A GENERALIZED RELATIVE UTILITY BASED CHOICE MODEL WITH MULTIPLE CONTEXT DEPENDENCIES

Junyi Zhang
Graduate School for International Development and Cooperation, Hiroshima University, 1-5-1 Kagamiyama, Higashi-Hiroshima, 739-8529, Japan; E-mail: zjy@hiroshima-u.ac.jp

Abstract
Representing context dependence has been attracting more and more attentions in behavioral studies. This study compares six types of context dependence models with in order to clarify the superiority of alternative-oriented relative utility (RU). The RU-based models include the RU model with relative interest (RURI model) and the multiple prospects model with relative interest (MPRI model). Comparison models are the random regret minimization (RRM) model and the relative advantage maximization (RAM) model, which are further improved by introducing the relative interest (RRM_RI and RAM_RI models). Conceptually, the RU covers all the features of the other models in an implicit but comprehensive way and especially, it can be extended to deal with time-oriented and decision maker-oriented context dependence. Thus, the RU is a more general concept. Even though the RU is originally specified to allow for the alternative-based context dependence, RURI and MPRI models are transformed to explicitly accommodate the attribute-based context dependence for comparison. An empirical study is carried out by using a stated preference (SP) data (1,872 samples) on Beijing drivers’ joint choice of departure time and driving route under the provision of dynamic travel information. It is confirmed that the MPRI model is superior to any of the other five models. Incorporating the relative interest into the RRM and RAM models improves the model performance.

Keywords: Relative utility, multiple context dependences, prospect, random regret minimization, relative advantage maximization, reference points, relative interest, simulation

Submission Data: March 24, 2012
Word count: 9,926 words (9,426 words + 1 Figure + 1 Table)
1. INTRODUCTION

The importance of incorporating context dependence into 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). Especially, 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 to adopt the concept of relative utility to represent the 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). The relative utility argues that utility is only meaningful relative to reference point(s), which is consistent with the prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Differently, the relative utility allows inclusion of multiple reference points in a systematic way. The influence of multiple reference points reflects general features of human decisions (e.g., Koop and Johnson, 2012; Lin et al., 2006).

Recently, two more appealing context-dependent choice models have been attracting some attentions, especially in transportation. One is the random regret minimization (RRM) model (Chorus et al., 2008, 2013) and the other is the relative advantage maximization (RAM) model (Kivetz et al., 2004; Leong and Hensher, 2012). The 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 the relative utility is specified to allow for the 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 have been already reflected in the relative utility models. The differences are that, (1) the existing relative utility models deal with the comparisons in a linear way while the RRM and RAM models do in a non-linear way; (2) the RRM model ignores the role of relative advantage, the RAM does not pay proper attention to the regret, and the 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, but 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 with the prospect theory.

The purpose of this study is to clarify how to incorporate the context dependence into choice models. This is done by, 1) comparing the original relative utility model with relative interest (RURI model) (Zhang et al., 2004) and its extended version (called multiple prospects model with relative interest (MPRI model) (Zhang et al., 2010, 2013) with the RRM and RAM models, and 2) to examine whether introducing unequal alternative evaluation structures (by
use of relative interest parameter) can improve the performance of RRM and RAM models. In the empirical study, we use an SP data on Beijing drivers’ joint choice of departure time and driving route under the dynamic travel information provision, which were adopted in our previous studies (Zhang et al., 2010, 2013), where 1,872 valid SP responses were collected.

In the remaining part 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 as well as RRM and RAM models with relative interest (RRM_RI and RAM_RI models) in Section 3. The data used in this study is explained in Section 4. Model estimation results and discussion are given in Section 5. Finally, the study is concluded in Chapter 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 literature.

It is revealed that composition of a choice set influences the evaluation of an alternative (composition effect: Timmermans et al., 1996). Alternatives gain share when they become intermediate options in the choice set (compromise effect: Kivetz et al., 2004). Adding a dominated alternative to the choice set increases the choice probability of some other alternatives (dominated-alternative effect: Huber, Payne and Puto, 1982; Pettibone and Wedell, 2000; Simonson and Tversky, 1992; Wedell and Pettibone, 1996). 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 “independence of irrelevant alternatives (IIA)” assumption)”. Some alternatives might be perceived as being more similar and therefore more substitutable (substitution and similarity effect: Borgers and Timmermans, 1988). The presentation format of the choice task leads individuals to attribute-wise processing of information (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 (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 (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 might be context-dependent. For example, Arentze et al. (2012) examined how truck drivers show 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 be due to “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 feature of context dependence might 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, 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.

