TRAVEL CHOICE MODELS THAT GENERATE PREFERENCES FOR COMPROMISE ALTERNATIVES: AN EMPIRICAL COMPARISON

Caspar G. Chorus
Transport and Logistics Group
Faculty of Technology, Policy and Management
Delft University of Technology
2600 GA Delft, The Netherlands
T: +31152788546, F: +31152782719
Email: c.g.chorus@tudelft.nl

Michel Bierlaire
Transport and Mobility Laboratory
School of Architecture, Civil and Environmental Engineering
Ecole Polytechnique Fédérale de Lausanne
Lausanne, Switzerland
Email: michel.bierlarie@epfl.ch

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ABSTRACT

Compromise alternatives have an intermediate performance on each or most attributes rather than having a poor performance on some attributes and a strong performance on others. The relative popularity of compromise alternatives among decision-makers has been convincingly established in a wide range of decision contexts. We discuss three choice models that capture a potential preference for compromise alternatives. One approach, which is introduced in this paper, involves the construction of a so-called compromise variable which indicates to what extent (i.e., on how many attributes) a given alternative is a compromise alternative in its choice set. Another approach consists of the recently introduced random regret-model form, where the popularity of compromise alternatives emerges endogenously from the regret minimization-based decision rule. A third approach consists of the contextual concavity model, which is known for favoring compromise alternatives by means of a locally concave utility function. Estimation results on a stated route choice dataset show that, in terms of model fit and predictive ability, the contextual concavity and random regret models appear to perform better than the model that contains an added compromise variable.

Keywords: Compromise effect; Route-choices; Random Regret; Contextual concavity

1. INTRODUCTION

Compromise alternatives have an intermediate performance on each or most attributes rather than having a poor performance on some attributes and a strong performance on others (relative to other alternatives in the choice set). In fields adjacent to transportation, most notably in consumer research[2], the preference among decision makers for compromise alternatives has been well established empirically as one of the most important and persistent choice set-composition effects (e.g., [1]-[4]). Attempts to capture this behavioral phenomenon have led to the development of different choice models that allow for capturing the popularity of compromise alternatives (e.g., [3]); the arguably most elegant and effective of these models is the so-called Contextual Concavity model or from here on CCM [3]. Although it seems quite obvious that also in many transportation contexts compromise alternatives exist[3], virtually no attention has been paid so far in our field to the development and testing of choice models that allow for capturing their relative popularity in the context of transportation related decision making.

This paper discusses and empirically tests the abovementioned CCM and two alternative discrete (travel) choice models that allow for capturing the relative popularity of compromise alternatives. One approach is based on creating a so-called compromise-variable for each alternative, which indicates to what extent (i.e., on how many attributes) an alternative is a compromise alternative in a given choice set. This approach is new, to the best of the authors' knowledge[4]. A second approach is based on the recently introduced Random Regret Minimization-approach or RRM from here on; see [5] and [6]. Although theoretical derivations

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[2] More specifically, preferences for compromise alternatives have been shown in the context of choices among apartments, among mouthwashes, among political manifestos, among investment portfolios, among on-line dates and among laptops, to name just a few examples.

[3] Take for example the situation where a traveler chooses between different mode-route-departure time combinations: some combinations may perform very well in terms of one attribute (like travel time, cost), while performing very poorly on others (like travel cost). Other combinations may perform reasonably (but not: very) well on all attributes. Such latter combinations are called compromise alternatives.

[4] Note that[1] presented a model that adds a dummy-variable to an alternative's utility function. The dummy-variable equaled 1 if an alternative was a compromise alternative in terms of both attributes considered in that study, and 0 otherwise. This approach resembles our approach, but is less sensitive, especially when the number of attributes increases.

and numerical examples presented in the two cited papers have suggested that Random Regret-based travel choice models are theoretically expected to assign relatively high choice probabilities to compromise alternatives, these papers do not present an empirical analysis of that claim. [7] do so, as they highlight how an estimated RRM-model favors compromise alternatives in the context of online date-selection data. However, in contrast with this paper, [7] do not present out-of-sample tests of predictive performance, nor do they compare the RRM-model with alternative model forms other than the linear-in-parameters logit model.

