Random Regret Minimization for consumer choice modelling: 
Assessment of empirical evidence

Caspar Chorus*1, Sander van Cranenburgh1, Thijs Dekker2

1 Transport and Logistics Group, Delft University of Technology
2 Institute for Transport Studies, University of Leeds

c.g.chorus@tudelft.nl / +31-152788546 / Jaffalaan 5, 2628BX Delft, the Netherlands

Abstract

This paper introduces to the field of marketing a regret-based discrete choice model for the analysis of multi-attribute consumer choices from multinomial choice sets. This random regret minimization model (RRM), which has two years ago been introduced in the field of transport, forms a regret-based counterpart of the canonical random utility maximization paradigm (RUM). Since its very recent introduction, a relatively small but growing body of literature has emerged focusing on RRM’s theoretical properties and on empirical comparisons with RUM. This paper assesses theoretical and empirical results that have been obtained so far, with the aim of finding out to what extent, when, and how RRM can form a viable addition to the consumer choice modeller’s toolkit. The paper shows that RRM or hybrid RRM-RUM models outperform RUM counterparts (which are equally parsimonious) in a majority of studies in terms of model fit and predictive ability. Although these differences in performance are quite small, the two paradigms often result in markedly different managerial implications due to often considerable differences in elasticities and market share forecasts. We elaborate on how RRM and RUM can be used jointly to arrive at ‘behaviourally robust’ marketing strategies.
1. Introduction

Recently, a discrete choice model based on regret-minimization premises has been introduced in the travel behaviour community (Chorus, 2010). The model (called Random Regret Minimization or RRM) is geared towards the analysis of choices made among multi-attribute alternatives from multinomial choice sets. It postulates that as long as alternatives are defined in terms of multiple attributes (which, as argued by for example Lancaster (1966) is usually the case in consumer choice settings), regret emerges from the process of trading off attribute-levels when making a decision. More specifically, the RRM model states that regret emerges when a non-chosen alternative outperforms a chosen alternative in terms of one or more attributes. The RRM model forms a regret-based counterpart of discrete (consumer) choice models that are based on the canonical linear-in-parameters Random Utility Maximization (RUM) theory (McFadden, 1973; Ben-Akiva & Lerman, 1985; Train, 2009). Like RUM models, the RRM model can be easily estimated (in either MNL, Nested Logit, Probit or Mixed Logit forms) using a range of (off-the-shelf) software packages.

Since its recent introduction, the RRM-model has received an increasing amount of attention from choice modellers in fields as diverse as transportation, urban planning, environmental economics and health economics (e.g., Chorus et al., 2011; Thiene et al., 2012; Kaplan & Prato, 2012; Beck et al., 2013; Guevara et al., 2013; Boeri et al., 2013; Hensher et al., 2013). The result of this growing interest is a rapidly growing body of empirical and theoretical papers. Most of these papers contrast the RRM model to the linear-in-parameters Random Utility Maximization (RUM) specification that has dominated the field of choice modelling for decades. These comparisons suggest that the RRM-model has a promising empirical performance and that it features a number of distinct and interesting behavioural properties (see the next sections for a more detailed discussion).

This contributions of this paper are twofold: First, it introduces the RRM model to the marketing research community as an additional tool in their choice modelling toolbox (Section 2). Second, the paper provides an integrative assessment of the RRM model’s potential as a consumer choice model, by exploring the evidence that emerges from the few dozens of available empirical comparisons with its linear-additive RUM-counterparts. The ‘data’ that we use, which are presented in Section 3, consist of 28 studies that have been published (or are accepted for publication) in peer-reviewed international journals and/or conference proceedings. Stated and Revealed preference datasets considered in these studies focus on a wide variety of choice contexts, including – but not limited to – choices among travel alternatives, leisure activities, durable goods, dating profiles, and health care options. RRM and RUM models are compared in terms of model fit (Section 4), predictive performance (Section 5), and generated output (such as market share forecasts) that is of relevance for marketing managers (Section 6). Section 7

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1 As shown in Chorus (2012a), the model covers choices over risky and non-risky outcomes.
2 See Schlereth & Skiera (2012) and Eckert et al. (2012) for two examples of Random Utility Maximization-based choice models published in this journal during the last year.
draws conclusions and discusses how the RRM model can be used in the process of designing effective marketing strategies; this section also proposes directions for further research.

Importantly, the aim of this paper is not to promote the RRM model, let alone to suggest that it may replace the canonical RUM model as a model of consumer choice. In fact, our overview of results shows that differences in model fit and predictive performance between the RRM and RUM model is frequently negligible, and that in some cases RRM performs better than RUM and vice versa. Moreover, we find that even in cases of comparable fit between the two specifications, the managerial implications derived from both models may vary substantially. As such, the RRM model allows the choice modeller to describe and predict a different type of behaviour. This supports the view that RRM is a valuable addition to the choice modeller’s toolbox. See section 7 for more discussion about how the added value of RRM can be put to use in combination with that of other models, including RUM.