There are two choice models developed during the early stage of choice model research, i.e., universal logit model (McFadden et al., 1977) and dogit model (Gaudry and Dagenais, 1979), which can be used to represent the 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), or 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.

Kahneman and Tversky (1979) found for gambling behavior that people’s decisions tend to be more sensitive to losses than to gains. Similar conclusions have been reached in finance, economics, consumer science, and political science and so on (Avineri and Chorus, 2010). Tversky and Simonson (1993) defined a value function with context-dependent and context-free preferences. In recent years, the prospect theory has been actively applied and improved (Van de Kaa, 2010a, b; Rose and Masiero, 2010; Timmermans, 2010; Van Wee, 2010). As argued by Timmermans (2010), however, “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 above-reviewed models, 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 be also used to represent the context dependence. Especially, they are more powerful than other existing models. Since these models are the focus in this study, details will be given in the next section.

What we can conclude from the above review are that, (1) there is no universally agreed definitions of the context and the context dependence, (2) development of context dependence models has been active, but not satisfactory, and there are therefore various unresolved research issues, including how to investigate the context dependence based on surveys and how to logically introduce the context dependence into choice models.

3. CONTEXT DEPENDENCE MODELING

Here, four types of context dependence models will be first introduced: RURI, MPRI, RRM, and RAM models. Second, the four models will be conceptually compared. Third, recognizing the behavioral importance of relative interest, two new models will be developed by introducing the relative interest into RRM and RAM models (two new models are called RRM_RI model and RAM_RI model, respectively). For simplifying the comparison and discussion, all the 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 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, the time can also 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 choices of other alternatives (i.e., the choice set composition effect is captured).

Second, an individual may compare the alternative(s) that 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 other alternative, serve as reference points. For example, Kahneman and Tversky (1979) acknowledged that a reference point may depend on expectations and social comparisons in part. Expectations are linked with the preference in future (Pervin, 1989), and goals serve as reference points and alter outcomes (Heath et al., 1999). Frederick and Loewenstein (1999) argued that past experience can be serviced as a candidate of reference point. In the context of health decision, it is revealed that past or future losses can serve as reference points (Schwartz et al., 2008). The influence of future expectation 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.

Third and lastly, to reflect the fact that a decision maker may compare the alternatives chosen by other persons, the following decision maker-oriented relative utility.

\[
U_{nit} = f\left( u_{nit} \mid \left( u_{n't'} : n' \in social \text{ reference group} \right) \right) \tag{3}
\]

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 kids safely and buying a house that is closer to the partner’s workplace and/or the kid’s school). The social reference group can be a small group of persons like household members, or an unspecified group of persons.
With the above-defined relative utilities, the principle of relative utility maximization was further proposed by Zhang et al. (2004a). It is assumed that an individual choose 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.

\[
U_{ni} = r_{ni} \sum_{j \neq i} (u_{ni} - u_{nj})
\]  

(4)

Note that time suffix \( t \) is omitted for the simplicity. In fact, \( r_{ni} \) can take any real value, in theory, but one of relative interest parameters must be fixed. For the ease of interpretation of model estimation results, it is usually assumed that \( 0 \leq r_{ni} \leq 1, \sum_{r_{ni}} = 1 \). 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, as shown below.

\[
U_{ni} = r_{ni} \sum_{j \neq i} w_{nij} (u_{ni} - u_{nj}), \quad w_{nij} \geq 0, \sum_{j \neq i} w_{nij} = 1
\]  

(5)

The advantage of introducing the weight parameter \( w_{nij} \) is that a quasi-nested choice model structure can be obtained by re-grouping alternatives in choice set into several bundles, which share a same weight parameter. Details refer to Zhang and Fujiwara (2004).

Note that all the 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 speaking, it is implicitly assumed that people show symmetric responses to advantageous and disadvantageous outcomes.

