Contrasts between utility maximisation and regret minimisation in the presence of opt out alternatives

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Abstract

An increasing number of studies of choice behaviour are looking at random regret minimisation (RRM) as an alternative to the well established random utility maximisation (RUM) framework. Empirical evidence tends to show small differences in performance between the two approaches, with the implied preference between the models being dataset specific. In the present paper, we discuss how in the context of choice tasks involving an opt out alternative, the differences are potentially more clear cut. Specifically, we hypothesise that when opt out alternatives are framed as a rejection of all the available alternatives, this is likely to have a detrimental impact on the performance of RRM, while the performance of RUM suffers more when the opt out is framed as a respondent being indifferent between the alternatives on offer. We provide empirical support for these hypotheses through two case studies, using the two different types of opt out alternatives. Our findings suggest that analysts need to carefully evaluate their choice of model structure in the presence of opt out alternatives, while any a priori preference for a given model structure should be taken into account in survey framing.

Keywords: random regret minimisation; opt out alternatives; stated choice; decision rules

1. Introduction

In the examination of alternative behavioural specifications of choice, the recent literature on discrete choice models has seen a small but growing number of studies comparing the well established Random Utility Maximisation (RUM) framework to the more recently proposed Random Regret Minimisation (RRM) paradigm. RRM assumes that the choice of an individual is motivated by the desire to avoid a scenario where the chosen alternative is outperformed by one or more non-chosen alternatives on one or more attribute (Chorus 2010). Model comparisons have occurred across a range of areas, with recent examples looking at the suitability of RRM in the context of leisure-related decision-making (Thiene et al. 2012), driver crash avoidance manoeuvres (Kaplan and Prato 2012), diet and lifestyle choices (Boeri et al., 2013), and automobile fuel choice by individuals (Hensher et al. 2013) and groups (Beck et

al. 2013). Almost without exception, these studies show very small, albeit significant, differences in model fits between the two paradigms, with the best fitting structure being dataset specific. Hess et al. (2012) and Boeri et al. (2014) go further by arguing that the choice of appropriate model structure might be person specific and exploit this in a model structure that uses a mixture of RUM and RRM within a latent class framework. This is expanded further by Hess & Stathopoulos (2014) who link the likely decision rule in such a mixture structure to latent character traits.

Chorus et al. (2014) combine evidence from in excess of forty published comparisons. The results of this review suggest that RRM or hybrid RRM-RUM models perform better than equally parsimonious RUM counterparts on a majority of datasets. However, the fact that differences are small may limit the RRM model's appeal, especially among practitioners, partly due to inertia but also the relative ease in which outputs suitable for welfare analysis (i.e. willingness-to-pay measures) can be computed in the RUM framework.

Whilst alternative behavioural frameworks that explain the choice process continue to be examined, there is concurrent interest in examining the role of methods used to elicit the choices themselves. In particular, one focus of attention is the presence of a baseline alternative within the choice set that represents a *status quo*, *do nothing*, *no choice* or *opt out* alternative. This is especially popular outside of a transport context, notably in environmental economics.

Treatment of the opt out alternative can be broadly categorised into two distinct approaches: specify an opt out such that the respondent is able to designate none of the alternatives as ones they would choose (see for example Kallas et al. 2011 and Louviere et al. 2001) or; specify the opt out alternative as a no opinion, or a position of indifference between the competing attributes (see for example Balcombe and Fraser 2011 and Fenichel et al. 2009). The role of opt outs within RUM has been an area of exploration for some time. For example, Olsen and Swait (1993) find that the behavioural processes captured by unconditional (unforced) and conditional (forced) choice models are not equivalent. Carson et al. (1994) speculate that such results may be attributable to respondents using the no-choice option to avoid making difficult choices, with such behaviour likely a function of task difficulty, respondent fatigue and/or characteristics. Kontoleon and Yabe (2003) find that within the RUM framework alone, how you frame the opt out can significantly affect the choice proportions for that alternative. Cantillo et al. (2010) find that respondents might place thresholds, or ranges, over the values of which attribute levels can take within a stated choice experiment, such that these respondent held perceptions create alternatives that are too similar; thus leading to indifference between alternatives.

Despite this ongoing research, the specific choice of approach used in surveys is seemingly arbitrary, with little or no consideration as to the impact on behaviour and appropriate modelling approach. A number of papers, e.g. Hess & Rose (2009), discuss the impact of the treatment of reference alternatives, but seemingly little consideration is given to the specific description of such alternatives in surveys. This lack of consideration is worrying in the context of RUM alone, but this paper extends on this literature by examining the role that two different framings of an opt out can play in determining which modelling approach, RUM or RRM, is more appropriate for the resulting data. Indeed, in the context of RUM and RRM, the specification of

the opt out alternative can, theoretically, impact very significantly on model comparisons primarily due to the different conceptual (behavioural) issues that underlie the two paradigms.

We propose two hypotheses: when an opt out option is included that suggests a *rejection of the choice alternatives* (e.g., '*none of these*'), this should have a negative impact on the performance of a RRM model, while having little to no impact on the performance of a RUM model and; when an opt out option is included that suggests a *rejection of the choice task* as a consequence of *indifference* between the choice alternatives (e.g., '*too close to call*'), this should have a negative impact on the performance of a RUM model, while having little to no impact on the performance of a RRM model.