Before the RRM model is presented in the next section, it should be mentioned that of course, the idea that anticipated regret plays an important role in (consumer) decision making is by no means new. Roughly speaking, two strands of related literature in the marketing research domain can be distinguished: a first body of literature (e.g., Simonson, 1992; Taylor, 1997; Spears, 2006; Strahilevitz et al., 2012) develops conceptual models which usually take the form of a series of hypotheses, which are subsequently tested based on data collected by means of questionnaires or behavioural experiments. A second body of literature (Hey & Orme, 1994; Inman et al., 1997; Bleichrodt et al., 2010; Chen & Jia, 2012) adopts a more formal perspective as it proposes and empirically tests mathematical models of regret-based decision making, usually inspired by the seminal Regret Theory proposed in the early 1980s (Loomes & Sugden, 1982; Bell, 1982, Fishburn, 1982).

The RRM-model differs in various ways from these previous approaches to model regret-based decision making (see Chorus (2012a) for an in-depth discussion of differences between RRM and Regret Theory). As will become clear in the next section, the RRM model predicts that the wish to minimize ‘attribute-level’ regret leads to semi-compensatory decision making and to preferences that are dependent on the composition of the choice set. As such, it makes more sense to view the RRM model as an addition to the literature on context-dependent discrete choice models (e.g., Kivetz et al., 2004; Roorderkerk et al., 2011) rather than as a new addition to the literature on regret-based decision making (see references above).

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3 An interesting finding that emerges from both bodies of empirical literature is that regret minimization is a particularly important determinant of decision making when choices are perceived by the decision maker as difficult, and important to him- or herself and/or to his or her relevant social peers (e.g. Zeelenberg & Pieters, 2007). It goes without saying that for many consumer choice situations, these conditions readily apply.
2. A Random Regret Minimization model of consumer choice

The RRM model (Chorus, 2010) has been designed to incorporate the notion of regret based decision making in non-risky choice models. The RRM model hypothesizes that, when confronted with a choice set, the decision-maker chooses the alternative from the set that has minimum anticipated regret. The regret of alternative \(i\) is given by Eq. 1. Accordingly, the left panel of Figure 1 depicts the regret of the considered alternative \(i\) with regard to attribute \(m\) when compared to another alternative \(j\). The right panel depicts the derivative of the regret function.

\[
RR_i = R_i + \varepsilon_i = \sum_{j \neq i} \sum_{m=1}^{M} \ln\left(1 + \exp\left[\beta_m \cdot (x_{jm} - x_{im})\right]\right) + \varepsilon_i
\]

Eq. 1

- \(RR_i\) denotes the random (or: total) regret associated with a considered alternative \(i\)
- \(R_i\) denotes the ‘observed’ regret associated with \(i\)
- \(\varepsilon_i\) denotes the ‘unobserved’ regret associated with \(i\)
- \(\beta_m\) denotes the estimable parameter associated with attribute \(x_m\)
- \(x_{im}, x_{jm}\) denote the values associated with attribute \(x_m\) for, respectively, the considered alternative \(i\) and another alternative \(j\)

This formulation of random regret features a number of convenient econometric properties: similar as in the random utility maximization framework, depending on the assumptions made.
regarding the random error term $\epsilon_i$, different choice models arise such as the MNL model, the Nested Logit model, and the Probit model. Similar to the RUM framework, more flexible (e.g. Mixed Logit) specifications of the regret function can control for unobserved regret heterogeneity by means of random parameters, and the introduction of error components may alleviate restrictions on the error structure of the model. In the case where the negative of the errors is assumed to be i.i.d. Extreme Value Type I, the classical MNL-form is obtained and choice probabilities are written as in Eq. 2.

$$P(i) = \frac{\exp(-R_i)}{\sum_{j=1}^{J} \exp(-R_j)}$$

Eq. 2

Another econometrically convenient property is that the RRM model features a smooth, differentiable and globally concave\(^4\) likelihood function. Therefore, it allows for easy estimation and enables easy implementation in exiting software packages.

The model proposed in Eq. 1 and visualized in Figure 1 incorporates seven behavioural intuitions relating to anticipated regret (assume for the moment that higher attribute values are preferred over lower ones).

1. when a considered alternative $i$ is outperformed by another alternative $j$ in terms of a particular attribute $m$ (hence $x_{im} - x_{jm} < 0$), the comparison of the considered alternative with the other alternative on that attribute generates anticipated regret.
2. anticipated regret increases with the importance of the attribute on which a considered alternative is outperformed by another alternative. This can easily be seen by looking at the right graph of Figure 1: $dR/dx$ asymptotically converges to $\beta$.
3. anticipated regret increases with the magnitude of the extent to which a considered alternative is outperformed by another alternative on a particular attribute: regret monotonically increases with $x_j - x_i$.
4. anticipated regret increases with the number of attributes on which the considered alternative is outperformed by another alternative: from Eq. 1 we see that the total anticipated regret is the sum of anticipated regrets across the $M$ attributes that may generate regret.
5. anticipated regret increases with the number of alternatives that outperform a considered alternative on a particular attribute: from Eq. 1 we see that the total anticipated regret is the summation of anticipated regrets across the all alternatives ($j \neq i$).