In summary, the advantage/disadvantage of \( u_{ni} \) relative to \( u_{nj} \), relative importance \( (w_{nij}) \) in deriving the advantage/disadvantage of \( u_{ni} \), and relative importance \( (r_{ni}) \) of each alternative in 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 the attribute-based comparisons and distinguishing the signs of \( x_{nk} - x_{nk} \) results in the MPRI, RRM, and RAM models. Allowing for the relative importance \( (r_{ni}) \) of each alternative in choice set under the framework of RRM and RAM models leads to the RRM_RI and RAM_RI model. These will be explained in details later. As implied by the meaning of weight parameter \( w_{nij} \), if preference of alternative \( i \) is independent from some alternatives (i.e., the weight is zero), then the relative utility can be specified into two parts: i.e., the context-independent and context-dependent preference. If whether comparison of an attribute between attributes brings an advantage or disadvantage depends on decision makers’ individual tastes, one can just directly estimate a parameter for \( x_{nk} - x_{nk} \). 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

The 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 \[ r, r_0 \leq \sum \text{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 quasi-nested choice structure, which is much more flexible and logical to represent complicated choice mechanisms with many alternatives than the nested logit model.

As a new extension, Zhang et al. (2005) applied the 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 the relative utility. Zhang (2006) conceptually discussed how to generalize the originally proposed three types of relative utility.

The concept of relative utility can be easily introduced into any utility-based choice models. Zhang et al. (2002) developed a combined dynamic SP/RP model with relative utility and heterogeneous relative interest (called r_SP/RP model) using an SP panel survey data on travel mode choice. Zhang et al. (2008) introduced the relative utility into the PCL (paired combinatorial logit) model (called r_PCL) that can represent both observed and unobserved inter-alternative similarities. A case study was done by use of data from a stated tour package choice experiment with respect to the tourism along the Asian Highway.

3.2 Multiple Prospects Model with Relative Interest (MPRI)

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

First, define the standard utility \( u_{ni} \) as follows:

\[
u_{ni} = \delta_i + \sum_k \pi_k x_{nik} + \sum_i \theta_{ns} z_{ns} + \epsilon_{ni}
\]

where, \( \epsilon_{ni} \) is a deterministic (or non-stochastic) term and \( \epsilon_{ni} \) indicates an error term. The standard utility is explained by alternative-specific attributes (\( x_{nik} \)), alternative-generic attribute (\( z_{ns} \)), and a constant term (\( \delta_i \)) in a linear way.

Substituting equation (6) into equation (5) results in,

\[
U_{ni} = r_{ni}(\delta_i + \sum_k \pi_k x_{nik}) + \eta_{ni}
\]

\[
\Psi_{ni} = \sum_{j \neq i} w_{nij} (\sum_k \pi_k (x_{nik} - x_{njk}))
\]

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

$$Ψ_{mi} = \sum_{k} \sum_{j} \pi_k \left( (d_{nij,k}^+ \Delta x_{nij,k})^\alpha - \lambda (d_{nij,k}^- \Delta x_{nij,k})^\beta \right)$$

Here, two dummy variables are introduced: $d_{nij,k}^+$ is equal to 1 if $\Delta x_{nij,k} = x_{nij} - x_{nj}$ is non-negative, 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 $\alpha$ and $\beta$ (equal to or smaller than 1) determine the convexity/concavity of the utility function, and $\lambda$ (equal to or larger than 1) describes the degree of loss aversion. In the above formulation, weight parameters ($w_{nij}$) are omitted for simplifying 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 Random Regret Minimization (RRM) Model

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:

$$R_{ni} = \delta_i + \left( -\tilde{R}_{ni} \right) + \sum_j \theta_{nj} z_{nj} + \varepsilon_{ni}$$

$$P_{ni} = \exp \left( \delta_i + \left( -\tilde{R}_{ni} \right) + \sum_j \theta_{nj} z_{nj} \right) / \sum_j \exp \left( \delta_j + \left( -\tilde{R}_{nj} \right) + \sum_k \theta_{jk} z_{jk} \right)$$

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

The choice probability $P_{ni}$ is obtained by assuming that $\varepsilon_{ni}$ 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 ($\delta_i, \delta_j$) and alternative-generic partial utilities ($\theta_{nj} z_{nj}, \theta_{jk} z_{jk}$) 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., extremeness aversion effect and compromise effect) (Chorus, 2013).