Section 2 introduces the CCM-model and the two alternative modeling approaches described above as alternatives for the CCM-approach. In section 3 and 4 the mentioned modeling approaches are compared (also with a linear-in-parameters logit model that does not allow for capturing any relative popularity of compromise alternatives) in the context of stated route choice data collected recently among a sample of Dutch commuters. Subsequently, estimation results (Section 3) and out-of-sample validation results (Section 4) are presented and discussed in detail. Conclusions and discussion are provided in section 5.

2. THREE MODELS THAT CAPTURE POTENTIAL PREFERENCES FOR COMPROMISE ALTERNATIVES

2.1. *A logit-model with a compromise variable*

The approach introduced here to generate potential preferences for compromise alternatives involves the construction of a so-called compromise-variable which measures the extent to which a given alternative, in the context of a given choice set, is a compromise alternative. More specifically, the variable indicates on how many attributes a particular alternative scores in-between the other alternatives in the sense of *not* having an extreme (highest or lowest) value on that attribute. In notation, assuming a choice set containing J alternatives i each being described in terms of M attribute-levels x_{im}, the compromise variable C_i can be denoted as follows:

$$C_i = \sum_{m=1..M} I_{im}(\min_m < x_{im} < \max_m) \quad (1)$$

Here, $\min_m = \min\{x_{1m}, \dots, x_{Jm}\}$, $\max_m = \max\{x_{1m}, \dots, x_{Jm}\}$, and $I_{im}(\min_m < x_{im} < \max_m)$ equals one if $\min_m < x_{im} < \max_m$ and zero otherwise. By definition, $C_i \in \{0,1, \dots, m, \dots, M\}$. When this compromise-variable is added to a conventional linear-in-parameters utility function, the following form is obtained:

$$V_i = \beta_C \cdot C_i + \sum_{m=1..M} \beta_m \cdot x_{im} \qquad (2)$$

Parameter β_C indicates the presence and strength of a preference for compromise alternatives (a positive sign is expected). Adding i.i.d. Extreme Value Type I errors results in logit-probabilities.

2.2. A regret-based logit-model

The second approach used in this paper to accommodate preferences for compromise alternatives is based on the recently developed Random Regret Minimization-approach (RRM) to discrete choice modeling [5]. The RRM-model postulates that, when choosing between alternatives, decision-makers aim to minimize anticipated random regret, and that the level of anticipated random regret that is associated with the considered alternative *i* is composed of an i.i.d. random error, which represents unobserved heterogeneity in regret and whose negative is Extreme Value Type I-distributed, and a systematic regret. Systematic regret is in turn conceived to be the sum of all so-called binary regrets that are associated with bilaterally comparing the considered alternative with each of the other alternatives in the choice set.

The level of binary regret associated with comparing the considered alternative with another alternative *j* is conceived to be the sum of the regrets that are associated with comparing the two alternatives in terms of each of their *M* attributes. This attribute level-regret in turn is formulated as $\ln\left(1 + \exp\left[\beta_m \cdot \left(x_{jm} - x_{im}\right)\right]\right)$. Systematic regret is thus written as:

$$R_i = \sum_{j \neq i} \sum_m \ln\left(1 + \exp\left[\beta_m \cdot \left(x_{jm} - x_{im}\right)\right]\right) \quad (3)$$

Acknowledging that minimization of random regret is mathematically equivalent to maximizing the negative of random regret, choice probabilities may be derived using a variant of the logit formulation: the choice probability associated with *i* equals $P(i) = \frac{\exp(-R_i)}{\sum_{j=1..J} \exp(-R_j)}$.[5] Note that the resulting model consumes as many parameters as a conventional linear-in-parameters logit-model, and that the model can be estimated using standard software-packages such as Biogeme and NLOGIT (version 5). The RRM-model has been tested empirically in a wide range of decision-contexts including but not limited to mode-, route-, departure time-, vehicle type-, and destination-choices. See [6] for a concise overview of this empirical evidence.