\(^4\) Under MNL specification.
6. when a considered alternative \( i \) outperforms another alternative \( j \) in terms of a particular attribute \( m \) (hence \( x_{im} - x_{jm} > 0 \)), the comparison of the considered alternative with the other alternative on that attribute generates (almost\(^5\)) no anticipated regret.

7. anticipated regret is, from the perspective of the analyst, partially ‘observable’ (in the sense that it can be explicitly linked to observed variables) and partially ‘unobservable’: hence, the error term in Eq. 1.

Given space limitations and in the light of the fact that previous publications provide more in-depth discussions of the properties of the RRM model (e.g., Chorus, 2010, 2012a), we choose to limit ourselves to a brief discussion of the arguably most important model property for consumer choice modellers: the RRM model features a particular type of semi-compensatory behaviour which results in preferences for compromise alternatives.

More specifically, due to the convexity\(^6\) of the regret-function, the RRM model imposes that improving an alternative in terms of an attribute on which it already performs well relative to other alternatives generates only a small decrease in regret (\( dR/dx < \beta/2 \)). However, deteriorating to a similar extent the performance on another equally important attribute on which the alternative has a poor relative performance may generate a substantial increase in regret (\( dR/dx > \beta/2 \)). This assumption, which is embodied in the functional form of the regret function, implies that, contrary to the linear-additive RUM model, the implied trade-offs that decision-makers make are to a large extent dependent on the composition of the choice set. For example, in the context of an RRM model the willingness to pay for an improvement of a quality-attribute will crucially depend on the performance of the alternative and its competition in terms of price and the quality-attribute.

RRM’s theoretical ability to accommodate a preference for compromise alternatives follows directly from the above mentioned semi-compensatory behaviour: the RRM-model postulates that having a (very) poor performance on one attribute causes much regret, while having a (very) strong performance on another attribute does not necessarily compensate for this poor performance. Therefore, RRM-models postulates that it is more effective (in terms of avoiding regret) to select a compromise alternative. Even when such a compromise alternative fails to

\(^5\) A previous version of the RRM-function (Chorus et al., 2008) featured a combination of two max-operators. That model postulated that regret equals (rather than approaches) zero when a considered alternative outperforms a competing alternative on a given attribute. While behaviorally intuitive, this model suffered from the fact that due to the max-operators’ discontinuities the resulting likelihood function was not globally differentiable. This implied that the model could only be estimated using custom-made code, and that elasticities and willingness to pay measures could not be obtained. The regret function proposed in Chorus (2010) and put forward in the current paper forms a smooth approximation of the 2008-model, while circumventing the econometric issues mentioned directly above.

\(^6\) Note that \( d^2R/dx^2 > 0 \) for all \( x \).
have a strong performance on any of the attributes (relative to the other alternatives in the set), RRM-models predict that it will still only generate modest levels of regret as long as it does not have a particularly poor performance on any of the attributes.

In fact, RRM’s ability to accommodate preferences for compromise alternatives is only an example of the broader notion embodied by the RRM model that preferences for alternatives, and trade-offs between attributes, are dependent on the composition of the choice set. This is an fundamental distinction between RRM models and linear-additive RUM models which postulate that preferences and trade-offs are not dependent on other alternatives in the choice set and their attributes (in other words: contrary to the linear-additive RUM model, the RRM model does not feature the Independence from Irrelevant Alternatives-property).

3. The ‘data’: empirical comparisons between RRM and RUM models

We focus on empirical comparisons between RRM and RUM as reported in articles that have been published in, or are forthcoming in, scientific journals, conference-proceedings, or reference guides. Eighteen publications emerged over the last two years encompassing a total of 28 empirical comparisons between RRM and RUM that meet these criteria. Table 1 presents these 28 comparisons. Hence, each row refers to a different dataset.

The columns present from left to right: the study identifier which we use in the remainder of this article as a reference; the name of the authors; the status: year in which the article is (to be) published; type of data (Stated Preference versus Revealed Preference); model specification (MNL or Mixed MNL); best model fit; best predictive ability; managerial implications; and choice type. Finally, the last row of Table 1 provides column totals.