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 Relative Advantage Maximization (RAM) Model

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:

$$RA_{ni} = \delta_i + RA_{ni} + \sum_n \theta_{ni}z_{ni} + \varepsilon_{ni}$$  \hspace{1cm} (11a)$$

$$P_{ni} = \exp\left(\frac{RA_{ni}}{\sum_j \exp(\sum_{i,j} RA_{nj})}\right)$$  \hspace{1cm} (11b)$$

$$RA_{ni}(i, j) = \sum_i A_{nk}(i, j) + \sum_k D_{nk}(i, j)$$  \hspace{1cm} (11c)$$

$$A_{nk}(i, j) = \begin{cases} 
\pi_{nk}x_{nik} - \pi_{jk}x_{njk} & \text{if } \pi_{nk}x_{nik} - \pi_{jk}x_{njk} \geq \tau_k^{i \rightarrow j} \\
0 & \text{otherwise} 
\end{cases}$$  \hspace{1cm} (11d)$$

$$\text{where, } RA_{ni} \text{ is systematic relative advantage, } RA_{ni}(i, j) \text{ indicates individual } n \text{'s random relative advantage of alternative } i \text{ to the competitor alternative } j, \text{ and } A_{nk}(i, j) \text{ and } D_{nk}(i, j) \text{ are the advantage and disadvantage of alternative } i \text{ over alternative } j \text{ with respect to attribute } k, \text{ respectively. } \tau_k^{i \rightarrow j} \text{ is a threshold to judge whether the difference between a pair of partial utilities } (\pi_{nk}x_{nik} - \pi_{jk}x_{njk}) \text{ is larger enough to generate the advantage. Analogue to } A_{nk}(i, j), \text{ } D_{nk}(i, j) \text{ can be calculated, too. Note that constant terms } (\delta_i, \delta_j) \text{ and alternative-generic partial utilities } (\theta_{ni}z_{ni}, \theta_{ji}z_{ji}) \text{ are added to the original version of RAM model.}$$

3.5 Conceptual Comparison

All the above four models share similar attribute-based comparisons in order to reach final choice decisions. Both RRM and RAM model as well as MPRI model treat the context dependence at the attribute level. In contrast, 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 non-linear way. Since the comparisons are made at the alternative/attribute level, all the four models emphasize the existence and importance of multiple reference points. Attribute-based comparisons allow analysts to capture substitution/similarity effect and choice set composition effect as well as availability effect. Since RRM, RAM, and MPRI models allow for non-linear comparisons, compromise effect and dominated-alternative effect can be explicitly captured.

The shortcoming of RRM model (e.g., ignores well-performing alternatives) is overcome in the RAM model while the shortcoming of RAM model (e.g., pay 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 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 benefit 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 non-linearity. 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 the relative interest to any utility-based choice models. Forth and not the last, it is possible to approximately present endogenous generation of choice set using a one-step modeling approach rather than conventional problematic two-step approach. These good features of relative interest motivate us to introduce it into the RRM and RAM models.

3.6 Introducing Relative Interest into 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 alternative in a choice set is reflected in the RURI and MPRI model, 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 re-named as RRM_RI model and RAM_RI model, which corresponding systematic regret \( R_{ni} \) and relative advantage function \( RA_{ni} \) are re-written as follows:

\[
R_{ni} = r_{ni} (\delta_i + (-\bar{R}_{ni}) + \sum \theta_{is} z_{ns}) + \varepsilon_{ni} \tag{12}
\]

\[
RA_{ni} = r_{ni} (\delta_i + \bar{RA}_{ni} + \sum \theta_{is} z_{ns}) + \varepsilon_{ni} \tag{13}
\]

In the following part of this paper, not only the RURI, MPRI, RRM, and RAM models, but also the RRM_RI and RAM_RI models will be estimated and compared.

4. DATA

We adopt an SP survey data collected in Beijing in May 2008, where it was assumed that drivers’ vehicles were equipped with a personal navigation device, which 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 – Truck road”, “Peak
hours – Ring road”, “Peak hours – Truck 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 (long and short time) and probability of arrival time delay (low: 20%; high: 60%) for the three routes in peak hours. 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 to stay at home in case of choosing peak hours and they would only have 30 minutes to stay at home in case of choosing off-peak hours.