One important difference between the RRM-model and the conventional linear-in-parameters logit model is that the RRM-model implies a particular type of semi-compensatory behavior. This is a direct result of the convexity of the regret-function: improving an alternative in terms of an attribute on which it already performs well relative to other alternatives generates only small decreases in regret. Deteriorating to a similar extent the performance on another equally important attribute on which the alternative has a poor relative performance may generate substantial increases in regret. As a result, the extent to which a strong performance on one attribute can make up for a poor performance on another depends on the relative position of each alternative in the set.

As explained in [5] and [6], RRM's theoretical ability to accommodate a preference for compromise alternatives follows directly from this particular type of semi-compensatory behavior. More specifically, the RRM-model predicts that having a (very) poor performance on

[5] Importantly, in contrast with other (travel) models and theories that are based on regret-minimization, the RRM-model focuses on so-called riskless choices (that is, choice situations in which the decision maker is assumed to know with certainty the values of the attributes of alternatives). The RRM model postulates that as long as alternatives are characterized in terms of multiple attributes, this implies that trade-offs have to be made by the decision-maker, and that as a result there will be regret in the sense that there will generally be at least one non-chosen alternative that outperforms a chosen one in terms of one or more attributes. Note though, that the RRM model can easily be extended to cover risky decision making as well, as explained in [6].

one attribute causes much regret, while having a (very) strong performance on another attribute does not necessarily compensate for this poor performance. As a result, RRM-models predict that it is more efficient (in terms of avoiding regret and gaining market share) to be a compromise alternative: even when a compromise alternative fails to 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.

The RRM model has in common with the CCM (see below) that 'non-compromise' alternatives are treated asymmetrically: it pays off more to avoid having a relatively poor performance on any attribute, than it does to achieve a very strong performance on one or more attributes. In contrast with the CCM, the RRM model generates preferences for compromise alternatives by definition, and irrespective of estimated parameter values. Whereas the CCM is capable of capturing preferences for compromise alternatives, extreme alternatives, or none of these (depending on the estimated value for the concavity parameter), the RRM model structure *postulates* a preference for compromise alternatives. To avoid repetition, and for reasons of space limitations, we refer to [5] and [6] for a more elaborate and formal discussion of how the RRM-model accommodates preferences for compromise alternatives.

2.3. The contextual concavity model

[3], who were the first to introduce the CCM-model, suggested that the utility associated with evaluating an attribute-level of an alternative is a power function of a term that equals the partworth utility associated with the level of that attribute for the alternative minus the partworth utility associated with the least-preferred value of that attribute in the given choice task. We use the following equation for the systematic utilities of choice alternatives (our notation, and assuming a choice set containing *J* alternatives each described in terms of *M* attributes *x*; index *i* represents an alternative, index *m* indicates an attribute):

$$V_i = \sum_{m=1..M} (\beta_m \cdot x_{im} - \beta_m \cdot \check{x}_m)^{\varphi^m} \qquad (4)$$

Here, $\check{x}_m$ stands for the least preferred level of attribute *m* in the context of the given choice task (in practice this is the attribute value which the analyst *believes* to be the least preferred), and φ^m is an attribute-specific concavity parameter which is expected (but not constrained) to be smaller than 1 and positive. As highlighted by [3], the CCM-model with a concavity parameter between 0 and 1 assigns a relatively high choice probability to compromise alternatives by means of downwardly adjusting the utilities of the best performing attributes to a greater extent than the utilities of attributes with an intermediate performance. This is due to the concavity of the utility function. As such, CCM's treatment of 'non-compromise alternatives' is intrinsically asymmetric: when $\varphi^m \in]0{,}1[$, it is more beneficial (in terms of attaining a higher choice probability) to avoid a relatively poor performance on any attribute, than it is beneficial to achieve a very strong performance on one or more attributes.