Our hypotheses are built on arguments first presented by Chorus (2012a). To summarise briefly, in a RRM model, opting out of a choice situation constitutes by definition a rejection of the *choice task itself* (i.e., a choice set or task may generate a large amount of regret, even when the alternatives are very attractive – and vice versa). In a RUM model, choosing the opt out alternative constitutes by definition a rejection of the *choice alternatives* (since the expected utility of a choice set or task does not depend on whether or not the choice between the alternatives in the set is difficult). As a consequence, we expect RRM to better capture the behavioural process when the opt out alternative refers to *indifference,* and poorly when the opt out refers to *rejecting* the alternatives on offer. The opposite is expected to apply for RUM. We should clarify at this stage that, especially in the context of stated choice data, we are not so much concerned with indifference arising as a result of alternatives being the same across attributes, but as a result of the advantages and disadvantages cancelling each other out, leading to very similar overall performance.

To test these hypotheses we compare the results from two separate stated choice surveys, one featuring a 'none of these' opt out alternative and another employing an 'I am indifferent' option. We estimate models under both the RUM and RRM methodologies, where we specifically estimate models without the opt out alternative and models that include it, with a view to testing the impact of the (formulation of the) opt out alternative on the performance of the two models. The results give empirical support to our hypotheses. A key point is that we are not focussing just on a comparison between RUM and RRM in the presence of (different formulations of) the opt out alternatives. Rather, we place the key emphasis on the impact, on each of the models, of adding in the opt out alternative and different formulations thereof. Across the two datasets, we see similar performance for RUM and RRM when not including the opt out alternative (equal performance in the binary dataset in one study), providing a good basis for comparison. When adding in the *none of these* alternative, we notice major deterioration in the performance of RRM only, while, when adding in the *indifferent* alternative, we see major deterioration in the performance of RUM only.

The remainder of the paper is organised as follows. The next section briefly summarises the methodological differences between RUM and RRM. We then present the two datasets used in our analysis, before section 4 presents the results of our empirical applications. Finally, we present the conclusions of the research.

2. Contrasts between RUM and RRM, and development of hypotheses

In a RUM model, the deterministic component of utility is typically given by a linear in parameters specification, such that, for alternative i, we have that:

$$V_i = \delta_i + \sum_m \beta_m x_{im} \qquad [1]$$

where β is a vector of estimated parameters associated with x_i, which is a vector of attributes relating to alternative i, while δ_i is an alternative specific constant, fixed to zero for one of the J alternatives in the choice set. Besides the choice alternatives, there is an opt out-option which is modelled by means of a an opt out constant γ. The probability of choosing alternative i, where i is not the opt out, is then given by:

$$P_i = \frac{\exp(V_i)}{\exp(\gamma) + \sum_{j=1..J} \exp(V_j)} \qquad [2]$$

The probability of choosing the opt out option is given by:

$$P_{opt\ out} = \frac{\exp(\gamma)}{\exp(\gamma) + \sum_{j=1..J} \exp(V_j)} \qquad [3]$$

In the RRM framework, the regret associated with alternative i is obtained as:

$$R_i = \delta_i + \sum_{j \neq i} \sum_m \ln\left(1 + \exp\left[\beta_m \cdot (x_{jm} - x_{im})\right]\right) \qquad [4]$$

where m is an index of attributes. The probability of choosing alternative i from the set containing choice alternatives and an opt out option is now given by:

$$P_i = \frac{\exp(-R_i)}{\exp(\gamma) + \sum_{j=1..J} \exp(-R_j)}, \qquad [5]$$

where, in contrast with Equation [2], the negative sign inside the exponential ensures regret minimisation, as opposed to utility maximisation.

The probability of choosing the opt out option in an RRM framework is given by:

$$P_{opt\ out} = \frac{\exp(\gamma)}{\exp(\gamma) + \sum_{j=1..J} \exp(-R_j)} \qquad [6]$$

Note that in this context, we have specified the constant in the RRM framework simply as γ, rather than the regret minimisation approach to constants put forward by Chorus (2012b), in which the differences across alternatives would also be calculated for the constants. In fact, the two formulations are mathematically equivalent in the sense that both result in the same choice probabilities and log-likelihoods. The magnitudes of the constants change, but this is not relevant of course (and certainly not in the context of our paper). Only when constants are interacted with socio-demographic variables do the two formulations differ in terms of model fit. Since − as explained above − the choice between the two formulations is without consequence for relevant estimation outcomes, it can be based on other criteria such as conceptual

and behavioural elegance. Under such criteria, the formulation presented in Chorus (2012b) can be considered conceptually and behaviourally more in line with regret minimization premises when the constants refer to alternatives that are comparable in other attributes. However, when, as in our paper, the constant does not refer to a particular choice alternative but to an opt out (being a fundamentally different choice option when compared to the other options in the choice set), the regret minimization-formulation presented in the tutorial (Chorus, 2012b) is less intuitive from a conceptual / behavioural viewpoint. In such a situation, treating the constant outside the regret function is a more easy to follow approach. Hence our decision to model the constant as we do here. We are treating the opt out not as an alternative like the 'real' alternatives in the choice set, but as a 'decision not to choose'.

A crucial difference between the two frameworks is that RRM postulates that the regret associated with an alternative depends on the performance of competing alternatives, as can be easily seen when inspecting equation [4]. On the contrary, RUM postulates that the utility of an alternative solely depends on that alternative's characteristics, as in Equation [1]. Chorus (2012a) argues that this difference has important implications for the interpretation of the expected regret, respectively expected utility, of the choice set. More particularly, that paper argues that the expected regret of a choice set is large when there is no clear 'winner' among the choice options, and that expected regret is small when such a clear 'winner' does exist. A *clear winner* would be an alternative which outperforms the other alternatives on most or all attributes. In the RRM framework, it is the *relative* performance of alternatives that matters. Note that this contrasts strongly with RUM and the notion of expected utility, which are based on the *absolute* performance of alternatives in the choice set. For further detailed explorations of the methodological differences between the two models, the reader is referred to Chorus (2010, 2012a).

