 016-125-305.

References

Adamowicz, W. L., Glenk, K., & Meyerhoff, J. (2014). Choice modelling research in environmental and resource economics. Chapter 27, pages 661-674, in Hess, S. & Daly, A. (Eds.) Handbook of Choice Modelling, Edward Elgar, Cheltenham, UK.

Batley R. 2016. Income effects, cost damping and the value of time: theoretical properties embedded within practical travel choice models. Transportation, in press. doi:10.1007/s11116-016-9744-0

Batley R. and Dekker, T. 2017. The intuition behind income effects of price changes in discrete choice models, and a simple method for measuring the compensating variation. ITS Working Paper, University of Leeds.

Batley R. and Ibanez, N. 2013a. Applied welfare economics with discrete choice models: implications for empirical specification. In: Choice modelling: the state of the art and the state of practice, Eds: Hess, S. and Daly, A., Edward Elgar, Cheltenham, UK.

Batley R. and Ibanez, N. 2013b. On the path independence conditions for discrete-continuous demand. Journal of Choice Modelling, 7, 13-23.

Ben-Akiva M. and Lerman, S. 1985. Discrete choice analysis: theory and application to travel demand. The MIT Press.

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(1), 32-47.

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. Logsums for utility maximizers and regret-minimizers, and their relation with desirability and satisfaction. Transportation Research Part A: Policy and Practice, 46(7), 1003-1012.

Chorus, C.G. and Bierlaire, M., 2013. An empirical comparison of travel choice models that capture preferences for compromise alternatives. Transportation, 40, 549-562.

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

Cochrane, R.A. 1975. A possible economic basis for the gravity model. Journal of Transport Economics and Policy, 9(1), 34-49.

Dagsvik, J.K. and Karlström, A., 2005. Compensating variation and Hicksian choice probabilities in random utility models that are non-linear in income. Review of Economic Studies, 72(1), 57-76.

Deaton, A. and Muellbauer, J. 1980. Economics and Consumer behaviour. Cambridge University Press.

De Jong, G., Daly, A., Pieters, M. and van der Hoorn, T. 2007. The logsum as an evaluation measure: review of the literature and new results. Transportation Research Part A: Policy and Practice, 41(9), 874-889.

Dekker, T., 2014. Indifference based Value of Time measures for Random Regret Minimisation models, Journal of Choice Modelling, 12, 10-20.

De Palma, A. and Kilani, K. 2011. Transition choice probabilities and welfare analysis in additive random utility models. Economic Theory, 46(3), 427-454.

EconometricSoftware (2012). NLOGIT Version 5.0 Reference Guide. (Plainview, NY, USA).

Edwards, W. 1961. Behavioral decision theory. Annual review of psychology, 12(1), 473-498.

Einhorn, H. J., and Hogarth, R. M. 1981. Behavioral decision theory: Processes of judgment and choice. Journal of Accounting Research, 1-31.

Guevara, C. A. and Fukushi, M. 2016. Modeling the decoy effect with context-RUM Models: Diagrammatic analysis and empirical evidence from route choice SP and mode choice RP case studies. Transportation Research Part B: Methodological, 93, 318-337.

Hanemann, M., 1984. Welfare evaluations in contingent valuation experiments with discrete responses. American Journal of Agricultural Economics, 66(3), 332-341.

Harris, A.J. and Tanner, J.C. 1974. Transport demand models based on personal characteristics. Transport and Road Research Laboratory Supplementary Report 65UC, Berkshire; Reprinted in the Symposium Proceedings of the Sixth International Symposium on Transportation and Traffic Theory, Sydney Australia.

Hensher, D. A., Greene, W. H. and Rose, J. M. 2015. Applied choice analysis: a primer. (Cambridge: Cambridge University Press), Second Edition.

Herriges, J.A. and Kling, C.L. 1999. Nonlinear income effects in random utility models, The Review of Economics and Statistics, 81, 62-72.

Hess, S., Polak, J., Daly, A. and Hyman, G. 2007. Flexible substitution patterns in models of mode and time of day choice: new evidence from the UK and the Netherlands. Transportation, 34(2), 213-238.

Jara-Diaz, S. and Videla, J. 1989. Detection of income effect in mode choice: theory and application. Transportation Research Part B: methodological, 23(6), 393-400.

Karlström, A. and Morey, E.R. 2001. Calculating the exact compensating variation in logit and nested-logit models with income effects: theory, intuition, implementation and application. Paper presented at the meeting of the American Economic Association, New Orleans, January 2001.

Krinsky I. and Robb A. L., 1986. On Approximating the Statistical Properties of Elasticities. The Review of Economics and Statistics, 68(4), 715-719.

Krinsky I. and Robb A. L. 1990. On Approximating the Statistical Properties of Elasticities: A Correction, The Review of Economics and Statistics, 72(1), 189-190.

Leong, W., Hensher, D.A. 2015. Contrasts of Relative Advantage Maximisation with Random Utility Maximisation and Regret Minimisation? Journal of Transport Economics and Policy, 49(1), 167-186.

Loomes, G. and Sugden, R. 1982. Regret theory: an alternative theory of choice under uncertainty. The Economic Journal, 92(368), 805-824.

