A GENERALIZED RELATIVE UTILITY BASED CHOICE MODEL WITH MULTIPLE CONTEXT DEPENDENCIES

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ABSTRACT
The representation of context dependence has been attracting increasing attention in travel behavior analysis. In the context of dynamic travel information, this paper conceptually and empirically compares six types of context dependence models: The first two models are built based on the concept of relative utility (RU): one is the RU model with relative interest (the RURI model) and the other is the multiple prospects model with relative interest (the MPRI model). The second two models are the random regret minimization (RRM) model and the relative advantage maximization (RAM) model. The last two models the RRM and RAM models with relative interest (called RRM_RI and RAM_RI models). Conceptually, relative utility covers all the features of the concepts of regret and relative advantage in an implicit but comprehensive way. Even though relative utility is originally specified to allow for alternative-based context dependence, the RURI and MPRI models are transformed to explicitly accommodate attribute-based context dependence. An empirical study is carried out by using stated preference data (1,872 samples) on drivers' joint choice of departure time and driving route under the provision of dynamic travel information, which were collected in Beijing in 2008. It is confirmed that the MPRI model outperforms the other five models.

Keywords: Relative utility, context dependence, prospect, regret, relative advantage, dynamic travel information, Beijing.

HIGHLIGHTS

(1) Multiple context dependences are modeled in the context of dynamic travel information.
(2) The concepts of relative utility and prospect are integrated.
(3) Models with regret and relative advantage are compared with relative utility models.
(4) A stated preference survey was conducted to capture departure time and route choice.
(5) Relative utility model with prospect outperforms the other comparison models.

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1. INTRODUCTION

The importance of incorporating context dependence into general choice models has been recognized for about half a century. Earlier studies dealt with spatial choice behavior (Rushton, 1969) and preference reversals in gambling decisions (Lichtenstein and Slovic, 1971). Since then, context dependence has been confirmed with respect to various types of human decisions (Kahneman and Tversky, 1979; Oppewal and Timmermans, 1991; Tversky and Simonson, 1993; Kokinov and Grinberg, 2001; McFadden, 2001; Zhang et al., 2004; Avineri and Chorus, 2010), including travel behavior. In particular, existing studies have repeatedly shown that context-dependent preferences are not mere artifacts but robust features of actual behavior (Swait et al., 2002).

Attempting to provide a general definition of the context, Zhang et al. (2004a) classified it into *alternative-specific*, *individual-specific*, and *circumstantial contexts* and proposed adopting the concept of relative utility to represent context dependence in a systematic way. It is argued that an individual usually evaluates an alternative in a choice set by comparing it with other alternatives (represented by *alternative-oriented relative utility*), perhaps with the alternatives the individual chose in the past (represented by *time-oriented relative utility*), and/or with the alternatives chosen by other individuals (represented by *decision maker-oriented relative utility*). Relative utility argues that utility is only meaningful relative to reference point(s), which is consistent with prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). By contrast, relative utility allows the inclusion of multiple reference points in a systematic way. The influence of multiple reference points reflects general features of human decisions (e.g., Lin et al., 2006; Koop and Johnson, 2012).

Recently, two more appealing context dependence models have been attracting attention, specifically in the field of transportation. One is the random regret minimization (RRM) model (Chorus et al., 2008, 2013); the other is the relative advantage maximization (RAM) model (Kivetz et al., 2004; Leong and Hensher, 2012). Regret and relative advantage are defined by first comparing pairs of alternatives at the attribute level in the form of the difference of corresponding partial utilities and then summing up the differences over all the attributes.

Even though relative utility is specified to allow for alternative-based context dependence, the relative utility function can be easily transformed to a collection of comparisons of alternatives at the attribute level. In this sense, the attribute-based context dependence represented in the RRM and RAM models is already reflected in the relative utility models. The differences are that: (1) existing relative utility models deal with the comparisons in a linear way while the RRM and RAM models do so in a nonlinear way; (2) the RRM model ignores the role of relative advantage, the RAM model does not pay appropriate attention to regret, and existing relative utility models treat the relative advantage and relative disadvantage (regret) symmetrically; and (3) unequal evaluation (relative importance) of different alternatives in a choice set is incorporated in the relative utility model with the help of a relative interest parameter for each alternative; however, the RRM and RAM models still assume that decision makers treat all the alternatives equally in choice decisions. To overcome the shortcoming of linear and symmetric treatment of alternative comparisons, Zhang et al. (2010, 2013) extended the relative utility model by integrating this with prospect theory.

The purpose of this study is to clarify how to incorporate context dependence into choice models. This is done by: 1) comparing the original relative utility model with relative interest (the RURI model) (Zhang et al., 2004) and its extended version, the multiple prospects model with relative interest (the MPRI model) (Zhang et al., 2010, 2013), with the RRM and RAM models; and 2) examining whether

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introducing unequal alternative evaluation structures (by use of the relative interest parameter) can improve the performance of the RRM and RAM models. In the empirical study, we use SP data on Beijing drivers' joint choice of departure time and driving route under the provision of dynamic travel information, where 1,872 valid SP responses were collected in Beijing in 2008.

In the remainder of the paper, existing studies of context dependence are briefly reviewed in Section 2, followed by a description of the RURI, MPRI, RRM, and RAM models in addition to the RRM and RAM models with relative interest (RRM_RI and RAM_RI models) in Section 3. The data used in this study are explained in Section 4. Model estimation results and discussion are given in Section 5 with concluding remarks offered in Section 6.

2. REVIEW OF CONTEXT DEPENDENCE STUDIES

Various existing studies show that choice depends on context and various types of context-dependent preferences have been explored and clarified in the literature.

It is reported that the composition of a choice set influences the evaluation of an alternative (the composition effect; Timmermans et al., 1996). Alternatives gain a share when they become intermediate options in the choice set (the compromise effect; Kivetz et al., 2004). Adding a dominated alternative to the choice set increases the choice probability of some other alternatives (the dominated-alternative effect; Huber et al., 1982; Simonson and Tversky, 1992; Wedell and Pettibone, 1996; Pettibone and Wedell, 2000;). The compromise effect and dominated-alternative effect are grouped as context effects by Camerer and Loewenstein (2004), who defined context effects as "ways in which preferences between options depend on what other options are in the set (contrary to the "independence of irrelevant alternatives (IIA)" assumption)." Some alternatives may be perceived as being more similar and therefore more substitutable (the substitution and similarity effect; Borgers and Timmermans, 1988). The presentation format of the choice task leads individuals to attribute-wise processing of information (the framing effect; Payne, 1976; Recker and Golob, 1979; Johnson and Meyer, 1984). It is also observed that the presence or absence of competing alternatives influences choice behavior (the availability effect; Anderson et al., 1992). When the complexity (defined by the number of alternatives, number of attributes, correlation between attributes, etc.) in choice tasks increases, decision makers usually use simple, local, and myopic choice strategies (the complexity effect; Olshavsky, 1979; Payne et al., 1988; Pfeiffer, 2012). Preferences or utilities may be valid over a limited set of circumstances (background effects) because variables that describe the background of choice situations may differentially affect the evaluations of the alternatives (Oppewal and Timmermans, 1991).