This brief presentation of the RUM and RRM models, and their respective behavioural interpretations, allow us to formulate hypotheses regarding the suitability of each framework in the context of the two different formulations of the opt out option: 'none of these' versus 'I am indifferent'.

As a first hypothesis, we expect a RRM model to do poorly – compared to RUM – when the opt out option is framed as a 'none of these' option, or at least for the inclusion of the opt out alternative to have a more detrimental impact on the RRM model than for RUM. In other words: we expect that the RRM model has difficulties with 'handling' the none of these-opt out, and that this is not the case the RUM model. The reason is that the role of the constant for the opt out option in an RRM model does not match the meaning ('none of these') assigned to the opt out-option in the choice task presented to participants. This can be seen as follows: by definition, high values of an opt out-constant in an RRM model imply that the expected regret of choosing from the choice alternatives is so high that opting out is preferred by choice makers in many observed choices. Similarly, low values of an opt out-constant in an RRM model imply that the expected regret of choosing from the choice alternatives is low enough for most people to want to choose an alternative from the set, rather than opting out.

Importantly, as can be clearly derived from the RRM equations summarised above, an alternative's regret and as such the expected regret of choosing from choice

alternatives says something about the *relative* performance of alternatives (i.e., the presence or absence of a clear 'winner' among the alternatives), and nothing about the *absolute* quality of the alternatives in that set: regret exists by the virtue of comparisons, and improving the performance of all alternatives to a similar extent does not change regrets (see Chorus, 2012a, for a more in-depth discussion). As a consequence, when the opt out option in an experiment is framed in a way ('none of these') as to suggest that people should choose it when none of the alternatives on offer is good enough for them, this framing in terms of *absolute* quality of the alternatives provides a mismatch with the meaning of an opt out constant in an RRM model, which is based on the *relative* quality of alternatives as outlined above.

On the other hand, we expect a RUM model to do poorly when the opt out option is framed as an 'I am indifferent' option, or at least for the inclusion of such an alternative having a more detrimental impact on RUM than on RRM. In other words: we expect that the RUM model has difficulties with 'handling' the indifference-opt out, and that this is not the case the RRM model. The reason is that the role of the opt out constant in a RUM model does not match this meaning assigned to the opt out option in the choice task. This can be seen as follows: by definition, high values of an opt out constant in a RUM model imply that the expected utility of choosing from the set of choice alternatives is so low, so that opting out is preferred by choice makers in many observed choices. Similarly, low values of an opt out constant in a RUM model imply that the expected utility of choosing from the set of choice alternatives is high enough for most people to want to choose an alternative from the set, rather than opting out. Importantly, as can be clearly derived from the RUM equations, an alternative's utility and as such the expected utility of choosing from a set of alternatives says something about the *absolute* performance of alternatives in the set, and nothing about the *relative* quality of (or the level of indifference between) the alternatives in that set: the utility of an alternative is a function only of its own attributes – those of competing alternatives are irrelevant. As a consequence, when the opt out-option in an experiment is framed in a way ('I am indifferent') as to suggest that people should choose the opt out option when the quality of the alternatives on offer is very similar (i.e., there is no clear winner), this framing in terms of *relative* quality of the alternatives provides a mismatch with the meaning of a constant in a RUM model, which is based on the *absolute* quality of alternatives as outlined above.

In mathematical terms, let us specifically assume that we are in the presence of *J* alternatives plus an opt out. Using a linear in parameters specification, we get the utility specifications in Equations [1] and [4] for alternative *i*, with say $\delta_1 = 0$, while we specify the opt out alternative as a simple constant in both models, i.e.:

$$V_{opt\,out} = R_{opt\,out} = \gamma \qquad\qquad [7]$$

Let us now assume that we apply the same change to a given attribute across the *J* alternatives in a linear in parameters and attributes specification, say we add Δ to x_{i1} for *i=1,...,J*, where this could for example represent an increase in cost across all options.

We then get:

$$V_i{}' = \delta_i + \sum_m \beta_m x_{im} + \beta_1\Delta, \; i=1,...,J \qquad\qquad [8]$$

and

$$R_i{}' = \delta_i + \sum_{j \neq i} \ln \left(1 + \exp \left[\beta_1 \cdot \left((x_{jm} + \Delta) - (x_{im} + \Delta) \right) \right] \right)$$
$$+ \sum_{j \neq i} \sum_{m=2}^{M} \ln \left(1 + \exp \left[\beta_m \cdot \left(x_{jm} - x_{im} \right) \right] \right), \; i=1,...,J \qquad [9]$$

It can easily be seen that $V_i{}' \neq V_i, i = 1, ..., J$, and with $\beta_1 < 0$, we would, when using Equations [8] and [7] in Equations [2] and [3], respectively, have that $P_i{}' < P_i$, while $P_{opt\ out}{}' > P_{opt\ out}$, i.e. the probability of opting out has increased. This would be consistent with alternatives having become worse across the board and reducing the likelihood of a respondent choosing to travel[1]. At the same time, we can see that Equation [9] collapses back to Equation [4]. As a result, we have that, within the RRM framework, $R_i{}' = R_i, i = 1, ..., J$ and consequently, $P_i{}' = P_i$ and $P_{opt\ out}{}' = P_{opt\ out}$. The regret between the J alternatives has stayed the same which means that if a respondent was *indifferent* between them before the change, he remains *indifferent* after the change. The key distinction is the use of absolute and relative quality in the two frameworks.