A few remarks can be made regarding the studies reported in Table 1. Firstly, looking at the far right column we see that while choice types are quite diverse, the majority refers to mobility and freight transport related choices. This is of course to be expected, given that the RRM model originates from the transportation community. Choice types closest to the marketing domain include choices among durable goods (car types – studies 21 and 24) and shopping destination choices (study 4). Secondly, it appears that most of the reported studies are based on SP-data: only six out of 28 use RP-data. Thirdly, the large majority of studies are based on the estimation of MNL-models. The only exceptions are studies 5, 25 and 26 (which report error component mixed logit models to accommodate panel and nesting effects), and study 28 (which reports a random parameter mixed logit model to accommodate random taste heterogeneity). As highlighted in the final section of this paper, these limitations in the scope of RRM-RUM comparisons – in terms of the types of choices, data, and model forms that have been considered so far – represent obvious directions for further research.
<table>
<thead>
<tr>
<th>ID</th>
<th>Authors</th>
<th>Year</th>
<th>Type of data</th>
<th>Model specification</th>
<th>Best model fit</th>
<th>Best predictive ability</th>
<th>Managerial relevant output</th>
<th>Choice type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Chorus</td>
<td>2010</td>
<td>x</td>
<td>x</td>
<td>b</td>
<td>x</td>
<td>x²</td>
<td>Routes/travel modes</td>
</tr>
<tr>
<td>2</td>
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<td>2010</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td>x</td>
<td>tie</td>
<td>Travel information options</td>
</tr>
<tr>
<td>3</td>
<td>Chorus</td>
<td>2010</td>
<td>x</td>
<td>x</td>
<td>c</td>
<td>tie</td>
<td>tie</td>
<td>Parking lots</td>
</tr>
<tr>
<td>4</td>
<td>Chorus</td>
<td>2010</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td>x</td>
<td>x²</td>
<td>Shopping destinations</td>
</tr>
<tr>
<td>5</td>
<td>Chorus and de Jong</td>
<td>2011</td>
<td>x</td>
<td>x</td>
<td>c</td>
<td></td>
<td>x</td>
<td>Departure times</td>
</tr>
<tr>
<td>6</td>
<td>Chorus et al.</td>
<td>2011</td>
<td>x</td>
<td>x</td>
<td>c</td>
<td></td>
<td>x</td>
<td>Policies (choices made by politicians)</td>
</tr>
<tr>
<td>7</td>
<td>Thiene et al.</td>
<td>2012</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td></td>
<td>x</td>
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<tr>
<td>8</td>
<td>Boeri et al.</td>
<td>2012</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td></td>
<td>x</td>
<td>Recreational destination choices</td>
</tr>
<tr>
<td>9</td>
<td>Chorus and Rose</td>
<td>2012</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td></td>
<td>x</td>
<td>Dating profiles (visitors of dating websites)</td>
</tr>
<tr>
<td>10</td>
<td>Chorus</td>
<td>2012b</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td></td>
<td></td>
<td>Routes</td>
</tr>
<tr>
<td>11</td>
<td>Kaplan and Prato</td>
<td>2012</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td></td>
<td>x</td>
<td>Evasive actions car</td>
</tr>
<tr>
<td>12</td>
<td>Greene</td>
<td>2012</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
<td>x</td>
<td>Travel modes</td>
</tr>
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</table>
Table 1: Overview of empirical comparisons between RRM and RUM

<table>
<thead>
<tr>
<th>Study</th>
<th>Year</th>
<th>Method</th>
<th>1xa</th>
<th>5xa</th>
<th>1xtle</th>
<th>Car types</th>
<th>Routes</th>
<th>Vaccination regimes for cervical cancer</th>
<th>Medical treatments of osteoporosis</th>
<th>Travel modes (freight transport)</th>
<th>Lifestyle-choices to prevent coronary heart disease</th>
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<tbody>
<tr>
<td>Leong and Hensher</td>
<td>2012</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prato</td>
<td>2013</td>
<td>x</td>
<td>x</td>
<td></td>
<td>tie</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Hensher et al.</td>
<td>2013</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chorus et al.</td>
<td>2013</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td></td>
<td>1x</td>
<td></td>
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<tr>
<td>Chorus and Bierlaria</td>
<td>2013</td>
<td>x</td>
<td>x</td>
<td>tie</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beck et al.</td>
<td>2013</td>
<td>x</td>
<td>x</td>
<td>b</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>de Bekker-Grob and Chorus</td>
<td>2013</td>
<td>x</td>
<td></td>
<td></td>
<td>a</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>de Bekker-Grob and Chorus</td>
<td>2013</td>
<td>x</td>
<td></td>
<td>tie</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boeri and Mastino</td>
<td>2013</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td></td>
<td></td>
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<tr>
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<td>2013</td>
<td>x</td>
<td>x</td>
<td>a</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

- a at 1% level of significance
- b at 5% level of significance
- c at 10% level of significance
- x Ex post analysis by the authors

Totals: 6 22 24 4 13 11 3 1 3 1 13

Table 1: Overview of empirical comparisons between RRM and RUM
4. RRM versus RUM: differences in model fit