Responses to alternative attributes may be context dependent. For example, Arentze et al. (2012) examined how truck drivers show the context-dependent influence of road attributes and pricing policies on route choice behavior. It is known that the rationalization of context-based choice is usually supported by the assumption of context-dependent preferences. However, Kriesler and Nitzan (2008) showed that context-based choice can result from the fact that some characteristics of the choice procedure, other than preferences, depend on the context.

Context-dependent decisions may provide adaptive responses to environments (Gigerenzer et al., 1999; Payne et al., 1993). Rosati and Stevens (2009) provided evidence that many instances of context-dependent choice probably result from adaptive benefits associated with different contexts, rather than resulting from simple cognitive biases. Such adaptive features of context dependence may be a common phenomenon of human decisions.

Swait et al. (2002) summarized 11 major forms of context-dependent preferences: habit- or experience-dependence effects, social interdependence, accountability effects, menu dependence, chooser dependence, mental accounting, choice bracketing, motivation effects, decoy effects, reference prices, and complexity effects. They emphasized the importance of context measurement tools (with respect to attitudes/perceptions, dynamics (history and expectations), mental models, task and context complexity, and context manipulation checks and debriefing protocols) and advancing choice models from the perspectives of reference dependence, choice set formation, taste heterogeneity, error components and heteroskedasticity, choice dynamics and sequential decision making, and prediction with context-sensitive models.

Two choice models were developed in the early stage of choice model research, namely the universal logit model (McFadden et al., 1977) and the dogit model (Gaudry and Dagenais, 1979), which can be used to represent context dependence. The universal logit model introduces the cross-effect of alternative *j′* on alternative *j* in describing the choice utility of alternative *j*, while the dogit model can be transformed into a two-stage choice process consisting of a choice set generation process and conditional on choice set selection, an outcome selection process. Conjoint-based surveys can be used to measure background effects (Oppewal and Timmermans, 1991) by introducing availability of alternatives (Anderson et al., 1992). On the other hand, Borgers and Timmermans (1988) developed a context-sensitive model of spatial choice behavior, where spatial closeness of different alternatives and dissimilarity between attributes of different alternatives are introduced.

For gambling behavior, Kahneman and Tversky (1979) found that people's decisions tend to be more sensitive to losses than to gains. Similar conclusions have been reached in areas such as finance, economics, consumer science, and political science (Avineri and Chorus, 2010). Tversky and Simonson (1993) defined a value function with context-dependent and context-free preferences. In recent years, prospect theory has been actively applied and improved (Rose and Masiero, 2010; Timmermans, 2010; Van de Kaa, 2010a, b; Van Wee, 2010). However, as argued by Timmermans (2010), "it is not readily evident that prospect theory is necessarily a sound theory for daily travel decisions; however, the notion of the existence of a reference point, associated with this theory and the specific curvature of the model, may be useful in some travel contexts."

In addition to the models reviewed above, the relative utility-based choice models (Zhang et al., 2004a, 2008, 2013; Zhang and Fujiwara, 2004), the RRM model (Chorus et al., 2008; 2013) and the RAM model (Kivetz et al., 2004; Leong and Hensher, 2012), can also be used to represent context dependence; they are more powerful than other existing models. Since these models are the focus in this study, details are given in the next section.

We can draw the following conclusions from the above review: (1) there is no universally agreed definition of context and context dependence; (2) the development of context dependence models has been active, but not satisfactory, and there remain various unresolved research issues including how to investigate context dependence based on surveys and how to logically introduce context dependence into choice models.

3. CONTEXT DEPENDENCE MODELING

Here, four types of context dependence models are first introduced: RURI, MPRI, RRM, and RAM models. Second, the four models are conceptually compared. Third, recognizing the behavioral importance of relative interest, two new models are developed by introducing relative interest into the RRM and RAM models (the RRM_RI model and the RAM_RI model, respectively). To simplify the comparison and discussion, all six models assume that error terms follow an independent and identical Gumbel distribution. Note that all the concepts introduced in this section can be easily extended to accommodate more general distributions of error terms.

3.1 The Relative Utility Model with Relative Interest (RURI)

(1) Model specification

To comprehensively reflect the influence of various context dependences, Zhang et al. (2004a) defined three types of relative utility with respect to an alternative (*j*), an individual (*i*), and time (*t*). As discussed later, time can refer to both the past and the future.

First, to reflect the relative influence of other alternatives ($j \neq i$) in a choice set on alternative *i*, the following alternative-oriented relative utility function is defined.

$$U_{nit} = f\left(u_{nit} \mid \left(u_{njt} : \forall \;\; j \neq i\right)\right) \tag{1}$$

The relative utility U_{nit} of alternative *i* that individual *n* derives at time *t* is defined as a function of standard utility functions of not only u_{nit} but also u_{njt} ($j \neq i$). It is obvious that u_{njt} serves as a reference point for choice, and adding/eliminating an alternative in the choice set influences the choice of other alternatives (i.e., the choice set composition effect is captured).

Second, an individual may compare the alternative/s that was/were chosen previously or will be chosen in the future. To capture this phenomenon, the following time-oriented relative utility function is defined, where *t′* refers to the previous or future point of time.

$$U_{nit} = f\left(u_{nit} \mid \left(u_{njt'} : t' \neq t \text{ and } \forall \ j\right)\right) \tag{2}$$

Here, the past and/or future alternatives, which can be the same alternatives under study and/or another alternative, serve as reference points. For example, Kahneman and Tversky (1979) acknowledged that a reference point may in part depend on expectations and social comparisons. Expectations are linked with the future preference (Pervin, 1989) and goals serve as reference points and alternative outcomes (Heath et al., 1999). Frederick and Loewenstein (1999) argued that past experience can be serviced as a candidate reference point. In the context of health decisions, it is reported that past or future losses can serve as reference points (Schwartz et al., 2008). The influence of future expectations on travel choice behavior has also been confirmed (e.g., Zhang et al., 2004b; Wang et al., 2010; Wu et al., 2011). Zhang et al. (2012) clarified that decisions on residential choice and car ownership over the life course are influenced by those in the past and the future in a considerably complicated way.

Finally, to reflect the fact that a decision maker may compare the alternatives chosen by other persons, we have the following decision maker-oriented relative utility.

$$U_{nit} = f\left(u_{nit} \mid \left(u_{n'jt} : \ n' \in \text{social reference group}\right)\right) \tag{3}$$

For example, owning a car or a house as a symbol of social status suggests that people decide to purchase the car or the house by comparing with other people (i.e., social reference group). Social comparisons suggest that decision makers take other people’s decisions seriously (see Suls and Wheeler, 2000). Such comparisons may also come from altruistic consideration (e.g., purchasing a bigger car for the sake of driving with children safely and buying a house that is closer to the partner’s workplace and/or the children’s school). The social reference group can be a small group such as household members, or an unspecified group of persons.

With relative utilities as defined above, *the principle of relative utility maximization* was further proposed by Zhang et al. (2004a), which assumed that an individual chose an alternative with the highest relative utility from his/her choice set.