McConnell, K.E., 1995. Consumer surplus for discrete choice models. Journal of Environmental Economics and Management, 29(3), 263-270.

McFadden, D., 1981. Econometric models of probabilistic choice. In: Structural analysis of discrete data: with econometric applications, Eds: C. Manski, MIT Press, Cambridge, Massachusetts.

McFadden, D., 1995. Computing willingness-to-pay in random utility models. Department of Economics, University of California, Berkeley.

Morey, E. 1994. What is consumer surplus per day of use, when is it a constant independent of the number of days use and what does it tell us about consumer surplus? Journal of Environmental Economics and Management, 26, 257-270.

Morkbak, M.R., Christensen, T. and Gyrd-Hansen, D. 2010. Choke price bias in choice experiments. Environmental and Resource Economics, 45(4), 537-551.

Neuberger, H. 1971. User benefit in the evaluation of transport and land use plans. Journal of Transport Economics and Policy, 5, 52-75.

Simonson, I. and Tversky, A. 1992. Choice in context: tradeoff contrast and extremeness aversion. Journal of Marketing Research, 29(3), 281-295.

Slovic, P., Fischhoff, B., and Lichtenstein, S. 1977. Behavioral decision theory. Annual review of psychology, 28(1), 1-39.

Small, K.A. and Rosen, H.S. 1981. Applied welfare economics with discrete choice models. Econometrica, 105-130.

Street, D., Burgess, L. and Louviere, J. 2005. Quick and easy choice sets: constructing optimal and nearly optimal stated choice experiments. International Journal of Research in Marketing, 22, 459-470.

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.

Tversky, A. and Kahneman, D. 1991. Loss aversion in riskless choice: A reference-dependent model. The quarterly journal of economics, 106(4), 1039-1061.

Train, K.E., 2009. Discrete choice with simulation. Cambridge University Press, New York.

UK Treasury 2011. The Green Book: Appraisal and evaluation in central government. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/220541/green_book_complete.pdf

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

Vermunt, J. K. and Magidson, J. (2014). Upgrade manual for Latent GOLD Choice 5.0. (Belmont, MA , USA).

Williams, H.C.W.L. 1977. On the formation of travel demand models and economic evaluation measures of user benefit. Environment and Planning A, 9, 285-344.

Appendix A: Monotonicity of RRM choice probabilities in price

In this Appendix, we follow Chorus (2010) and define the RRM choice probabilities by (A.1) and assume respondents select the alternative generating the least amount of regret and that the negative of the additive random error ε_i in $RR_i = R_i + \varepsilon_i$ follows a Type I Extreme Value distribution.

$$\pi_i = \frac{\exp\left(-R_i\right)}{\sum_j \exp\left(-R_j\right)} \tag{A.1}$$

Since cheaper alternatives are preferred over more expensive alternatives we assume $\theta_p < 0$, such that R_i is increasing in the price of i and simultaneously R_j is decreasing in the price of i as alternative j becomes relatively cheaper (see A.2 and A.3).

$$\frac{\partial R_i}{\partial p_i} = -\theta_M \sum_{j \neq i} \frac{\exp\left(\theta_M \left(p_j - p_i\right)\right)}{1 + \exp\left(\theta_M \left(p_j - p_i\right)\right)} > 0 \text{ for } \theta_M < 0 \tag{A.2}$$

$$\frac{\partial R_j}{\partial p_i} = \theta_M \frac{\exp\left(\theta_M \left(p_i - p_j\right)\right)}{1 + \exp\left(\theta_M \left(p_i - p_j\right)\right)} < 0 \text{ for } \theta_M < 0 \text{ and } \forall j \neq i \tag{A.3}$$

The derivative of π_i with respect to p_i can then be described by (A.4). Implementing (A.2) and (A.3) and noting that $0 < \pi_i < 1$ brings us to the conclusion that π_i is monotonically decreasing in p_i.

$$\frac{\partial \pi_i}{\partial p_i} = \pi_i \left(\sum_{j \neq i} \pi_j \cdot \frac{\partial R_j}{\partial p_i} - \left(1 - \pi_i\right) \frac{\partial R_i}{\partial p_i} \right) < 0 \text{ for } \theta_M < 0 \tag{A.2}$$

Since π_i is monotonically decreasing in p_i, $\sum_{j \neq i}^{J} \pi_j$ is increasing in p_i by definition. The non-linearity of the regret function, however, precludes stating that the choice probability of each other alternative j increases. The first and third terms within the brackets of (A.5) are positive, but the summation over q is negative. Hence, the sign of (A.5) is unknown a priori. For example, increasing the price of i may leave R_j unaffected as it is already much cheaper than i, but may significantly reduce the regret of the alternatives described by q. As such, alternative j may become relatively unpopular compared to q and experience a reduction in choice probability despite having unchanged regret.

$$\frac{\partial \pi_j}{\partial p_i} = \pi_j \left(\left(\pi_j - 1\right) \frac{\partial R_j}{\partial p_i} + \sum_{q \neq i,j}^{J} \pi_q \frac{\partial R_q}{\partial p_i} + \pi_i \frac{\partial R_i}{\partial p_i} \right) \tag{A.5}$$