Because neither model can be seen as a special case of the other model (as both models consume the same number of parameters) it is necessary to perform a test for non-nested models to examine whether differences in model fit are statistically significant. The Ben-Akiva and Swait test (1986) is such a test and is the one we use in this study. This test generates an upper limit for the probability that, given that the final-log-likelihood of model A is higher than that of model B, model B still provides the best representation of the data-generating process. As such, the upper limit can be seen as a conservative estimate of the *p*-value indicating the significance of the difference in model fit. Most of the studies presented in Table 1 report this statistical comparison. Where this is not the case (for example in studies 1 – 4 and studies 13 – 19) this test can be carried out *ex post* based on the reported estimation results. The conclusions are as follows7:

As can be seen in Table 1, at a significance level of 5%, in 10 studies the RRM model fits the data significantly better than the RUM model, while in 11 studies the RUM model fits the data significantly better. In three studies, the RRM model fits the data better, yet at a significance level of 10%. In three studies model fit differences (which are in favour of RRM) are not significant at a 10%-level, and are reported in the Table as a tie. Possibly more important than the statistical significance of the differences in model fit is the size, and therefore relevance, of the differences; it appears that in all cases the differences are small.

The question may be asked whether possible determinants of the sign of these differences in model fit can be identified. For example, are there social-demographic segments e.g. male or female, or young or old, which are more inclined to make choices in accordance with the premises of RRM or RUM, or are there contextual factors, such as time pressure or importance of the decision, which result in a structurally better fit of one or other model type?

As far as the social-demographic determinants are concerned, the studies from Table 1 offer the following insights: different segments often lead to differences in model fit, but these appear not to be structural (generic over datasets). In addition, these differences in model fit are significant rather than substantial, so a more detailed examination of possible structural differences between social-demographic segments in terms of the relative model fit of RRM and RUM appears not to be a particularly urgent direction for future research.

The role of contextual factors is clearer, although the relatively small number of empirical studies available provides reason for caution when drawing general conclusions. The consumer-psychological literature provides a starting point for an analysis of the role of contextual factors as a determinant of the differences in model fit between the RRM and the RUM: as mentioned in the introduction, a series of empirical studies (see Zeelenberg & Pieters (2007) for an

7 Note that we report comparisons for 27 (rather than 28) studies, since study 12 (which is further discussed elsewhere in this article) only involves a comparison between a RUM model and a so-called hybrid RUM-RRM model.
overview) have shown that the minimization of anticipated regret especially plays a role when a particular choice is either difficult and/or important for the decision makers and/or when they anticipate having to be able to defend their choice to others. With this information in mind, it is not surprising that studies into car type choices (studies 21 and 24), evasive actions in the face of a potential accident (11), policy choices of politicians (6), choices between dating profiles (9), health-related choices (28) and choices of goods transporters (27) in general show a better fit for RRM whilst choices between, for example, leisure time activities (studies 7 and 8) and highway routes (studies 13, 14, 16, 18 and 19) in general show a better fit for RUM.

Besides the comparison of RRM and RUM models, a number of studies (more specifically study 4 (reported in Chorus et al., 2013) and studies 12, 13-19, 22, 25, 26) also report a comparison between RRM, RUM and so-called hybrid RUM-RRM models. These hybrid models assume that the decision maker processes some attributes following the RRM model and others using the linear-additive RUM model. Testing all possible RUM-RRM attribute combinations in terms of model fit shows that the hybrid model often performs better than a model that assumes the same rule of behaviour (RRM or RUM) for each attribute. More specifically, in studies 4 (reported in Chorus et al., 2013), 12, 15, 17, 18, 19, 22, and 25 at least one of the hybrid specifications are found to generate a better model fit than either the RUM or RRM models. The differences are again small but mostly statistically significant at conventional levels.

When we incorporate hybrid models in our over-all model fit comparison, it appears that in about one-third of the cases (i.e. datasets) a full RUM model has the best model fit whilst for another third of cases the full RRM model has the best fit. For the remaining third of the cases a hybrid RUM-RRM model gives the best fit. In other words, in approximately two-thirds of the cases a model that to a greater or lesser degree is based on regret minimisation provides a better model fit than a model fully based on utility maximization.

5. RRM versus RUM: differences in external validity

To explore differences in external validity between RRM and RUM, we look at two measures of predictive power on hold-out data: likelihood of the hold-out data given the estimated model, and hit rate. In total, 8 of the 28 studies reported one or both measures. Six of these 8 studies (studies 1, 2, 3, 4, 22, 23) reported a measure based on the likelihood of the hold-out data given the estimated model. This concerns the so-called mean-likelihood, which calculates for each

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^ Note that when alternatives encompass \( M \) attributes, there exist \( 2^M \) possible RRM-RUM attribute combinations. However, it should be mentioned here that the estimation of hybrid models is greatly facilitated in the software package NLOGIT 5, which provides the option of indicating per attribute whether it should be processed as a ‘RUM-attribute’ or a ‘RRM-attribute’. This is an important practical advantage, particularly when the number of attributes increases (and thus also the number of possible combinations of rules of behaviour to be explored).
observation (observed choice) from the hold-out data the probability of that observation given the estimated model, and from that calculates the average. Only one study reported a so-called hit rate or ‘percentage correctly predicted’ (11). The hit rate was calculated ex post by the authors for five other studies (1, 2, 3, 4, and 23) while not being reported in these publications themselves. Below we provide an overview of the differences between RRM and RUM in terms of all these published and unpublished results.