To specify an operational relative utility function, Zhang et al. (2004) proposed the following alternative-oriented relative utility with relative interest parameters (r_{ni}), which are used to reflect the fact that people may not equally evaluate different alternatives in a choice set.

$$U_{ni} = r_{ni} \sum_{j \neq i} \left(u_{ni} - u_{nj}\right) \tag{4}$$

Note that time suffix *t* is omitted for simplicity. In fact, r_{ni} can take any real value, in theory, but one of the relative interest parameters must be fixed. For ease of interpretation of model estimation results, it is usually assumed that $0 \leq r_{ni} \leq 1, \sum_i r_{ni} = 1$. The relative utility model with equation (4) is a non-IIA choice model.

Zhang and Fujiwara (2004) extended equation (4) by adding a weight parameter w_{nij} for each comparison at the alternative level.

$$U_{ni} = r_{ni} \sum_{j \neq i} w_{nij} \left(u_{ni} - u_{nj} \right),\ w_{nij} \geq 0\,,\ \sum_{j \neq i} w_{nij} = 1 \tag{5}$$

The advantage of introducing the weight parameter w_{nij} is that a quasinested choice model structure can be obtained by regrouping alternatives in the choice set into several bundles, which share the same weight parameter. For details, refer to Zhang and Fujiwara (2004).

Note that all comparisons in equations (1)–(5) do not distinguish between advantageous and disadvantageous outcomes. In other words, gain, loss, and/or regret are not explicitly emphasized. More precisely, it is implicitly assumed that people show symmetric responses to advantageous and disadvantageous outcomes.

In summary, the advantage/disadvantage of u_{ni} relative to u_{nj}, the relative importance (w_{nij}) in deriving the advantage/disadvantage of u_{ni}, and the relative importance (r_{ni}) of each alternative in the choice set are three key constructs. Depending on how to make use of these three constructs, various types of context dependence can be represented. Allowing for attribute-based comparisons and distinguishing the signs of $x_{nik} - x_{njk}$ result in the MPRI, RRM, and RAM models. Allowing for the relative importance (r_{ni}) of each alternative in the choice set under the framework of RRM and RAM models leads to the RRM_RI and RAM_RI models. These are explained in detail later. As implied by the meaning of weight parameter w_{nij}, if the preference of alternative i is independent from some alternatives (i.e., the weight is zero), then the relative utility can be specified as two parts, namely the context-independent and context-dependent preference. If whether comparison of an attribute with other attributes brings an advantage or disadvantage depends on decision makers' individual tastes, one can directly estimate a parameter for $x_{nik} - x_{njk}$. Thus, decomposing the relative utility in different ways can generate choice models with more general context dependence.

If relative interest and weight parameters are equal across alternatives, then the RURI model collapses into the conventional multinomial logit model if error terms follow an independent and identical Gumbel distribution. If either relative interest parameters or weight parameters are different across alternatives, the resulting choice model is a non-IIA model. This implies that relative utility models can include standard utility models as special cases.

(2) Existing applications

Relative utility models (Zhang et al., 2004a) were first developed to present stated choices of destinations and stop patterns using data collected in the Netherlands in 2000; an r_MNL model (a multinomial relative utility model) and an r_NL model (a nested relative utility model) were developed, respectively. Wang et al. (2009) applied the r_MNL model to evaluate dynamic travel information using the same data in this study.

Fujiwara et al. (2004) made the first attempt to build a relative utility mode by assuming that $0 \leq r_{ni} \leq 1, \sum_i r_{ni} = 1$ to represent a stated joint choice of information device, information acquisition behavior, and travel mode under the provision of multimodal travel information. Relative interest parameters were defined as a function of individual attributes and other factors. In reality, people may not equally deal with comparisons with different alternatives. To reflect this behavioral phenomenon, Zhang and Fujiwara (2004) added a weight parameter. Regrouping the weight parameters at the travel mode choice level results in a quasinested choice structure, which is much more flexible and logical in representing complicated choice mechanisms with many alternatives than the nested logit model.

As a new extension, Zhang et al. (2005) applied relative utility to represent endogenous generation of choice set in the context of parking place choice. Yamane et al. (2007) developed an aggregate choice model based on relative utility. Zhang (2006) conceptually discussed how to generalize the three originally proposed types of relative utility.

The concept of relative utility can be easily introduced into any utility-based choice model. Zhang et al. (2002) developed a combined dynamic SP/RP model with relative utility and heterogeneous relative interest (the r_SP/RP model) using SP panel survey data on travel mode choice. Zhang et al.

(2008) introduced relative utility into the paired combinatorial logit (PCL) model (the r_PCL model), which can represent both observed and unobserved inter-alternative similarities. A case study was conducted with data from a stated tour package choice experiment with respect to tourism along the Asian Highway.

3.2 The Multiple Prospects Model with Relative Interest (MPRI)

To overcome the shortcoming of the RURI model, Zhang et al. (2010, 2013) integrated relative utility with the concept of prospect theory. We call this improved model the multiple prospects model with relative interest (the MPRI model), which is specified below.

First, we define the standard utility u_{ni} as follows:

$$u_{ni} = v_{ni} + \varepsilon_{ni} = \delta_i + \sum_k \pi_k x_{nik} + \sum_s \theta_{is} z_{ns} + \varepsilon_{ni}, \tag{6}$$

where, v_{ni} is a deterministic (or nonstochastic) term and ε_{ni} indicates an error term. The standard utility is explained by alternative-specific attributes (x_{nik}), alternative-generic attributes (z_{ns}), and a constant term (δ_i) in a linear way.

Substituting equation (6) into equation (5) gives:

$$U_{ni} = r_{ni}\left(\varphi_i + \Psi_{ni} + \sum_s \mu_{is} z_{ns}\right) + \eta_{ni}, \tag{7}$$

$$\Psi_{ni} = \sum_{j \neq i} w_{nij} \left(\sum_k \pi_k \left(x_{nik} - x_{njk} \right) \right), \tag{8}$$

where

$$\varphi_i = \sum_{j \neq i} w_{nij} \left(\delta_i - \delta_j \right) = \Delta\delta_i \sum_{j \neq i} w_{nij} = \Delta\delta_i, \ \Delta\delta_i = \delta_i - \delta_j,$$

$$\mu_{is} = \sum_{j \neq i} w_{nij} \left(\theta_{is} - \theta_{js} \right) = \Delta\theta_{is} \sum_{j \neq i} w_{nij} = \Delta\theta_{is}, \ \Delta\theta_{is} = \theta_{is} - \theta_{js},$$

$$\eta_{ni} = \sum_{j \neq i} r_{ni} w_{nij} \left(\varepsilon_{ni} - \varepsilon_{nj} \right) = r_{ni} \Delta\varepsilon_{ni} \sum_{j \neq i} w_{nij} = r_{ni} \Delta\varepsilon_{ni}.$$