As [3] note, when φ^m equals 1, the CCM model is equivalent to a linear-additive logit model and when φ^m is greater than 1, there is a preference for extreme alternatives rather than compromise alternatives. Note that the term 'contextual' refers to the fact that the concavity is exhibited relative to the least preferred attribute level. By adding i.i.d. errors to the observed utilities, a logit-model is obtained. To avoid repetition, and for reasons of space limitations, we refer to [3] for a more elaborate and formal discussion of how the CCM assigns higher choice probabilities to compromise alternatives.

Before moving to the empirical part of the paper, it should be noted that there is a fundamental difference between the CCM- and RRM-models on the one hand, and the compromise variable-model on the other hand. That is, in the first two models preferences for compromise alternatives *emerge* from behavioral premises that themselves do not directly or explicitly refer to compromise alternatives or compromise seeking behavior. In the CCM-model these preferences emerge from locally concave utility functions, and in the RRM-model they emerge from convex regret-functions. In contrast, the compromise variable-model postulates explicitly that individuals are focused on identifying and choosing compromise alternatives. It may also be noted at this point that of the three models that generate preferences for compromise alternatives, the RRM is the most parsimonious: it consumes no more parameters than a linear-in-parameters logit model.

3. A STATED ROUTE-CHOICE EXPERIMENT

The data collection effort focused on route choice behavior among commuters who travel from home to work by car. A total of 550 people were sampled from an internet panel maintained by IntoMart, in April 2011. Sampled individuals were at least 18 years old, owned a car, and were employed. It was taken care of that the sample was representative for the Dutch commuter in terms of gender, age and education level. Of these 550 people, 390 filled out the survey (implying a response rate of 71%).

Respondents to the survey were asked to imagine the hypothetical situation where they were planning a new commute from home to work (either because they had recently moved, or because their employer had recently moved, or because they had started a new job). They were asked to choose between three different routes that differed in terms of the following four attributes[6], with three levels each: average door-to-door travel time (45, 60, 75 minutes), percentage of travel time spent in traffic jams (10%, 25%, 40%), travel time variability (±5, ±15, ± 25 minutes), and total costs (€5.5, €9, €12.5). Note that for these attributes the least-preferred values per choice task are easily identified, since it may be safely assumed that for each attribute, lower values are preferred over higher ones.

Using the Ngene-software package [8], a so-called ‘optimal orthogonal in the differences’-design of choice sets was created [9] to ensure a statistically efficient data collection. This design resulted in nine choice tasks per respondent and 3510 choice observations in total. Figure 1 shows one of these tasks. It may be noted here that the choice-task presented in Figure 1 presents a genuine compromise alternative: route B scores in-between the other two routes in terms of every singly attribute. In other words, its compromise-variable takes on the value four, while those of alternatives A and C take on the value zero.

[6] Note that these attributes have been repeatedly found by other studies to be of considerable importance in determining route choice behavior, although they are unlikely to be the only relevant factors in this decision.

1	Route A	Route B	Route C
Average travel time (minutes)	45	60	75
Percentage of travel time in congestion (%)	10%	25%	40%
Travel time variability (minutes)	±5	±15	±25
Travel costs (Euros)	€12,5	€9	€5,5
YOUR CHOICE	□	□	□

Figure 1: An example route choice-task featuring a full-fledged compromise alternative

Importantly, this particular choice set is the only one in the experiment with such a full-fledged compromise alternative: other choice sets feature compromise-variable scores lower than four. For example, the choice set depicted in Figure 2 results in the following values for the compromise-variable: C(A) = 2, C(B) = C(C) = 1. In this latter choice set, alternative A is still a compromise-alternative, but only to a limited extent: it has an extreme performance on two out of four attributes (congested travel time and travel costs).