As far as the mean-likelihood is concerned, the performance of the RRM-model is found to be slightly better than that of the RUM-model: for three studies (1, 2, 4) hold out data are more likely given the RRM-model than the RUM-model, while in two cases (studies 3 and 23) the two models perform equally well, and only study 22 reports a better performance of the RUM model. However, it should be noted that these differences between RUM and RRM are, without exception, small.

The RRM-model also performs slightly better than the RUM-model as far as the hit rate is concerned: in three of the eight cases (studies 4, 11, 23) the RRM-model produces a higher hit rate; in only one case the hit rate of the estimated RUM-model is higher (study 1) and in the other two cases both models perform equally well (studies 2 and 3). The differences in hit rates are more substantial than differences in mean-likelihood, although never larger than a few percentage points. As such the results in terms of external validity are comparable to those in terms of model fit, with the possible exception of the hit rate results.

Interestingly enough, it appears that the differences in model fit and external validity between RUM and RRM are generally not consistent when compared across measures: there is only one study (number 4) where the comparison in model fit as well as both the mean-likelihood and the hit rate all indicate a superior performance by the one and the same model type (in this case RRM).

6. RRM versus RUM: differences in managerial implications

Even though most (consumer) choice modellers are very much interested in the performance of models in terms of model fit and external validity, it is clear that consumer choice models need to ultimately serve a ‘higher’ goal: the quantitative support of marketing management. It is therefore important to examine the differences between RUM and RRM in terms of the managerially relevant output both models produce (such as estimates of willingness to pay, elasticities, and market share forecasts). This section, rather than aiming to examine which model type performs better, aims to determine in what ways and to what extent the two models differ in terms of the generated managerially relevant output. Of the 28 studies, 12 presented some form of managerially relevant output. For reasons of succinctness, we here focus on studies that reported elasticities, market share forecasts, or willingness-to-pay
measures\textsuperscript{9}, and we discuss only those studies in which the magnitude of the difference between RRM and RUM was non-trivial. Note that formal derivations of RRM-based elasticities and willingness to pay measures are provided in Hensher et al. (2013) and Chorus et al. (2013), respectively.

Study 7 focuses on itinerary route choices of visitors to a natural area in the Dolomites. Elasticities are calculated (for RRM and RUM models) for attributes such as the presence of waymarkers and possible access fees. For most of the attributes the RRM-elasticities were greater than the RUM-counterparts – in most cases the differences were about 10%. The extent to which the market share of a route was influenced by imposing access fees was also examined. For the chosen variant the effect predicted by the RUM model (3.10% decrease in the market share) was greater than the effect predicted by the RRM (2.06% decrease in market share).

Study 11 examined evasive manoeuvres by car drivers just before an (potential) accident. Elasticities were calculated for estimated RRM and RUM models. Given that indicator-variables are present (such as “use of safety belts” (0/1)) pseudo-elasticities were used which gives the effect on the chance of a particular evasive manoeuvre when an indicator variable changes from ‘0’ to ‘1’. For the large majority of variables the RRM pseudo-elasticity is 5 - 10% larger than the RUM pseudo elasticity.

Study 12 calculated the (cost) elasticities for a RUM model and a hybrid RUM-RRM model in the context of travel mode choices. Differences between the two model forms were substantial, up to more than 100%. In this study it was found that the elasticities generated by the hybrid model were substantially smaller than those generated by the RUM model.

The focus of study 21 was on the preferences of consumers for cars which use alternative fuels. The authors calculated elasticities based on the estimated RUM and RRM models and concluded that the differences between the two model types was substantial – up to 19%. Without exception, price elasticities based on RRM appeared to be greater than the RUM counterparts.

Study 22 examined route choices of Australian commuters. Measures of the willingness to pay for travel time reductions (in jargon: ‘value-of-time’) were computed for RRM and RUM models. It is shown in that paper that for RRM models, the calculated measures depend on the relative performance of the alternative in terms of travel time and costs. This is of course in line with the behavioural premises underlying RRM (see Section 2 for details). Differences between the two model types were substantial: the RUM model predicts a value-of-time of 0.20 Australian dollars per minute while the RRM value-of-time varies between 0.03 Australian dollars per minute and

\textsuperscript{9}Some of the studies reported in Table 1 reported measures of consumer surplus for RUM and RRM models. While this is an important form of model output in the context of transportation and environmental economics (where the evaluation of benefits associated with non-market goods is a key research interest), this form of output is less relevant in most consumer choice / marketing contexts and therefore not discussed in this paper.
1.34 Australian dollars per minute, depending on the composition of the choice set (average value is 0.23 Australian dollars per minute). More specifically: in line with the discussion presented in section 2 the RRM model generates a high willingness to pay for travel time reductions when a considered route was relatively cheap and slow, and a low willingness to pay for travel time reductions when a considered route was relatively expensive and fast. Moreover, it is shown how changes in travel times and costs of competing routes lead to changes in the predicted willingness to pay for a reduction of a considered route’s travel time.