To further illustrate this issue, let us consider an example, where, in a stated route choice experiment, choice set 1 contains three alternative routes (A, B, and C) between an origin and destination. Suppose route A's travel time equals 40 minutes, that of B equals 45 minutes, and that of C equals 50 minutes. Travel costs (including a toll) are 5 euros for A, 2.5 for B and 0 for C. The individual can choose either A, B, or C or she can choose a 'no travel' opt out. Now suppose that in choice set 2, the travel times of all three routes are increased by 30 minutes, while costs are increased by 2.5 euros for all routes. Clearly, one expects many more people choosing the 'no travel' opt out (implying that the alternatives on offer are less likely to be good enough for a sampled individual). However, it is easily seen that the regrets associated with the alternatives are the same in both choice sets, given that the attribute differences across alternatives remain the same. In other words, for the RRM model – including its opt out constant – choice sets 1 and 2 are identical. As a consequence, the model is unable to accommodate the relative popularity of the opt out option in choice set 2. On the contrary, the RUM model (including its opt out constant) is likely to be better able to accommodate the difference between sets 1 and 2, as it will correctly predict that the opt out option is more attractive in set 2 than in set 1.

The same example can be used to highlight this mismatch between the meaning of a constant in an RUM model and the 'I am indifferent' framing of the opt out option. Clearly, one expects no differences between choice situations 1 and 2 in terms of the number of people choosing the opt out option for reasons of being indifferent between the three routes. However, the utilities associated with the alternatives are of course very different in choice sets 1 and 2. In other words, for the RUM model – including its opt out constant – choice sets 1 and 2 are very different, whereas a participant in both sets is equally likely to be indifferent between choice options. As a consequence, the RUM model is unable to accommodate the fact that the opt out options in choice

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[1] When working with a non-linear utility specification, a situation where all alternatives are made worse by the same amount in utility will not equate to an equal change in the attributes.

sets 1 and 2 are equally likely to be chosen. On the contrary, because of its focus on relative performance of alternatives, the RRM model (including its opt out-constant) seems better able to accommodate the similarity (in terms of the popularity of the 'I am indifferent' opt out) between sets 1 and 2: in both situations, as mentioned further above, the RRM model predicts similar levels of regret (since both situations are similar in the extent to which there is a clear 'winner'). As such the RRM model is more likely to correctly predict a similar inclination in choice sets 1 and 2 to either select an alternative from the set, or the 'I am indifferent' option.

At this point, it is also worth making the link to the discussion in Chorus (2012a). Although they focused on welfare implications (i.e., the expected regret of a choice set), rather than on choice probabilities of opt out alternatives, the reasoning presented in that paper can be straightforwardly transferred to the context of this paper: the starting point in both papers is that in the RRM-paradigm, the expected regret of a choice set is large (ie, the welfare associated with the choice set is 'low') when there is no clear winner in the set of choice alternatives. In the context of our paper, we take this idea one step further by hypothesizing that when a choice set's expected regret is large (or, the associated welfare is low), people will be relatively inclined to opt out, i.e. refrain from choosing one of the choice alternatives. Combining these two ideas, we then arrive at the implication that the RRM-model predicts that when there is no clear winner in a choice set, people will be relatively inclined to opt out.

3. Data for case studies

To test the hypotheses set out in Section 2, we make use of data from two separate stated choice studies, which are described in what follows. We acknowledge already at this stage that our results relate to just two datasets, which, while being more comprehensive than many studies using just a single source, nevertheless creates extensive scope for further analysis using other data.

3.1 First case study

The first case study use stated choice data relating to willingness to pay for an advanced Public Transport information service. In total, 204 travellers were interviewed while riding a train and each respondent was presented with nine choice tasks containing three alternative travel information types and a '*none of these*' option (resulting in 1,836 observed choices). Four attributes were used to describe the alternatives in the choice task.

First, the type of information provided by the service has three possible levels:

- *Times* (only travel time information is provided – the base level);
- *Times & Search* (in addition to travel time information, the service also provides an option to search for alternative routes); and
- *Times & Advice* (in addition to travel times, advice on the best route is also provided).

Second, there is variation across alternatives & tasks in relation to who has to take the initiative to provide/acquire the information:

- *Traveller Initiative* (only the traveller can take the initiative to acquire information – the base level);
- *Info Initiative* (only the service can take the initiative to provide information); and
- *Both Initiative* (both can take the initiative).

Third, the survey varied the reliability of the information provided by the service, where *unreliability* is expressed by how many minutes earlier or later a vehicle would be relative to the time provided by the service (levels: 0, 2.5 and 5).

Finally, the cost of using the information service was also altered, where *cost* was set at either €0, €0.15 or €0.30.

With respect to the sample, respondents were recruited in intercity trains in the Netherlands using written questionnaires. Previous work with this data has found that the sample of respondents is sufficiently heterogeneous and represents all traveller-type categories well (Molin et al., 2009).