7	Route A	Route B	Route C
Average travel time (minutes)	60	75	45
Percentage of travel time in congestion (%)	10%	25%	40%
Travel time variability (minutes)	±15	±25	±5
Travel costs (Euros)	€5,5	€12,5	€9
YOUR CHOICE	□	□	□

Figure 2: An example route choice-task without a full-fledged compromise alternative

4. EMPIRICAL ANALYSES

Four models were estimated on the choice data, using the Biogeme-freeware package [10], [11]: first, a linear-in-parameters logit-model was estimated (Model I). Then, the compromise variable was added to the equation (Model II). Subsequently, the RRM-model was estimated (Model III). Finally, the CCM-model is estimated (Model IV).

With respect to Model II, it may be noted that we also estimated a model where the parameter associated with the compromise variable was allowed to vary randomly between respondents (but not within choices made by the same respondent). This panel-specification allows for compromise preferences to be considered as personality traits. The panel model resulted – as is to be expected – in a slightly higher model fit and a significant (though not large) estimated value for the standard deviation of the compromise parameter. Other estimation results remain similar to those obtained for the non-panel model. To allow for a meaningful comparison across the four models, we have chosen not to consider the panel-specification in the remainder of this paper, and focus on the logit specifications instead.

With respect to Model III and Model IV, it may be noted that we also tested for significant compromise parameters. However, in the context of the CCM-model the associated parameter was insignificant at any reasonable level. In the context of the RRM-model, the associated parameter was only significant at a 10%-level. Furthermore, the RRM-model with the added compromise variable performed worse than the RRM-model without compromise variable in terms of every singly test of out-of-sample predictive ability. Therefore we only report results for the CCM-model and RRM-model without compromise variable.

With respect to Model IV, the following remarks need to be made: first note that [3] also presented a Normalized CCM, called NCCM. This model takes into account possible differences in observed attribute-ranges across alternatives, between choice tasks. Since in our data, the chosen experimental design implied that attribute ranges across alternatives did not differ between choice tasks (for example, travel times always varied between 45 and 75 minutes within each choice task), this NCCM gave the exact same model fit on our data as did the CCM, but with a more complicated model form. From here on, the NCCM is therefore ignored in this paper. Furthermore, note that we also estimated a CCM-variant which constrained all attribute-specific concavity-parameters to be equal. This led to a significant loss in model fit, also when corrected for the associated gain in degrees of freedom. Results from this constrained model are therefore not reported here. Furthermore, note that the estimated concavity parameters for attributes ‘travel time’ and ‘travel time variability’ were not significantly different from one at any reasonable level of significance (implying absence of concavity for those attributes). Restricting these parameters to one led to the same model fit, but with an associated gain of 2 degrees of freedom. This latter CCM-model variant is the one presented in Table 1. In this model, the estimated concavity parameter for ‘travel costs’ is significantly different from one at a 5% level of significance, while the estimated concavity parameter for ‘% of travel time spent in congestion’ is significantly different from one at a 1%- level of significance.

Table 1: Estimation results (robust t-values between brackets)

	Model I Base-model	Model II Base-model + Compromise-variable	Model III RRM-model	Model IV CCM-model
Average travel time	-.0673 (-35.13)	-.0695 (-34.21)	-.0468 (-32.50)	-.0697 (-33.46)
% of travel time in congestion	-.0273 (-17.39)	-.0295 (-17.42)	-.0181 (-16.66)	-.0358 (-11.83)
Travel time variability	-.0316 (-11.86)	-.0320 (-11.92)	-.0210 (-11.86)	-.0314 (-11.91)
Travel costs	-.173 (-21.52)	-.164 (-19.36)	-.113 (-20.28)	-.241 (-5.78)
Compromise-variable	-	.1100 (5.27)	-	-
Concavity par. (travel costs)	-	-	-	.6984 (5.47)
Concavity par. (% time spent in congestion)	-	-	-	.422 (5.57)
Nr of cases Final-LL Adj. Rho-square	3510 -2613 .321	3510 -2600 .324	3510 -2605 .323	3510 -2589 .327