The orthogonal design, a common exercise in SP surveys, is used to generate SP cards assuring that attributes are virtually independent of each other. As a result, 16 SP cards are obtained, and randomly grouped into four blocks, each of which includes four SP cards. Each respondent was asked to answer only one block.

Four typical areas in Beijing were selected. Travel distance and time are calculated depending on the selected areas. Depending on pairs of origins and destinations, respondents were assigned with three or four alternatives. Drivers at the selected parking facilities were randomly contacted by interviewers and as a result, 624 drivers answered questionnaire sheets on site and totally, 2,496 valid SP responses were obtained. For simplifying the discussion, this study only adopted the SP data with four alternatives (1,872 SP responses).

5. MODEL ESTIMATION AND DISCUSSION

Here, we estimate the previously-described six types of context-dependent choice models that describe Beijing drivers’ stated choice behavior with respect to departure time and driving routes: RUIR, MPRI, RRM, RAM, RRM_RI, and RAM_RI models.

Only travel time is introduced as the alternative-specific attribute, and therefore the context in this study refers to the alternative-specific context with respect to the travel time.

5.1 Explanatory Variables

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

Regret is calculated as shown in equation (10c). Since unknown parameters are included in the specification of the regret, equation (10) endogenously identifies the influence of regret. Concretely, the regret of alternative $i$ is calculated as $R_i = \sum_{j \neq i} \ln \left( 1 + \exp \left( \pi_k \left( t_{nj} - t_{ni} \right) \right) \right)$, where $t_{ni}$, $t_{nj}$ are the travel time 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 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 surely not that easy. 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 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 the travel time as the alternative-specific variable, to improve the model accuracy, we selected different alternative-generic variables for explaining 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 of road network for “Peak hours – Truck road”, ownership of car navigation system and error of travel time prediction for “Peak hours – Branch road”, and trip purpose for “Off-peak hours – Truck 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 Accuracy

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 to estimate the three prospect parameters. Before figuring out 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 $\lambda = 2.25$, and 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 narrower range of loss aversion parameter $\lambda$ but smaller step sizes of iterations while Figure 2 illustrates the results for wider range of loss aversion parameter $\lambda$ but 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 former two models perform slightly better than the latter two models without introducing the relative interest parameters, but the difference of model accuracy is not large enough. To further confirm whether differences of model accuracy between the former two models and the latter two models are statistically significant or not, a $\chi^2$ test is conducted, where the degree of freedom is three and the corresponding critical $\chi^2$ value is 7.82. The $\chi^2$ statistic value for comparing the RRM and MPRI (RURI) models is 10.94 (10.72), which is larger than the critical value 7.82, and that 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 be also 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. In this sense, 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 $\alpha$ from 0.1, 0.2, 0.4, ..., 1.0 (step size: 0.2), $\beta$ from 0.1, 0.2, 0.4, ..., 1.0 (step size: 0.2), and $\lambda$ from 1.0, 1.2, 1.4, ..., 6.0 (step size: 0.2). The log-likelihood values are shown in Figure 1. It is 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 $\chi^2$ statistic 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 prospect parameters, we re-conducted the simulation by adopting a wider
range of the $\lambda$ value ($\alpha = 0.1, 0.3, ..., 0.9; \beta = 0.1, 0.3, ..., 0.9; \lambda = 5.0, 5.5, 6.0, 6.5, ..., 19.5$). It is however found that the maximum log-likelihood is just -2340.91. It seems that it is difficult to find log-likelihood values larger than -2334.61 (See Figure 1). The results of MPRI model with the simulated best set of prospect parameters “$\alpha = 1.0, \beta = 0.1, \lambda = 1.0$” are shown before the MPRI model with prospect parameters “$\alpha = $ 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 estimated (the last two models: RRM_RI and RAM_RI models in Table 1). It is observed that introducing the relative interest parameter surely leads to bigger log-likelihood values. The adjusted McFadden’s Rho-squared value is 0.0937 for RRM_RI model and 0.0936 for RAM_RI model, respectively, which are slightly larger than those of MPRI model with prospect parameters “$\alpha = \beta = 0.88$ and $\lambda = 2.25$” and RURI model. Even in case that introducing the relative interest parameter, the adjusted McFadden’s Rho-squared value of MPRI model with the simulated best set of prospect parameters is still larger than those of RRM_RI and RAM_RI models.