3.2 Second case study

The second case study is an examination of salary and travel time trade-offs in the Stockholm region of Sweden. The sample consisted of dyadic households, wherein each member of the household was required to make decisions, independently of the other member, as if they were acting on behalf of the household. Within the experiment, two different scenarios were administered. The first required respondents to consider the hypothetical scenario that their workplace would be moved to a location that would imply a longer commuting time and that this disutility would be compensated by a higher monthly net wage. All other characteristics, including commuting cost, commuting mode, other work characteristics, and housing characteristics, were assumed to remain unchanged. Two levels of each attribute were used in all possible combinations and always compared to the respondents' present situation. These levels were 10 minutes and 25 minutes per one-way commuting trip and 500 SEK and 1,000 SEK in net wage per month (at the time of the survey 11 SEK was equal to approximately €1). In the second stated choice experiment, the respondents were given choice scenarios where four attributes in each alternative were changed compared to the present situation. These attributes were; own commuting timeand own wage (*Sal_Own*), and the spouse's commuting time and wage. In these scenarios, both their own workplace and that of their spouse, were assumed to be relocated. Common across both games was the presentation of two competing alternatives along with a third *Indifferent* option. We do acknowledge that there is somewhat of a risk that a respondent who likes *neither* of the options but is only given the opportunity to opt out by saying he/she is *indifferent* may indeed do so. Nevertheless, the strength of our empirical evidence suggests that such problems are rare with the data at hand. The same risk of confounding should not arise in the first case study, where a respondent who is *indifferent* between two alternatives is more likely to still choose one of them than to choose the *none of these* option, if that is what presented.

Responses were collected from 2,358 respondents (1,179 household couples) providing 9,432 observations from the first game and 10,609 from the second. For a more detailed discussion of the sample refer to Swärdh and Algers (2009).

4. Estimation results

As stated earlier, our empirical work does not simply seek to offer a comparison between RUM and RRM in the two datasets, as any differences in performance could be partly resulting from a variety of factors beyond the presence and particular formulation of the opt out alternative. Rather, we look at the specific impact that the inclusion of the opt out alternative (and a particular formulation thereof) has on estimation results and statistical fit for each of the two models. To this extent, two sets of models were estimated on each of the datasets, models using the data without the opt out alternative (with any choices of this alternative being removed), and models on the full data. Each time, both a RUM and RRM specification were estimated. The aim behind the estimation on the reduced data is to offer a comparison between RUM and RRM in the absence of an opt out alternative. This then allows us to draw valid conclusions as to the impact of the opt out alternative in either of the two models, especially since, as we will see below, very similar, respectively identical performance is obtained for the two models when the opt out is not included.

All models were coded and estimated in Ox 6.2 (Doornik, 2001), where the likelihood function was coded in such a way as to take into account the repeated choice nature of the data, leading to a correction of the robust standard errors obtained with the sandwich estimator (cf. Daly & Hess, 2011). We estimated models of differing levels of sophistication. The more sophisticated the models became, i.e. the more of the behaviour was explained by the specification of the models, the bigger the differences in the impact of the opt out became between RUM and RRM, reinforcing our theoretical claims. The presentation of detailed results below focusses on a specification of an underlying MNL structure but with added panel effect error components that were distributed identically but independently across alternatives, with a mean of zero and a standard deviation of σ and with integration carried out at the level of respondents, thus capturing correlation in the error term across respondents, but maintaining homoscedasticity across alternatives. We also present overview results (in terms of fit) for other models, namely a base model without the error components, and models with taste heterogeneity.

4.1. First case study

The survey for the first case study included a *none of these* alternative as the opt out. As mentioned above, we first estimated RUM and RRM models on the subset of the data where the none of these option was NOT chosen. This leads to a reduction in the sample size to 1,463 observations. The results of these estimations are summarised in the first part of Table 1. We see that RUM outperforms RRM in terms of adj. ρ^2, but the difference is very small indeed, in line with much of the published literature. The table also includes parameter ratios relative to the cost coefficient, although these are not to be interpreted as willingness-to-pay estimates in the RRM model. Using *time*

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information only as the base, we obtain positive and significant estimates for *time & search*, and *time & advice*. Similarly, using *traveller initiative* as the base, we observe positive estimates for the remaining two levels, where the first of these is however not significantly different from zero in either model, suggesting that the option where only the service can take the initiative to provide information is perceived by respondents to be no better or worse than the option where only the traveller can take the initiative to acquire information. *Unreliability* and cost have negative and significant effects in both models. The standard deviation (σ) of the error component is significant in both models, with similar estimates. Crucially, this comparison on the data without the opt out alternative suggests no distinct advantages for either model framework that could be seen as being specific to the data at hand. This will allow us in turn to draw more reliable conclusions for the comparison when moving to the models including opt out alternatives.

Next, we estimated RUM and RRM models on the full data, including choices for the *none of these* option. We observe that when including the full set of alternatives, RUM obtains a substantially better fit on the data than RRM. In conjunction with the fact that performance was very similar on the data without the opt out alternative, this suggests that the inclusion of the opt out alternative has a more detrimental impact on the RRM model; this in turn provides a strong indication that the RRM model has difficulties handling the none of these-opt out. Moreover, when looking at the ratios of parameters, the RUM results are overall quite consistent with those from the model estimated for the subset of the data excluding the *none of these* option[2], while the RRM-ratios are very different from those obtained on the subset of the data. In both models, *time & search* loses in significance, i.e. becomes less different from the base scenario of travel time information only, but the drop in significance is much larger for RRM than for RUM. Furthermore, the coefficient for *both initiative* becomes insignificant in the RRM model, but not the RUM model, while, in RRM, we also obtain a suspiciously large constant for the opt out alternative. An inability for RRM to accommodate the importance of absolute (rather than relative) performance of the alternatives is to blame for this, in line with our theoretical discussions. In conjunction with the fact that RUM and RRM ratios were very similar on the subset of the data excluding the none of these option, and that the ratios for RUM change far less than those for RRM when including the none of these-opt out alternative, these findings suggested bias in the RRM results in the presence of a *none of these* opt out alternative.