A number of relevant findings appear in Table 1: first, it appears that in all four models the estimated travel-related parameters have the expected sign and are highly significant. What is important to note when inspecting Table 1, is that parameters associated with the four attributes appear to hardly differ between the linear-in-parameter logit models with and without the added compromise variable (I versus II). This suggests that the compromise variable is actually picking up a distinct behavioral effect that is not confounded with the direct effects of attributes themselves. This can also be seen when inspecting the (direct) mean elasticities which give the percentage change in choice probability resulting from a percentage change in one of the alternative's attribute's levels (Table 2): also here, differences between models with- and without the compromise variable are small.

Table 2: Direct elasticities (95%-confidence intervals between brackets)

	Model I **Base-model**	**Model II** **Base-model + Compromise-variable**	**Model III** **RRM-model**
Average travel time	-2.82 [-2.97, -2.67]	-2.91 [-3.08, -2.74]	-3.03 [-3.20, -2.85]
% of travel time in congestion	-.47 [-.52, -.42]	-.51 [-.56, -.46]	-.48 [-.53, -.43]
Travel time variability	-.32 [-.37, -.28]	-.33 [-.37, -.28]	-.33 [-.38, -.28]
Travel costs	-1.06 [-1.15, -0.98]	-1.00 [-1.09, -0.91]	-1.06 [-1.15, -0.97]

The reason for including RRM-elasticities in Table 2 is that, in contrast with parameter values themselves which cannot be compared directly between linear-in-parameters logit-models and RRM-models[7], elasticities can be compared across regret- and utility-based model types. Table 2 and 3 show that elasticities are roughly equal across the RRM- and linear-in-parameters logit models (Model I and Model III). This is in line with findings from previous studies ([12], [13]) although these latter two studies reported differences that were somewhat larger than those we found on our data.

In terms of model fit, it is seen that differences between models are small. More specifically, it appears that in the context of our data the RRM-model (Model III) outperforms the linear-in-parameters logit-model (Model I), while a still better model fit is obtained by Model II (linear-in-parameters logit-model + compromise variable). Model IV (CCM-model) achieves the highest fit, also when correcting for the number of parameters. Using the Likelihood-ratio statistic for nested models (Models I, II, and IV) and Ben-Akiva & Swait's test [14] for nonnested models (model III versus the other three models) it is found that all differences in model fit are significant at a 5%-level.

Interestingly, while the four models' fit is roughly equal, their implied predictions can differ more substantially. Take for example the choice set depicted in Figure 1. Table 3 presents the mean choice probabilities predicted for the three different routes, based on the parameter estimates reported in Table 1. In line with expectations, Models II, III, and IV each predict a higher mean choice probability for the compromise alternative (Route B) than does Model I (linear-in-parameters logit model without compromise variable). It appears that especially the model which includes a compromise variable (Model II) attaches a higher choice probability to Route B.

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[7] In a (linear-in-parameters) RUM formulation, a parameter represents the amount of utility that is gained or lost by increasing or decreasing the performance in terms of the corresponding attribute by one unit. Quite differently, in a RRM-setting parameters reflect the *upper bound* of the extent to which a unit in- or decrease in performance on an attribute influences (bilateral) regret. Whether or not this upper bound is reached for a one unit in- or decrease in an attribute's value depends on the performance of other alternatives in the set in terms of the attribute.

To test whether these results are statistically significant, we also computed 95%-confidence intervals. This was done by making 1,000 draws from the multivariate normal distribution of the estimates (as implied by their means, standard errors and covariances) and computing choice probabilities for routes A, B and C for each multi-dimensional draw. The interval spans the values from the 5% and the 95% quantiles of the generated values[8].