Comparisons between any pair of alternatives lead to three types of outcome: positive, negative, and indifferent outcomes. To reflect decision makers' different responses to different outcomes, Zhang et al. (2010, 2013) integrated relative utility with the concept of prospect theory by respecifying the above Ψ_{ni} as follows:

$$\Psi_{ni} = \sum_k \sum_{j \neq i} \pi_k \left(\left(d^+_{nij,k} \Delta x_{nij,k} \right)^{\alpha} - \lambda \left(- d^-_{nij,k} \Delta x_{nij,k} \right)^{\beta} \right). \tag{9}$$

Here, two dummy variables are introduced: $d^+_{nij,k}$ is equal to 1 if $\Delta x_{nij,k}$ ($= x_{nik} - x_{njk}$) is nonnegative, otherwise 0, and $d^-_{nij,k}$ is equal to 1 if $\Delta x_{nij,k}$ is negative, otherwise 0 (i.e., $d^+_{nij,k}\Delta x_{nij,k}$ represents the gain from comparison and $-d^-_{nij,k}\Delta x_{nij,k}$ indicates the loss). Parameters α and β (equal to or smaller than 1) determine the convexity/concavity of the utility function, and λ (equal to or larger than 1) describes the degree of loss aversion. In the above formulation, weight parameters (w_{nij}) are omitted to simplify the model structure. Needless to say, the MPRI model is also a non-IIA choice model.

Zhang et al. (2010) estimated the MPRI model using the original set of prospect parameters estimated by Tversky and Kahneman (1992), and Zhang et al. (2013) simulated the influence of prospect parameters on model estimation results.

3.3 The Random Regret Minimization (RRM) Model

The RRM model assumes that each alternative is assessed against all other alternatives in a choice set by minimizing anticipated regret (Chorus, 2008, 2013). The random regret R_{ni} and the corresponding choice probability P_{ni} are defined as follows:

$$R_{ni} = \delta_i + \left(-\tilde{R}_{ni}\right) + \sum_s \theta_{is} z_{ns} + \varepsilon_{ni}\,, \tag{10a}$$

$$P_{ni} = exp\left(\delta_i + \left(-\tilde{R}_{ni}\right) + \sum_s \theta_{is} z_{ns}\right) \Big/ \sum_j exp\left(\delta_j + \left(-\tilde{R}_{nj}\right) + \sum_s \theta_{js} z_{ns}\right), \tag{10b}$$

$$\tilde{R}_{ni} = \sum_{j \neq i} \sum_k ln\left(1 + exp\left(\pi_k \left(x_{njk} - x_{nik}\right)\right)\right). \tag{10c}$$

The choice probability P_{ni} is obtained by assuming that ε_{ni} follows a Gumbel distribution and acknowledging that minimization of random regret (R_{ni}) is mathematically equivalent to maximization of the negative random regret. The term $\tilde{R}_{ni}$ indicates systematic regret. Here, constant terms (δ_i, δ_j) and alternative-generic partial utilities ($\theta_{is} z_{ns}, \theta_{js} z_{ns}$) are added.

It is obvious that the RRM model is a non-IIA choice model. The model is able to capture semi-compensatory choice behavior and predict choice set composition effects (e.g., the extremeness aversion effect and the compromise effect) (Chorus, 2013).

The RRM model emphasizes the role of regret in choice decisions; however, it ignores how decision makers evaluate those well-performing attributes (Leong and Hensher, 2012).

3.4 The Relative Advantage Maximization (RAM) Model

The RAM model (Kivetz et al., 2004) "interprets the value of an attribute in comparison to its counterpart values in all other alternatives as either an advantage or a disadvantage" (Leong and Hensher, 2012). Originally, the RAM model was developed to explain the compromise effect in choice experiments. The random relative advantage function RA_{ni} and the corresponding choice probability P_{ni} of the RAM model can be defined as follows:

$$RA_{ni} = \delta_i + \overline{RA}_{ni} + \sum_s \theta_{is} z_{ns} + \varepsilon_{ni}\,, \tag{11a}$$

$$\overline{RA}_{ni} = \sum_{j \neq i} \overline{RA}_n(i,j), \tag{11b}$$

$$P_{ni} = exp\left(\overline{RA}_{ni}\right) \Big/ \sum_j exp\left(\overline{RA}_{nj}\right), \tag{11c}$$

$$\overline{RA}_n(i,j) = \sum_k A_{nk}(i,j) \Big/ \left(\sum_k A_{nk}(i,j) + \sum_k D_{nk}(i,j)\right), \tag{11d}$$

$$A_{nk}(i,j) = \begin{cases} \pi_{ik} x_{nik} - \pi_{jk} x_{njk} & if\ \pi_{ik} x_{nik} - \pi_{jk} x_{njk} \geq \tau_k^{i \to j} \\ 0 & otherwise \end{cases}, \tag{11e}$$

where $\overline{RA}_n$ is systematic relative advantage, $\overline{RA}_n(i,j)$ indicates individual *n*'s random relative advantage of alternative *i* to the competitor alternative *j*, and $A_{nk}(i,j)$ and $D_{nk}(i,j)$ are the advantage and disadvantage of alternative *i* over alternative *j* with respect to attribute *k*, respectively. $\tau_k^{i \to j}$ is a threshold to judge whether the difference between a pair of partial utilities ($\pi_{ik} x_{nik} - \pi_{jk} x_{njk}$) is large enough to generate the advantage. Analogue to $A_{nk}(i,j)$, $D_{nk}(i,j)$ can also be calculated. Note that constant terms (δ_i, δ_j) and alternative-generic partial utilities ($\theta_{is} z_{ns}, \theta_{js} z_{ns}$) are added to the original version of the RAM model.

Similar to the RRM model, the RAM model is also a non-IIA choice model. Contrary to the RRM model, the RAM model emphasizes the role of relative advantage of each alternative with respect to each attribute. However, maximizing the relative advantage means that less importance is attached to the role of regret (or disadvantage).

3.5 Conceptual Comparison

The above four models share similar attribute-based comparisons in order to reach final choice decisions. The RRM and the RAM models, as well as the MPRI model, treat context dependence at the attribute level. In contrast, the RURI model can deal with the comparison at both the attribute level and the alternative level. Different from the RURI model, in which only linear comparisons are included, the other three models compare different alternatives in a nonlinear way. Since the comparisons are made at the alternative/attribute level, all four models emphasize the existence and importance of multiple reference points. Attribute-based comparisons allow analysts to capture the substitution/similarity effect and the choice set composition effect as well as the availability effect. Since the RRM, RAM, and MPRI models allow for nonlinear comparisons, the compromise effect and the dominated-alternative effect can be explicitly captured.

The shortcoming of the RRM model (e.g., it ignores well-performing alternatives) is overcome in the RAM model while the shortcoming of the RAM model (e.g., it pays less attention to the relative disadvantages, an approximate of the regret) is overcome in the RRM model. The RURI and MPRI models share the advantages of the RRM and RAM models and do not suffer from their disadvantages, but the RURI model implicitly assumes that marginal responses to relative advantages (gain) and disadvantages (loss or regret) are symmetric.

For example, comparing car and train, train users can sleep and read newspapers inside the train, but car users cannot. In this case, such benefits of using the train can be captured in the RAM model but not in the RRM model. On the other hand, for example, it is difficult to judge the advantages (gain) and disadvantages (loss or regret) when comparing train A with leather seats and train B with advanced textile seats in the long-distance travel mode choice, when comparing shopping centers with different interior designs, or when comparing tourist destinations with different types of hot spring.