Table 1: Case study 1 – "None of these" opt out

	Opt out excluded				"None of these" included			
	RUM		RRM		RUM		RRM	
	Parameter estimates (*t*-ratio)							
Times & Search	0.2384	(2.2)	0.1713	(2.38)	0.1881	(1.61)	0.0986	(1.39)
Times & Advice	0.6961	(6.19)	0.448	(5.99)	0.6625	(5.51)	0.3914	(5.66)
Info-Initiative	0.0195	(0.18)	0.0366	(0.5)	-0.0206	(-0.18)	-0.1038	(-1.57)
Both-Initiative	0.228	(2.2)	0.1736	(2.54)	0.2342	(2.19)	0.1048	(1.65)
Unreliability	-0.0772	(-3.48)	-0.0532	(-3.58)	-0.1019	(-4.26)	-0.0679	(-4.43)

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[2] We note that the effect of Info-Initiative changes sign, however the significance of this variable is negligible and the sign switch is likely a function of this.

Cost	-0.9407	(-17.24)	-0.6565	(-15.85)	-1.0893	(-17.73)	-0.7081	(-15.6)
"None of These"	---	---	---	---	1.7297	(9.5)	8.6616	(74.48)
σ	0.3474	(3.96)	0.3269	(3.62)	0.9226	(12.25)	0.7714	(10.96)
Model fit statistics								
Observations	1,463		1,463		1,836		1,836	
Log-Likelihood	-1,171.42		-1,174.22		-1,894.68		-2,015.90	
adj. ρ^2	0.2668		0.2651		0.2525		0.2048	
Parameter/cost Ratio								
Times & Search	-0.253		-0.261		-0.173		-0.139	
Times & Advice	-0.740		-0.682		-0.608		-0.553	
Info-Initiative	-0.021		-0.056		0.019		0.147	
Both-Initiative	-0.242		-0.265		-0.215		-0.148	
Unreliability	0.082		0.081		0.094		0.096	

As mentioned above, we also estimated a base model without the error components and a model that accounts for taste heterogeneity in addition to the panel effect, where we made use of a negative lognormal distribution for the cost coefficient. The aim of summarising the results across specifications in Table 2 is to illustrate the consistency in findings across specifications. The results show improvements in model fit for both structures when increasing model complexity. More importantly however, we also see that increases in model sophistication lead to a bigger gap between the models in terms of the impact of adding in the opt out alternative, where the relative drop in fit for RRM vs RUM increases across the three specifications.

Table 2: Case study 1 – "None of these" opt out, additional results

		without opt-out	with opt-out	change in fit	RRM vs RUM relative drop in fit
base models	**RUM**	-1,174.91	-2,003.25	-828.34	
	RRM	-1,177.09	-2,096.81	-919.72	1.11
with error components	**RUM**	-1,171.42	-1,894.68	-723.26	
	RRM	-1,174.22	-2,015.90	-841.68	1.16
with random cost coefficient	**RUM**	-1,147.00	-1,809.88	-662.88	
	RRM	-1,145.97	-1,980.64	-834.67	1.26

4.2. Second case study

The analysis of the data for the second case study was conducted separately for game 1 (own situation only) and game 2 (situation for husband and wife). The results are summarised in Table 3 and Table 4 respectively. This survey made use of a *"I am indifferent"* opt out, and like in the first case study, we once again estimated models on the full data as well as on a subset excluding the opt out alternative and any tasks where it was chosen.

Looking first at the results on the subset of the data excluding the opt out, the results in Table 3 and Table 4 show that RUM and RRM produce identical model fits and parameter estimates, which is a well known characteristic of the models when

estimated on binary data (cf. Chorus, 2010). This is in fact a key benefit for this case study as it will allow us to put more emphasis on any differences occurring when adding in the opt out alternative. The models show significant negative estimates of the sensitivity to increases in travel time and significant positive estimates of the sensitivity to increases in salary. The signs are consistent across sensitivities for the respondent's attributes as well as those of their partner (cf. Table 4). In both sets of the data, we see a significant estimate for the standard deviation (σ) of the error component.

Turning to the models estimated on the full data, and thus now also including a constant for the opt out alternative, we observe that RRM obtains a substantially better fit to the data than is the case for RUM, in both games 1 and 2. Additionally, in the model for game 1, the parameter for salary is no longer statistically significant in the RUM model, with the same applying to the parameter for the partner's salary for the RUM model in game 2 (and the one for the respondent's salary being only significant at lower levels of confidence). Moreover, while the ratios against the cost parameter remain very similar between the reduced data and full data for the RRM model, this is not the case for the RUM model, where we see an increase by a factor of 83 in game 1, with increases by factors of 52 and 65 in game 2. These findings suggest that in this case study, the RUM estimates are biased. The size of the changes observed for both estimates and t-ratios in the RUM models when moving from the restricted data to the full data offers convincing support for our theoretical discussions that RUM is likely to have difficulties handling data with an "*indifferent*" opt out alternative, once again especially given that in the case of the binary base data, we have the strong starting point of equivalence between RUM and RRM.