Study 23 focuses on route choices of Dutch commuters (routes being specified in terms of travel times, costs and other attributes). Estimated elasticities for RUM and RRM models hardly differ, with the exception of the travel time elasticity which is nearly 10% greater for the RRM model than for the RUM model. Estimated models were also used to predict market shares for alternative routes and the possible presence of a compromise effect was given particular attention. In line with theoretical expectations (Chorus, 2010, 2012a – see also Section 2 of the current paper) the RRM model (27%) predicted a substantially higher choice probability than the RUM model (23%) to a ‘compromise’ route.

Study 26 reports how much monetary compensation is needed to offset nausea-related side effects of an Osteoporosis treatment. While the estimated linear-additive RUM predicts that a compensation of 655 euros would be sufficient (irrespective of the composition of the choice set), the RRM-model predicts that a compensation of only 550 euros is needed when competing treatments trigger nausea. However, when competing treatments have no nausea-related side effects, the RRM predicts that a compensation of 668 euros is needed to compensate for the same nausea-related side effect of the considered alternative (implying a difference of more than 20%). These findings of choice set composition-dependent trade-offs are again fully in line with the behavioural premises underlying the RRM-model.

Taken together, it can be concluded that the differences between RUM and RRM in terms of managerially relevant output (elasticities, market shares, trade-offs) are sometimes quite substantial. This leads to a somewhat paradoxical situation in combination with findings reported in Sections 3 and 4, in the sense that despite the fact that differences between the two model forms in terms of model fit and external validity are often very small, they can lead to quite different managerial implications, partly caused by the choice set dependence of preferences in the RRM model.

To further illustrate this paradox, consider a study not reported in Table 1 (since the paper is still under review): this study analysed preferences of company car users in terms of alternative fuel vehicles. Estimated RUM and RRM models achieved a very similar fit with the data (the difference, in favour of RRM, was only different at a 10% level). However, when both models were used to predict market shares of different alternatives in a hold-out sample containing two-thirds of the data, differences between RUM and RRM in terms of predicted market shares were often large: in 26% of the cases the difference between the market share predicted by RRM and RUM was larger than five percentage points and in no less than 13% of the cases it was more than ten percentage points. Furthermore, in 7% of the cases the two models each
indicated a different alternative as the most popular of a certain choice set. In these latter cases, it was mostly a compromise alternative which was identified as a ‘winner’ by the RRM model while being a runner-up in the context of RUM.

The next section considers the question of what implications this somewhat paradoxical combination (i.e., the combination of a generally very similar empirical performance and a sometimes quite large difference in managerially relevant output) has for the possible role of the RRM model in supporting marketing management strategies.

7. Conclusions and discussion

The results presented in the three preceding sections trigger the question to what extent and in what ways the recently introduced Random Regret Minimization (RRM) model can be most effectively implemented as an alternative for or in combination with the canonical Random Utility maximization (RUM) model, to support the development of effective marketing strategies. The choice between the two model types is not always an easy one: while on many datasets either one or the other model (RRM or RUM) is statistically preferred over the other in terms of model fit, differences are nearly always small. Furthermore, it is often the case that a model type that has a better model fit than the other model type for a certain dataset scores less well than the competing model type in terms of predictive ability on hold out data. Even though these marginal and sometimes conflicting differences between RRM and RUM in terms of model fit and predictive ability often make it difficult to identify which model performs best on the given data it is also true, as shown in the previous section, that the two models can lead to markedly different managerially relevant output. The choice of model form (RUM vs. RRM) can therefore have a substantial practical impact.

This means that there are basically three options left to determine the role of RRM for supporting the design and selection of marketing strategies. Firstly, RRM could be applied in the situations where it has shown to perform better than RUM, for example in terms of model fit with relevant data. Whether or not this approach is appropriate is debatable, given the small differences between the two models in terms of model fit. However, strictly speaking there is a case for estimating both RUM and RRM models on a given dataset and then, in case of statistically significant differences in fit, choosing one of the models for further analyses and the derivation of managerially relevant output.

A second option is to include other criteria, rather than basing a choice between model types only on generally very small differences in empirical performances. There are various arguments for using the RUM model based on such secondary criteria, but the same is also true for using the RRM model. The advantage of the conventional linear-additive RUM model is that it is the standard (although not undisputed) among researchers and practitioners and that it has a proven ‘track record’. The RUM model needs no introduction and the characteristics of the
model are well known and therefore easily interpretable. In contrast, the RRM model is only two years old and thus ‘the new kid in town’: it still needs to earn its reputation.