The concept of relative interest introduced in the RURI and MPRI models has several attractive features. First, it is the unequal relative interest parameters across alternatives (and/or weight parameters) that make the RURI model a non-IIA model without introducing any nonlinearity. Second, as will be seen later, the relative interest parameter increases the variation level of utility function, and as a result, it can improve the model accuracy. Third, heterogeneous responses to alternative attributes at the alternative level can be easily represented by defining the relative interest parameter as a function of observed factors. Fourth, it is easier to introduce relative interest to any utility-based choice models. Finally, it is possible to approximately present endogenous generation of choice set using a one-step modeling approach rather than the conventional problematic two-step approach. These positive features of relative interest motivate us to introduce it into the RRM and RAM models.

3.6 Introducing Relative Interest into the RRM and RAM Models

Conventional choice models assume that individuals recognize different alternatives in the choice set equally. Unequal evaluation (or relative importance) of different alternatives in a choice set is reflected in the RURI and MPRI models, but it is not a specific feature that is only applicable to the RURI and MPRI models. Such relative importance of different alternatives is widely observed as a general feature of human decisions (e.g., Coleman, 1973; Gupta, 1989). The RRM and RAM models with relative interest are renamed the RRM_RI model and the RAM_RI model, with corresponding systematic regret $\tilde{R}_{ni}$ and relative advantage function $\overline{RA}_{ni}$ rewritten as follows:

$$R_{ni} = r_{ni}\left(\delta_i + \left(-\widetilde{R}_{ni}\right) + \sum_s \theta_{is} z_{ns}\right) + \varepsilon_{ni}, \tag{12}$$

$$RA_{ni} = r_{ni}\left(\delta_i + \overline{RA}_{ni} + \sum_s \theta_{is} z_{ns}\right) + \varepsilon_{ni}. \tag{13}$$

In the following section, the RURI, MPRI, RRM, and RAM models, along with the RRM_RI and RAM_RI models, are estimated and compared.

4. DATA FROM A STATED PREFERENCE SURVEY

We adopt SP survey data collected in Beijing in May 2008, where it was assumed that drivers' vehicles were equipped with a personal navigation device that could provide drivers with dynamic traffic information. In the SP survey, four alternatives of joint choice of departure time and driving route are assumed: trunk road during off-peak hours, ring road, trunk road, and branch road during peak hours (hereafter, expressed as "Off-peak hours – Trunk road," "Peak hours – Ring road," "Peak hours – Trunk road", and "Peak hours – Branch road," respectively). The assumed attributes and levels are travel purpose (business, recreation), error of dynamic travel information prediction (high: 30%; low: 10%), timing constraint for arrival time (whether being late is allowed or not), travel distance for the three routes (long, medium, and short distance), travel time for the three routes (long and short time), and probability of arrival time delay (low: 20%; high: 60%) for the three routes in peak hours. The above attributes are statistically combined together to form a set of attributes for SP choice tasks by applying an orthogonal table method to guarantee the independence between these attributes. As a result, 16 SP profiles are obtained. To reduce respondents' answering burden, these 16 profiles are grouped into four balanced blocks. Each respondent received only one block with four profiles and was asked to choose one alternative from the four alternatives. The probability for arrival time delay during off-peak hours is set at 0% and the travel time during off-peak hours is also fixed. Drivers were told that they would have 2 hours for staying at home before departure in the case of choosing peak hours and only 30 minutes in the case of choosing off-peak hours.

Four major areas were selected to capture typical OD (origin and destination) trips: (1) CBD (central urban area: between the famous WangFuJing street and Beijng station); (2) WangJing district (a residential area in the northeastern area between the 4th and 5th ring roads (close to Beijing Airport); (3) ZhongGuanCun district (an educational and IT-related area in the northwestern area between the 3rd and 5th ring roads); and (4) The Second Office Area (a governmental function area in the southern area between the 2nd and 3rd ring roads). Travel distance and travel time were calculated based on the selected four areas.

The SP survey was conducted using the face-to-face interview at major parking facilities of the above four survey areas in May 21~23, 2008 with the help of local university students. Drivers who parked their cars at the selected parking facilities of the four survey areas were randomly reached and as a result, 624 drivers agreed to participate in the survey and 2,496 valid SP responses were successfully obtained in total. Most of the respondents were males (78%). Share of respondents aged 20~39 years old was 72%. The primary occupation (63.6%) was a full-time company worker, followed by the self-employed (17.3%) and governmental staffs (6.9%). And, 51.6% of respondents visited the survey areas at least two or three times per week. SP choice results showed that on average, trunk road in off-peak hours was the most preferred alternative (45%), followed by ring road in peak hours (27%).

5. MODEL ESTIMATION AND DISCUSSION

Here, we estimated the previously described six types of context dependence models that describe Beijing drivers' stated choice behavior with respect to departure time and driving routes: the RURI, MPRI, RRM, RAM, RRM_RI, and RAM_RI models. The only alternative-specific attribute is travel time, and therefore the context in this study refers to the alternative-specific context with respect to travel time.

5.1 Explanatory Variables

Gain and loss with respect to travel time for an alternative are calculated by directly comparing the travel time of other alternatives in the choice set one by one. Specifically, gain for alternative *i* is identified if its travel time is shorter than that of alternative *j*, and loss occurs in the case that travel time is longer.

Regret is calculated as shown in equation (10c). Since unknown parameters are included in the specification of regret, equation (10) endogenously identifies the influence of regret. The regret of alternative *i* is calculated as $\tilde{R}_{ni} = \sum_{j \neq i} ln\left(1 + exp\left(\pi_k \left(t_{nj} - t_{ni}\right)\right)\right)$, where t_{ni}, t_{nj} are the travel times of alternatives *i* and *j*, respectively.

Calculating relative advantage and disadvantage of the RAM model originally requires a comparison of partial utilities of the same attributes between pairs of alternatives in the choice set. However, the partial utilities include unknown parameters in a more complicated way than that in the RRM model. Even though it is possible in theory to endogenously estimate the relative advantage together with the threshold (see equation (11e)), the estimation task is certainly not straightforward. Following Leong and Hensher (2012), we assume that lower values of travel time are preferred to higher values and consequently are perceived as an ‘advantage’, higher values of travel time are seen as a ‘disadvantage’, and the advantage of alternative *i* over *j* with respect to attribute *k* is simply the corresponding advantage of *j* over *i* with respect to the same attribute.

In a previous study (Zhang and Fujiwara, 2004), heterogeneous relative interest is represented as a function of some observed variables. To avoid unnecessary confusion as much as possible, we directly estimated the relative interest parameters in this study.

Since the SP survey only introduced travel time as the alternative-specific variable, to improve the model accuracy, we selected different alternative-generic variables to explain the utilities of different alternatives based on a preliminary study. We selected gender, age, and timing constraint of arrival for “Peak hours – Ring road,” familiarity with road network for “Peak hours – Trunk road,” ownership of car navigation system and error of travel time prediction for “Peak hours – Branch road,” and trip purpose for “Off-peak hours – Trunk road.”