Table 3: Choice probability predictions

(percentages, rounded; based on routes presented in Figure 1;

95% confidence intervals between brackets)

	Route A	**Route B**	**Route C**
Model I Base-model	70 [68, 72]	23 [22, 24]	7 [6, 8]
Model II Base-model + Compromise-variable	65 [62, 68]	30 [27, 32]	6 [5, 7]
Model III RRM-model	67 [65, 69]	27 [26, 28]	6 [6, 7]
Model IV CCM-model	66 [63, 68]	29 [26, 31]	6 [5, 7]

[8] The same approach was used to derive confidence intervals for the elasticities, as presented in Table 2.

The resulting confidence intervals suggest that Model I (the base model) provides significantly different forecasts for the choice probability of the compromise alternative (route B) when compared to the three models that capture preferences for compromise alternatives: Model I's mean prediction for B is not within the other three models' 95% confidence interval and vice versa. Another result can be obtained from the confidence intervals: it appears that Model III (the RRM model) is more precise than Model II (linear-in-parameters logit with compromise variable) and has a similar precision as Model I (the base model). This suggests an advantage, in terms of precision, of the RRM model.

4.2. Model validation: out-of-sample predictions

The data were split into an estimation-sample and a validation-sample by means of randomly selecting two thirds of cases for estimation and leaving the remaining one third (1192 cases) for testing out-of-sample predictive ability analyses. Estimation results of the four models on the estimation-sample are very similar to those reported in Table 1 (in terms of parameter values as well as model fit statistics) and are not reported here for reasons of brevity. The following types of generic validation analyses are performed in the context of the validation sub-sample and are summarized in Table 4: first, the likelihood of chosen alternatives is computed for each case in the validation set and for all four models; the mean of these likelihoods is reported. Results for the different models suggest that the CCM-model has a slightly worse performance than the other three differences, although it should be noted that differences in terms of this metric are very small and in fact can be ignored. Second, the log-likelihood of the validation sample (in the context of each of the four models as estimated on the estimation sample) is reported. The CCM-model performs best, in terms of this metric. The lowest row of Table 4 shows the rho bar squared computed for the four models in the context of the validation data. Also in the context of this metric, differences are small – although the difference between the CCM-model and the other models in favor of the former is worth noting. Note that in contrast with the previous two measures, the rho-bar squared penalizes added parameters.

Table 4: Predictive ability out-of-sample (best results per metric underlined)

	Model I **Base-model**	**Model II** **Base-model + Compromise-variable**	**Model III** **RRM-model**	**Model IV** **CCM-model**
Mean likelihood of chosen alternative	<u>0.555</u>	<u>0.555</u>	<u>0.555</u>	0.554
Log-likelihood of validation sample	-913	-910	-913	<u>-905</u>
Rho bar squared	.300	.301	.300	<u>.304</u>

As a second test of out-of-sample performance, we focus on the ability of the four models to predict the popularity of compromise alternatives in particular (see Table 5). More specifically, for each of the nine choice tasks we identified the compromise alternative (being the alternative with the highest score on the compromise variable). Subsequently, the actual 'market share' (relative choice frequency) for this alternative is observed in the context of those cases (out of the 1192 selected cases) that corresponded with the particular choice task. Because in the validation sample the number of observations differed across the nine choice tasks, differences between observed and predicted market shares per task were weighted according to the relative share of observations available per choice task in the validation sample. Finally, choice probability predictions made by applying the four models are computed, and compared with the actually observed market shares. Three metrics are reported in Table 5: the mean deviation (positive values indicate an *under*estimation of the choice probability for the compromise alternative, whereas negative values indicate an *over*estimation); the mean absolute deviation (which returns positive numbers by definition); and the Root Mean Squared Error (which also returns positive numbers by definition).