On the other hand, the RRM model fits well within the increasingly popular paradigm of behavioural economics. As opposed to RUM, the RRM model is not built on axiomatic principles such as that of non-transitivity or the normative principle of the ‘Independence from Irrelevant Alternatives’ (IIA-property). In contrast, the RRM model is built on a particular behavioural idea: the concept of regret minimization, which is not necessarily rational and therefore may conflict with axioms in the neo-classical economics\(^\text{10}\). The properties of the RRM model follow directly from its underlying behavioural premises (Chorus 2012a, b). When certain properties of the RRM-model conflict with neo-classical axioms, it appears that there is an abundance of empirical evidence in (consumer) psychology supporting these properties. The most obvious example of this is the fact that the RRM model predicts the compromise effect. This effect conflicts with the above-mentioned IIA-principle, although the supporting empirical evidence from consumer psychology is very persuasive (e.g., Simonson, 1989; Kivetz et al., 2004). More generally speaking, there is empirical evidence for the proposition that the minimization of anticipated regret plays an important role in decision making, particularly when choices are seen as difficult and important – see Zeelenberg and Pieters (2007) for an overview, or see Corricelli et al. (2005) who, using neuroimaging techniques, show that the area of the human brain that is active when decision-makers experience regret after having made a (poor) choice, is also highly active split seconds before they make a choice. In their words “anticipating regret is a powerful predictor of future choices”. Depending on the view of the analyst or marketing manager (that is, dependent on the weight given to the different afore-mentioned characteristics, possibly in combination with empirical performance-related criteria) choices for RUM and RRM can be justified.

There is however also the option of not choosing for either of the two models but to implement them both simultaneously and then, based on the outcomes, to set up a number of ‘behavioural scenarios’ using either a RUM, RRM or hybrid RUM-RRM model (for example, one scenario based on RUM-elasticities and another scenario based on RRM and/or hybrid RUM-RRM elasticities). Similarly, a ‘behavioural confidence interval’ can also be created, using both the RUM and the RRM outcomes. Using scenario analyses and/or sensitivity analyses, marketing strategies can subsequently be developed and selected which score relatively well from both a regret minimization and utility maximization perspective (for example in terms of the expected

\(^{10}\) The phrase ‘not necessarily’ is used here as it is very difficult to assign to the concept of rationality a universally accepted definition interpretation. It is as such difficult to give the RRM-model the label (ir)rational. Striving for minimum regret can be seen on the one hand as a rational aim (e.g., Zeelenberg, 1999). On the other hand, most economists agree that models that do not meet the IIA-criterion, such as the RRM model, cannot be referred to as rational (see for example Arrow (1950)). Without going into too much detail here, it would appear that the RRM fits better in the growing field of ‘behavioural economics’ than in the dominant and conventional field of ‘neo-classical economics’ which uses more strict definitions of rationality.
effects of the demand for a product or service). In other words: by jointly using outcomes from RUM and RRM / Hybrid RUM-RRM models, marketing strategies can be developed and/or selected which are robust from a behavioural perspective: the selected measures have been shown to score relatively well, regardless of the assumed behavioural premises (regret minimization or utility maximization). To the authors, this third option seems to be the most fruitful one.

It would also be interesting to use the RRM model specifically in situations where context effects (such as the compromise effect) are expected to play an important role. For many such effects there is overwhelming empirical evidence available from consumer choice studies. Since regret exists as a result of the comparison between competing alternatives, the RRM model by definition predicts that the regret of an alternative can be influenced by changing the composition of the choice set (without altering the alternative itself). As such, the RRM model offers the possibility of examining the potential of marketing strategies aiming composing choice sets in a way that is optimal for a certain marketing strategy. In such a context the RRM model can provide managerially relevant information which complements the information generated by linear-additive (and context-independent) RUM models.

However, it is obvious that (much) more work is needed before the potential of RRM model in the context of consumer choice and marketing research can be fully understood and realized. Important directions for future research include:

- estimation of RRM models on consumer choice data (so far, most datasets focused on transportation, leisure and health related choices);
- comparison of RRM and RUM on Revealed Preference data (as opposed to Stated Preference data);
- estimation of more sophisticated RRM model forms allowing for, e.g., random heterogeneity in terms of tastes and scale (so far, the majority of RUM-RRM comparisons focused on the rather simple MNL-model form);
- comparisons between RRM and non-RUM models such as models designed to capture context effects\(^\text{11}\) (e.g., Kivetz et al., 2004; Rooderkerk et al., 2011).

Notwithstanding these and other important knowledge gaps, we believe – based on the results reported in this paper – that the evidence that has so far accumulated in fields adjacent to marketing research suggest that RRM may in time become a viable addition to the toolkit of consumer choice modellers.

\(^{11}\) We know of only two papers that provide comparisons between RRM and non-RUM models (Leong & Hensher, 2012; Chorus & Bierlaire, 2013). In light of the small number of studies involved, we refrain from drawing conclusions from these comparisons.
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