In addition to the above variables, we also introduce a common constant term of the three alternatives during peak hours to explore travelers’ unobserved propensity of choice behavior.

5.2 Model Performance

Model estimation results for the six types of models are shown in Table 1. As stated in previous studies (Zhang et al., 2010, 2013), existing model estimation techniques are not suitable for estimating the three prospect parameters. Before exploring better estimation methods, we first estimated the MPRI model by adopting the original set of prospect parameters estimated by Tversky and Kahneman (1992), i.e., $\alpha = \beta = 0.88$, and $\lambda = 2.25$; then, to find a better set of prospect parameters, we repeatedly estimate the MPRI model by changing the values of prospect parameters. Figure 1 shows the simulation results for a narrower range of loss aversion parameter λ but with smaller step sizes of iterations; Figure 2 illustrates the results for a wider range of loss aversion parameter λ but with larger step sizes of iterations.

The adjusted McFadden’s Rho-squared is 0.0933 for the MPRI model ($\alpha = \beta = 0.88$ and $\lambda = 2.25$), 0.0933 for the RURI model, 0.0924 for the RRM model, and 0.0931 for the RAM model, respectively. The first two models perform slightly better than the last two models without introducing the relative interest parameters, but the difference of model accuracy is not very large. To further confirm whether differences of model accuracy between the first two and last two models are statistically significant, a χ^2 test was conducted, where the degree of freedom is three and the corresponding critical χ^2 value is 7.82. The χ^2 value for comparing the RRM and MPRI (RURI) models is 10.94 (10.72), which is larger than the critical value 7.82; the value for comparing the RAM and MPRI (RURI) models is 6.94 (6.72), which is smaller than the critical value 7.82. Therefore, it can be concluded that the RAM model is in no way inferior to the RURI model.

At first sight, it can also be concluded that the RAM model is not inferior to the MPRI model. Remember that the estimated results of this MPRI model are obtained by assuming that $\alpha = \beta = 0.88$ and $\lambda = 2.25$, which are drawn from the study by Tversky and Kahneman (1992) in the context of stock exchange. Consequently, the applicability of these prospect parameters to the travel behavior analysis should be questioned (Zhang et al., 2013). To check the sensitivity of the log-likelihood to the above three prospect parameters, we re-estimated the MPRI model by changing α from 0.1, 0.2, 0.4, …, 1.0 (step size: 0.2), β from 0.1, 0.2, 0.4, …, 1.0 (step size: 0.2), and λ from 1.0, 1.2, 1.4, …, 6.0 (step size: 0.2). The log-likelihood values are shown in Figure 1. It was found that the maximum log-likelihood (–2334.61) is reached when $\alpha = 1.0$, $\beta = 0.1$, and $\lambda = 1.0$ (MPRI model (Simulated Best) in Table 1). Comparing this maximum log-likelihood with that of the RAM model (–2344.46), the χ^2 value is 19.70, which is clearly larger than the critical value 7.82. This suggests that the MPRI model in fact performs better than the RAM model from the perspective of model accuracy. To further confirm the sensitivity of the log-likelihood to the prospect parameters, we reconducted the simulation by adopting a wider range of the λ value ($\alpha = 0.1, 0.3, …, 0.9$; $\beta = 0.1, 0.3, …, 0.9$; $\lambda = 5.0, 5.5, 6.0, 6.5, …, 19.5$). However, it was found that the maximum log-likelihood is just –2340.91; it appears difficult to find log-likelihood values larger than –2334.61 (see Figure 1). The results of the MPRI model with the simulated best set of prospect parameters "$\alpha = 1.0$, $\beta = 0.1$, and $\lambda = 1.0$" are shown before the MPRI model with prospect parameters "$\alpha = \beta = 0.88$ and $\lambda = 2.25$" in Table 1.

One good feature of the MPRI and RURI models is that a relative interest parameter is introduced with respect to each alternative in the choice set. In fact, the same relative interest parameter can also be introduced to the RRM and RAM models; the RRM and RAM models with relative interest are thus estimated (the last two models: RRM_RI and RAM_RI in Table 1). It is observed that introducing the relative interest parameter clearly leads to larger log-likelihood values. The adjusted McFadden's Rho-squared value is 0.0937 for the RRM_RI model and 0.0936 for the RAM_RI model, which are slightly larger values than those of the MPRI model with prospect parameters "$\alpha = \beta = 0.88$ and $\lambda = 2.25$" and the RURI model. Even in the case of introducing the relative interest parameter, the adjusted McFadden's Rho-squared value of the MPRI model with the simulated best set of prospect parameters is still larger than the values of the RRM_RI and RAM_RI models.

In summary, we can draw the following conclusions: (1) the MPRI model with a best set of prospect parameters is superior to any other model; (2) the RURI model performs better than the RRM model without relative interest; (3) the RAM model without relative interest is not inferior to the RURI model; and (4) introducing the relative interest parameter into the RRM and RAM models can improve their model accuracy. However, we should note that the differences of model accuracy between the MPRI and RURI models and other models are not very large. Thus, we can conclude that introducing nonlinear context dependence together with relative interest can improve the model accuracy of choice behavior. Needless to say, incorporating nonlinear context dependence and relative interest is not only for the purpose of improving model accuracy. More importantly, nonlinear context dependence and relative interest can also be used to capture more general behavioral choice mechanisms, which will be explained below.

5.3 Influence of Content-dependent Travel Time

All six models estimated that the context-dependent travel time is statistically influential to the joint choice behavior. In addition, signs of travel time parameters are all logical. The negative sign of travel time in the RURI model is because the travel time is represented as a simple difference between two alternatives. In contrast, the MPRI model represents the influence of travel time in the form of "gain–loss," and therefore, the positive parameter means that drivers prefer gains to losses. In the RRM model, the negative parameter of regret with respect to travel time suggests that drivers dislike regret. In the RAM model, the positive sign of the relative advantage with respect to travel time is also consistent with our expectation.

The original set of prospect parameters "$\alpha = \beta = 0.88$ and $\lambda = 2.25$" suggests that decision makers are more sensitive to loss than to gain. In contrast, the simulated best set of prospect parameters "$\alpha = 1.0$, $\beta = 0.1$, and $\lambda = 1.0$" shows that drivers are almost insensitive to increased travel time (i.e., loss) from competitor alternatives, but significantly sensitive to reduced travel time (i.e., gain). In particular, the sensitivity to gain is higher in the MPRI model with the simulated best set of prospect parameters than in the MPRI model.

5.4 Relative Interest Parameters

Comparing the relative interest parameters of the RURI model and the MPRI model with the original set of prospect parameters, the two models show similar patterns of relative importance attached to different choice alternatives, with the highest interest in the alternative “Peak hours – Ring road” and the lowest interest in the alternative “Peak hours – Trunk road” (the highest relative interest parameter is 2.2–2.8 times higher than the lowest value). On the other hand, the simulated best set of prospect parameters (MPRI model (Simulated Best) in Table 1) estimates that drivers attach the highest importance to the alternative “Peak hours – Trunk road,” which is 5.6 times higher than the alternative “Peak hours – Ring road” with the least importance.