Table 3: Case study 2 – "Indifferent" opt out game 1

	Opt out excluded				"Indifferent" included			
	RUM		RRM		RUM		RRM	
	Parameter estimates (*t*-ratio)							
Own travel time	-0.3229	(-27.3)	-0.3229	(-27.3)	-0.0734	(-26.35)	-0.2561	(-37.79)
Own salary	4.2960	(23.53)	4.2960	(23.53)	0.0118	(1.57)	3.1143	(30.06)
"Indifferent"	---	---	---	---	5.4905	(20.9)	6.2509	(41.52)
σ	1.7335	(20.3)	1.7335	(20.3)	1.2043	(18.02)	1.4565	(23.89)
	Model fit statistics							
Observations	8,929		8,929		9,432		9,432	
Log-Likelihood	-3,404.93		-3,404.93		-6,608.48		-5,371.62	
adj. ρ^2	0.4787		0.4787		0.3620		0.4813	
	Parameter/cost ratio							
Own travel time	-0.075		-0.075		-6.239		-0.082	

Table 4: Case study 2 – "Indifferent" opt out game 2

	Opt out excluded		"Indifferent" included	
	RUM	RRM	RUM	RRM
	Parameter estimates (*t*-ratio)			

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Own travel time	-0.2516	(-24.05)	-0.2516	(-24.05)	-0.0636	(-17.89)	-0.2367	(-27)
Own salary	3.6491	(21.11)	3.6491	(21.11)	0.0177	(1.67)	3.1509	(23.19)
Partner's travel time	-0.2455	(-26.87)	-0.2455	(-26.87)	-0.0663	(-16.94)	-0.2315	(-28.89)
Partner's salary	3.0330	(16.34)	3.0330	(16.34)	0.0126	(1.26)	2.8481	(17.47)
"Indifferent"	---	---	---	---	7.7962	(15.87)	9.4107	(39.84)
σ	2.0072	(22.45)	2.0072	(22.45)	2.1269	(19.36)	2.1592	(25.82)
Model fit statistics								
Observations	10,064		10,064		10,609		10,609	
Log-Likelihood	-3,694.57		-3,694.57		-6,539.03		-5,409.53	
adj. ρ^2	0.4969		0.4969		0.4384		0.5354	
Parameter/cost Ratio								
Own travel time	-0.069		-0.069		-3.599		-0.075	
Partner's travel time	-0.081		-0.081		-5.265		-0.081	

Finally, Table 5 contains an overview of the results across different model specifications, where we focus on game 1, given the similarity in results for game 2. In addition to the base model and the model from Table 3, we also include results from a model with age and gender interactions for travel time and salary, respectively. Consistent with Table 2, we see improvements in fit with increasing model sophistication as well as a widening of the gap between RUM and RRM in the model including the opt out, though the changes are not as substantial as in Table 2 when it comes to adding deterministic (as opposed to random) taste heterogeneity.

Table 5: Case study 2 – "Indifferent" opt out, additional results for game 1

		without opt-out	with opt-out	change in fit	RRM vs RUM relative drop in fit
base models	**RUM**	-3,810.15	-6,925.41	-3,115.26	
	RRM	-3,810.15	-5,849.98	-2,039.83	0.65
with error components	**RUM**	-3,404.93	-6,608.48	-3,203.55	
	RRM	-3,404.93	-5,371.62	-1,966.69	0.61
with socio-demographics	**RUM**	-3,399.03	-6,607.63	-3,208.60	
	RRM	-3,399.03	-5,366.83	-1,967.80	0.61

5. Discussion and Conclusion

As summarised in Chorus et al. (2013), there are now a substantial number of studies offering empirical comparisons between RUM and RRM models. The general finding is of small differences in model performance, with the specific advantages of the two models being dataset specific, or even person specific, as outlined in Hess et al. (2012). A key characteristic of many of these studies is that they did not include an explicit opt out alternative, partly due to arguments in Chorus (2012a) stating that RRM may be less suitable for the analysis of choices where an opt out alternative is presented, since this alternative cannot be compared to other alternatives at the attribute level, having no attributes in common, and without such attribute level comparisons, there can be no regret.

In this paper, we have argued that that the reality is more subtle than anticipated by Chorus (2012a) in the sense that the presence of opt out alternatives can, depending on their formulation, impact the performance of RRM as well as RUM models. Indeed, based on the behavioural differences between RUM and RRM, we hypothesise that, compared to the situation where the choice model does not feature an opt out alternative, the performance of RRM can be expected to deteriorate when the opt out option is framed as a '*none of these*' option, and that the performance of RUM can be expected to deteriorate when the opt out option is framed as a '*too close to call*' or '*indifferent*' option. This argument is based on the contrast between a situation where all alternatives are rejected by a respondent (which is in line with the meaning of the opt out constant in a RUM model) and a situation where the alternatives are too similar to one another to make a meaningful choice (which is in line with the meaning of the opt out constant in an RRM model).