Table 5: Ability to predict market shares of compromise alternatives

(best results per metric underlined)

	Model I **Base-model**	**Model II** **Base-model + Compromise-variable**	**Model III** **RRM-model**	**Model IV** **CCM-model**
Mean deviation (percentage points)	1.7	-1.3	<u>0.0</u>	-0.7
Mean absolute deviation (percentage points)	4.2	3.3	<u>3.0</u>	3.1
Root mean squared error (RMSE) (percentage points)	4.8	4.1	3.8	<u>3.6</u>

Starting with the mean deviation, it appears that the linear-in-parameters logit model without a compromise variable underestimates the choice probability of compromise alternatives, while the addition of a compromise variable leads to an overestimation of compromise alternatives' choice probabilities. This finding is in line with intuition. The RRM-model appears to very accurately predict the market share of compromise alternatives when evaluated in terms of this metric. Also when considering the mean absolute deviation, the RRM-model appears to outperform the other models, although the difference with the CCM-model is very small. In terms of the RMSE, the CCM-model appears to do best, closely followed by the RRM-model.

5. CONCLUSIONS AND DISCUSSION

This paper presents and tests models that are able to capture potential preferences for so-called compromise alternatives, in the context of route choice data. (compromise alternatives have an intermediate performance on each or most attributes rather than having a poor performance on some attributes and a strong performance on others.) One approach involves the construction of a so-called compromise variable, which indicates to what extent (i.e., on how many attributes) a given alternative is a compromise alternative in its choice set. Another approach consists of using a Random Regret-model form (RRM). In the context of this latter model-type, preferences for compromise alternatives emerge from the underlying model structure. The two proposed model forms are compared with the Contextual Concavity-model (CCM), which has shown its worth in terms of generating preferences for compromise alternatives by means of a locally concave utility function. The comparison is based on a stated route choice dataset.

In terms of model fit, the CMM appears to have a slight (but statistically significant) edge over the other presented model forms, also when correcting for the number of parameters which is higher for the CMM-model. A validation exercise on one third of the data that was not used for estimation shows that differences between models in terms of generic out-of-sample predictive ability are small; a mixed picture emerges regarding the performance of the different models, although the CCM and the RRM-model appear to outperform the other models (among these two models, no clear 'winner' can be identified).

In this light it is worth noting that the RRM-model is the most parsimonious model of the four models used (together with the relatively poor performing linear-in-parameters logit-model). This suggests that the RRM-model may be considered a viable alternative for the CCM-model, especially when the number of attributes increases (because increases in attribute-numbers imply increases in the number of parameters used by the CCM-model if attribute-specific concavity parameters are estimated). As another more general reflection, our findings suggest that the two models where preferences for compromise alternatives emerge indirectly from model structures and behavioral premises (such as locally concave utility functions or convex regret functions) perform better empirically than the model that explicitly postulates (by means of a compromise-variable) that decision-makers identify and choose compromise alternatives.

A number of directions for future research come to mind. First, there is an obvious need to study to what extent results obtained in this study hold in the context of other travel choice-related datasets (not only stated preference, but also revealed preference datasets). Moreover, it would be interesting to find out if there are circumstances or personality traits that trigger the kind of decision-making that results in preferences for compromise alternatives. In this light, it is interesting to point at the fact that the stated choice experiment reported in this paper also included a number of Likert-scale questions to respondents concerning their attitude to decision-making in general and in the context of the stated choice experiment. We found that on the sub-sample of individuals that (stated that they) found it important to make the 'right' choices in the experiment, a large and significant parameter associated with the compromise variable was found, while this parameter was insignificant in the context of the sub-sample of individuals that (stated that they) did not find it important to make the 'right' choices in the experiment. Similarly, we found that on the sub-sample of individuals that (stated that they) found it difficult to make decisions when the stakes are high, a large and significant parameter associated with the compromise variable was found, while the parameter was insignificant on the sub-sample of individuals that (stated that they) did not find it difficult to make decisions when the stakes are high.

Although in the context of other similar Likert-scale questions no significant differences between sub-samples were obtained, this does suggest that the ability of models to generate preferences for compromise alternatives might be particularly important in the context of choices that are considered by decision-makers to be important and/or difficult. Note that these results are in line with findings reported in the consumer choice literature (e.g., [1]). More research is needed to test these preliminary findings.

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