Relative interest parameters from the RRM_RI and RAM_RI models show different patterns from the MPRI and RURI models. The most important alternative in the RRM_RI model is “Off-peak hours – Trunk road” while the alternative “Peak hours – Ring road” is regarded as the most important in the RAM_RI model, which is the same as the MPRI model with the simulated best set of prospect parameters.

5.5 Different Influential Factors in Relative Utility Models and Other Models

Common features of the MPRI, RURI, RRM, and RAM models are first noted. Drivers with business trip purposes are more likely to travel during off-peak hours and use trunk roads. If being late is permitted, drivers prefer to choose peak hours and use ring roads. Gender and age are not influential. All four models also estimate a significantly negative constant term, meaning that unobserved/omitted factors discourage the choice of peak hours in Beijing.

As for error of travel time prediction, however, relative utility models and RRM and RAM models show a completely different picture. Relative utility models (MPRI, RURI) estimated a negative and statistically significant parameter, but RRM and RAM models estimated a positive and insignificant parameter. The negative parameter suggests that, if the prediction error is lower (i.e., the accuracy is higher), drivers are more likely to use branch roads during peak hours. Such preference seems realistic because traffic congestions often occurs on major roads in Beijing over a longer time of a day, forcing many drivers to avoid use of major roads. In this sense, results of RRM and RAM models seem problematic. Introducing relative interest into RRM and RAM models seems not effective to correct such unrealistic results.

Other differences between the MPRI/RURI models and the RRM/RAM models are also clarified. The MPRI/RURI models estimate that the ownership of car navigation system and the familiarity with road network do not significantly affect the joint choice; however, the RRM/RAM models confirm their significant influence. The RRM/RAM models provide logical estimations of the influence of the familiarity with road network in the sense that it is consistent with the survey observation. However, all four models show that the estimated parameter signs are all negative, which is contrary to the survey observation.

In the MPRI model with the best set of prospect parameters “$\alpha = 1.0$, $\beta = 0.1$, and $\lambda = 1.0$” (MPRI model (Simulated Best) in Table 1), the constant term becomes insignificant, but the ownership of car navigation system and familiarity with road network become significant. Other parameters show the same signs and statistical significance as those in the MPRI model with the original set of prospect parameters from Tversky and Kahneman (1992).

Introducing relative interest parameters into the RRM and RAM models improved the model accuracy, but familiarity with road network is estimated to be inconsistent with the observed SP responses. The constant term in the RAM_RI model becomes positive, which is different from the other models. Other parameters show a consistent trend with the RRM/RAM models without relative interest parameters.

6. CONCLUSION

Human behavior, including travel behavior, is context dependent. This phenomenon is not an exceptional case, rather a robust feature of actual human behavior. It is also true that people may not always attach equal importance to each alternative in a choice set. This study makes an additional effort to simultaneously model these two types of choice decision-making mechanisms by extending the relative utility model (a non-IIA choice model) developed by Zhang et al. (2004a) to deal with asymmetric responses to gain and loss in the same relative utility modeling framework with relative interest parameters, which are used to accommodate unequal evaluation of different choice alternatives. With this extension, both multiple reference points (an original feature of the relative utility model) and nonlinear context dependence are accommodated. Different from previous studies (Zhang et al., 2010, 2013), this study conceptually and empirically compared the performance of four major types of content-dependent choice model (the RURI, MPRI, RRM, RAM, RRM_RI, and RAM_RI models; all are non-IIA choice models) using SP survey data of Beijing drivers' departure time and driving route choice behavior under the provision of dynamic travel information. Even though the original concept of relative utility emphasizes alternative-based comparisons, this study transformed the original model structure to explicitly reflect attribute-based comparisons, as in the RRM and RAM models. In addition, relative interest parameters were also introduced into the RRM and RAM models. It is empirically confirmed that in this case study, the MPRI model is superior to any other model, even when introducing relative interest parameters into the RRM and RAM models (i.e., RRM_RI and RAM_RI models). It is also clarified that introducing relative interest parameters clearly improved the performance of the RRM and RAM models. In summary, alternative-/attribute-based comparisons, nonlinear responses, and relative interest are three powerful "spears" to "defeat" the "shield" of context dependence. Furthermore, drivers' asymmetric responses to travel time and realistic responses to the prediction error of travel time were also estimated. Different influential factors were also found between relative utility models and other models. Thus, the effectiveness of relative utility models was confirmed from not only model accuracy, but also the revealed choice behavioral mechanisms.

Conceptually, the original concept of relative utility covers all the features of the MPRI, RRM, and RAM models. More importantly, because relative utility includes three types of reference points, it may serve as a meta-concept to represent bounded rationality in a more logical way than other relevant concepts. It is expected that further decomposing the original relative utility concept could contribute to a better understanding of context dependence. The above six models should be recompared by distinguishing the preference into context-dependent and context-independent preferences, as proposed by Tversky and Simonson (1993). Introducing not only alternative-oriented relative utility, which is the focus in this study, but also time-oriented and decision maker-oriented relative utilities could further improve the abilities of relative utility to represent and explain the influence of various types of context dependences across space and over time. Since the relative utility concept can be easily introduced into any utility-based choice model in theory, as shown in previous studies (Zhang et al., 2002, 2008), context-dependent mechanisms that are examined in this study should be further investigated using other types of choice model structures by conducting more case studies.

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Table 1. Model Estimation Results