An analyses on two datasets, one featuring a '*none of these*' opt out, the other featuring an '*indifferent*' opt out, provides empirical support to our theoretical arguments. In the absence of data containing observations for the same sample with both types of opt outs presented as an experimental condition, we made use of an approach where we estimated models with and without (particular formulations of) the opt out alternative. The expectation from the theoretical premises underlying, respectively, the RUM and RRM model would then be that the inclusion of a *none of these* opt out would have detrimental effects on RRM (but not on RUM), while the inclusion of an *indifferent* option would do the same for RUM (but not on RRM), each time in comparison to a model estimated on the restricted data without opt out alternative. This is exactly what happens in the empirical analysis. In the context of data from a stated choice survey featuring a '*none of these*' opt out option, RUM achieves superior model fit when compared to an equally parsimonious RRM model once the opt out is included, while, prior to this, the two models were very similar in output and model performance. Moreover, additional analyses suggest that obtained parameters are likely to be biased in the RRM model after including the opt out. In contrast, in the context of data from a stated choice survey featuring an '*I am indifferent*' opt out option, RRM achieves a model fit that is far superior to that of the equally parsimonious RUM model when including the opt out, while, on the restricted data, the two models are identical. In this case, additional analyses suggest that the estimated parameters are likely to be biased in the RUM model. Crucially, and to restate the earlier point, we can draw these conclusions due to the fact that, in both case studies, a base analysis on the data excluding the opt out alternatives provided very similar (or equal) performance for RUM and RRM. This suggests very strongly that the resulting differences in performance are due to the definition of the opt out alternative, rather than the context of the datasets.

Our findings are in line with earlier work that reported RUM-RRM comparisons in the context of 'none of these'-opt outs (e.g. Thiene et al., 2012), although it should be noted that Chorus & Rose (2013) report a better model fit for RRM (compared to RUM) in the context of a 'none of these' opt out. The difference in model fit between RRM and RUM that was presented in Chorus & Rose (2013), while in favour of RRM, was however very small. Additionally however, that work only looked at a RUM-RRM comparison on the full data, rather than studying the impacts of the

inclusion of the opt out on either model. Unpublished analyses[3] on the same dataset used in Chorus & Rose (2013) show that when choices for the 'none of these' opt out were excluded, the difference between RRM and RUM (in favour of the former) increases substantially (from 12 to 47 log-likelihood-points). This potentially suggests some different underlying reasons for an advantage of RRM in the Chorus & Rose (2013) data – looking at the rather specific context of online dating - and the results are thus still in line with the hypotheses and results presented in this paper, in the sense that a decrease in RRM performance is found when including a *none of these* opt out. In other words, the difference between results with (published) and without (unpublished) the none of these opt out on the Chorus & Rose (2013) data suggests, just like the analyses presented in this paper, that the presence of none of these-opt outs negatively impacts the performance of RRM, and that the model – contrary to RUM – has difficulty handling the none of these-opt out. This is of course fully in line with the key premise of our paper.

Across the two studies, our empirical findings show that model fit performance is in line with expectations, and that differences in model fit are potentially quite large once the opt out is included, which contrasts strongly with the very small differences between the two paradigms when estimated on choice sets not featuring an opt out alternative. It should also be noted that the inclusion of the error components capturing correlation across choices between respondents further accentuated the differences in fit between the structures after including the opt out in the data while the differences in the base data remained essentially the same as in a simple MNL model. Similar observations can be made for the inclusion of taste heterogeneity. This suggests that a better model specification seems to leave less noise 'uncaptured' in the model, and hence causes more pronounced differences (in terms of fit) between decision rules underlying the model if one of the two decision rules is more appropriate for the data at hand.

Our results thus suggests that an analyst's choice between RRM and RUM may be driven, apart from other factors, by the particular framing of the opt out option in the choice experiment and vice versa. Clearly, the decision of which specific framing of the opt out option to use in a survey is a different issue, and depends on a number of factors, including the survey context. Nevertheless, where analysts have a strong a priori preference for a given modelling approach, this potentially needs to be taken into account in the framing of the survey.

In closing, we should acknowledge that with results coming from two separate datasets, there is a possibility that part of the differences in relative performance between RUM and RRM are driven by distinctions between the datasets other than the specification of the opt out alternative. However, we also found similar results on another dataset with an indifference alternative (namely the data from Cantillo et al., 2010), with a bigger impact on RUM of including the opt out[4]. Future work should seek to provide further insights by conducting a controlled study where each respondent is faced with two types of experiments, using the two different specifications for the opt out. The results that we have uncovered in these two datasets may not be universal, but we hope are sufficient to prompt modellers to consider

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[3] These unpublished results are available from the third author in the form of a working paper.
[4] Results available from the first author on request.

different behavioural specifications based on the opt out they have constructed in their survey process. We encourage other authors to take this starting point and to continue to build on the limited knowledge base that currently exists in this area. Indeed it might be worthwhile considering previous work in a new light. Regret minimisation has been shown to be a relevant co-determinant of decision making when choices are difficult or no one alternative is clearly better than others; Carson et al. (1994) speculated that respondents opt out if choices are too hard and Cantillo et al. (2010) found that in some instances respondents have plasticity in their preferences such that they find it difficult to differentiate alternatives and thus an indifference opt out is most appropriate in this instance. Importantly, this paper provides further evidence, albeit in a different space, that much more careful consideration should be given to the framing of an opt out alternative, or what modelling approach is used, than current practice seemingly exhibits.

An area for future work that the authors seek to investigate, which would allow us to isolate the effect of the opt out alternative, is to conduct a survey where half of the sample is presented with one type of opt out definition and the second half with the other type should be used[5], or even where all respondents get both types of choices. However, the differences especially in fit between RUM and RRM that we obtain in the two samples is much bigger than what has been observed in other studies not focussing on the role of opt out alternatives, and this leads us to believe with some confidence that the reason for these differences lies in the presence and definition of the opt out alternative, again noting the emphasis on contrasting performance with and without the opt out.

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[5] We thank an anonymous referee for this valuable suggestion.

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