Explanatory variables \ Model	MPRI model (Simulated Best)			MPRI model			RURI model			RRM model			RAM model			RRM_RI model			RAM_RI model		
	Parameter		t-statistic	Parameter		t-statistic	Parameter		t-statistic	Parameter		t-statistic	Parameter		t-statistic	Parameter		t-statistic	Parameter		t-statistic
Constant term (1~3) (reference: off-peak hours - trunk road)	0.7724		1.454	-1.4625	**	-3.326	-1.3703	*	-2.036	-0.4492	**	-3.624	-0.3591	**	-2.826	-3.0590	+	-1.752	1.3130	+	1.703
Individual attributes																					
Gender (1: male; 0: female) (1)	-1.0846		-0.776	-0.1716		-0.429	-0.2521		-0.564	-0.0843		-0.660	-0.0973		-0.762	-0.1493		-0.259	-0.4009		-0.445
Age (1)	-0.0915		-1.002	-0.0017		-0.053	-0.0829		-0.401	-0.0022		-0.237	-0.0038		-0.398	0.0098		0.218	-0.0123		-0.181
SP attributes																					
Trip purpose (1: Business; 0: Recreation) (4)	1.6018	**	2.811	1.1873	+	1.780	1.1970	+	1.887	0.3582	**	3.783	0.4990	**	5.224	0.9193	*	2.153	1.6118	**	4.315
Timing constraint of arrival (1: Being late is permitted; 0: not permitted) (1)	5.0542	*	2.555	1.4517	**	3.145	1.5591	*	3.142	0.4646	**	4.597	0.5001	**	4.931	2.1467	**	3.266	3.6582	**	3.000
Error of travel time prediction (two levels: 10% and 30%) (3)	-10.7376	*	-2.293	-4.7750		-1.493	-4.3298		-1.495	0.0739		0.432	0.0928		0.543	1.1275		1.490	1.8716		0.529
Travel time	($\alpha = 1.0$, $\beta = 0.1$, $\lambda = 1.0$)			($\alpha = \beta = 0.88$, $\lambda = 2.25$)																	
Gain - Loss	0.1116	**	7.308	0.0333	**	5.598															
Difference between alternatives							-0.0373	**	-5.770												
Regret										-0.0182	**	-6.452				-0.0934	**	-5.141			
Relative advantage													0.2343	**	6.809				0.2343	**	6.809
Other attributes																					
Ownership of car vavigation system (1: Yes; 0: No) (3)	-1.8742	*	-2.041	-0.8129		-1.037	-0.6472		-0.940	-0.4578	**	-2.844	-0.4289	**	-2.658	-0.9874		-1.309	-4.7122		-1.225
Familarity of road network in Beijing (2)	-0.0947	+	-1.690	-0.2092		-0.872	-0.1261		-0.636	0.0278	+	1.646	0.0277	+	1.654	-0.3882		-1.394	-0.1188	+	-1.690
Relative interest parameter																					
(1) Peak hours - Ring road	0.0902	**	3.560	0.3343	**	3.928	0.3000	**	3.964							0.2316	**	4.044	0.1437	**	4.672
(2) Peak hours - Trunk road	0.5026	**	6.828	0.1188	*	2.509	0.1348	*	2.313							0.1206	**	4.480	0.4284	**	6.700
(3) Peak hours - Branch road	0.1709	*	2.345	0.2518	**	3.610	0.2816	*	3.496							0.2747	**	4.363	0.0752		1.099
(4) Off-peak hours - Trunk road	0.2363	**	6.039	0.2951	*	2.297	0.2835	**	2.721							0.3731	**	3.126	0.3527	**	7.080
Initial log-likelihood	-2595.14			-2595.14			-2595.14			-2595.14			-2595.14			-2595.14			-2595.14		
Converged log-likelihood	-2334.61			-2340.99			-2341.1			-2346.46			-2344.46			-2339.96			-2340.36		
Adjusted McFadden's Rho-squared	0.0958			0.0933			0.0933			0.0924			0.0931			0.0937			0.0936		
χ^2 test (critical value = 7.82; degree of freedom: 3)										23.70 (a), 10.94 (b), 10.72 (c)			19.70 (a), 6.94 (b), 6.72 (c)								
Sample size (SP responses)	1872			1872			1872			1872			1872			1872			1872		

(Note) (i) +: significant at 10% level; *: significant at 5% level; **: significant at 1% level.

(ii) (1) ~ (4): choice alternatives ((1) Peak hours - Ring road; (2) Peak hours - Trunk road; (3) Peak hours - Branch road; (4) Off-peak hours - Trunk road)

(iii) Some explanatory variables are differently introduced to the four choice alternatives, which are identified with the numbers (1) ~ (4).

(iv) χ^2 test: whether the RRM (RAM) model is different from the MPRI model (a) and RURI model (b).

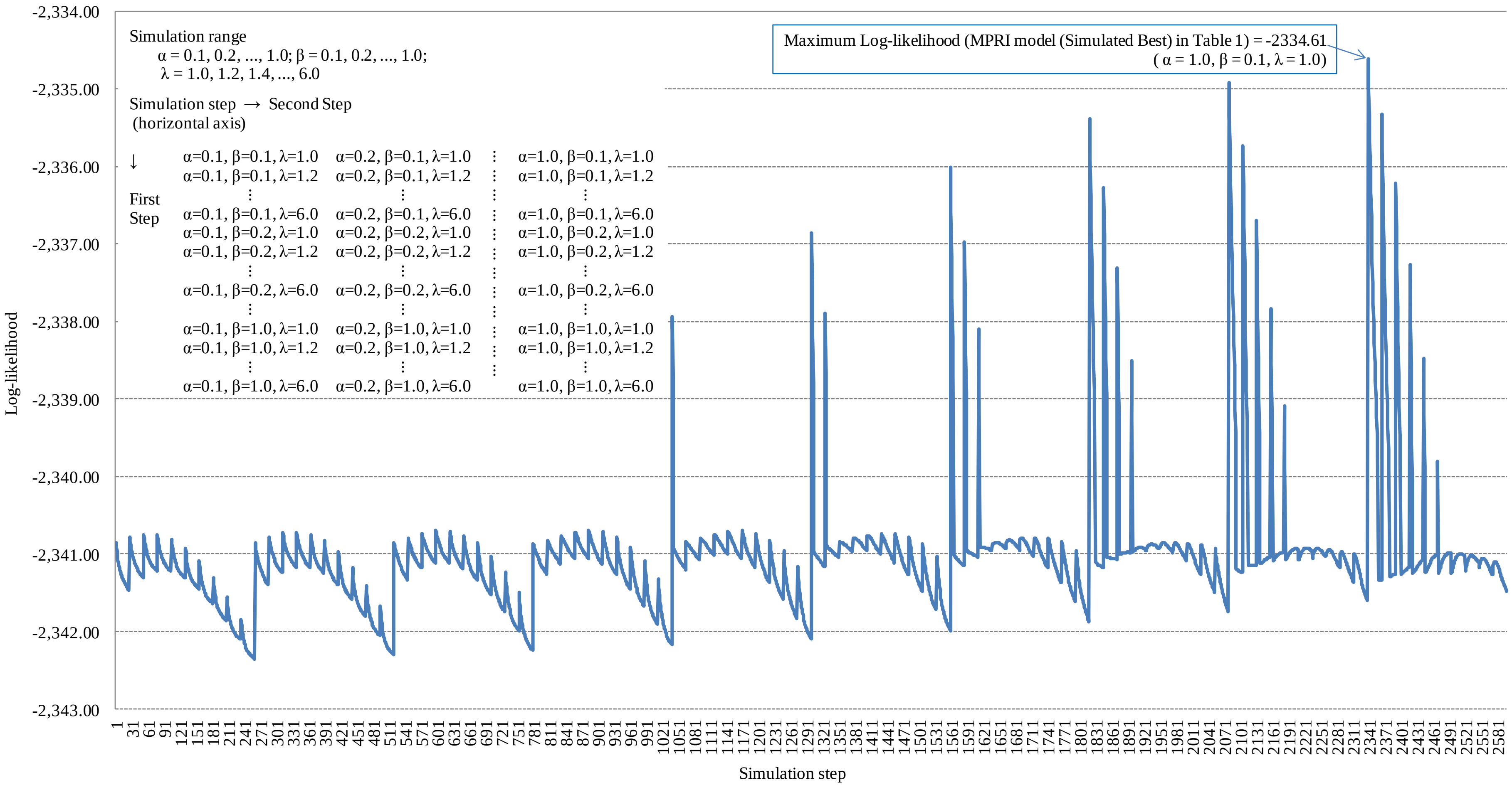

Figure 1. Simulation results of MPRI model: Narrower range of loss aversion parameter and smaller step sizes of iterations