In summary, it can be concluded that,
1) the MPRI model with a best set of prospect parameter is superior to any other models,
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.

But we have to honestly say that the differences of model accuracy between MPRI/RURI models and other models are not that large. Admitting this point, we can conclude that introducing non-linear context dependence together with relative interest can improve the model accuracy of choice behavior.

5.3 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: the highest interest in the alternative “Peak hours – Ring road” and the lowest interest in the alternative “Peak hours – Truck road” (the highest relative interest parameter is 2.2~2.8 times higher than the lowest one). On the other hand, the simulated best set of prospect parameters (MPRI model (Simulated Best) in Table 1) estimate that drivers attach the highest importance to the alternative “Peak hours – Truck 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 – Truck road” while the alternative “Peak hours – Ring road” is regarded to be most important in the RAM_RI model, which is the same as the MPRI model with the simulated best set of prospect parameters.

5.4 Content-dependent Variable

All the six models estimated that the context-dependent travel time is statistically influential to the joint choice behavior. And 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, positive parameter means that drivers prefer gains more than loss. In the RRM model, the negative parameter of regret with respect to the travel time suggests that drivers dislike the regret. In the RAM model, positive sign of relative advantage with respect to the travel time is also consistent with our expectation.

The original set of prospect parameters “$\alpha = 0.88$ 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 the increased travel time (i.e., loss) from competitor alternatives, but significantly sensitive to the reduced travel time (i.e., gain). Especially, the sensitivity to gain is higher in the MPRI model with the simulated best set of prospect parameters than in the MPRI model.

5.5 Other Variables

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

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 the significant influence. 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 the 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 the 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 the 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 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 human 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, not only multiple reference points (an original feature of the relative utility model), but also nonlinear context dependence are accommodated. Different from our previous studies (Zhang et al., 20120, 2013), this study conceptually and
empirically compared the performance of four major types of content-dependent choice models (i.e., RURI, MPRI, RRM, RAM, RRM_RI, and RAM_RI models: all are non-IIA choice models) using an 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 the alternative-based comparisons, this study transformed the original model structure to explicitly reflect the attribute-based comparisons, just like the RRM and RAM models. In addition, relative interest parameters were also introduced into the RRM and RAM models. It is empirically confirmed that the MPRI model is superior to any other models, 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 surely improved the performance of RRM and RAM models. In summary, alternative/attribute-based comparisons, non-linear responses and relative interest are three powerful “spears” to “defeat” the “shield” of context dependence.

Conceptually, the original concept of relative utility covers all the features of MPRI, RRM and RAM models in an implicit but comprehensive way. It is expected that further decomposing the original relative utility concept could contribute to a better understanding of the context dependence. The above six models should be re-compared 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 focused in this study, but also time-oriented and decision maker-oriented relative utilities could further improve the abilities of relative utility in representing and explaining the influence of various types of context dependencies across space and over time. Since the relative utility concept can be easily introduced into any utility-based choice models in theory, just like the ways we did 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. Since the relative utility model was not developed for specific types of travel behavior, all the above research issues should be examined with respect to different types of human decisions in order to clarify its generality as a new type of human choice decision model. To confirm the influence of cultural contexts on human decisions, it might be worth implementing a worldwide international comparison study.

ACKNOWLEDGEMENT

This research is supported by the Grants-in-Aid for Scientific Research (A) “Development of Cross-Sector Urban Planning and Management Methodologies by Establishing Theory of Citizens’ Life Decisions and Behavior (Principal Researcher: Prof. Junyi Zhang, Hiroshima University)” (No.22246068) of the Japan Society for the Promotion of Science (JSPS). We would also like to express our sincere appreciation to Mr. Waiyan Leong and Prof. David A. Hensher, Institute of Transport and Logistics Studies, The Business School, The University of Sydney for their advices on the estimation of the RAM model.

REFERENCES

behaviour research. European Journal of Transport and Infrastructure Research, 10 (4), 293-298.
(25) McFadden, D., Train, K. and Tye, W.B. (1977) An application of diagnostics tests for the
independence from irrelevant alternatives property of the multinomial logit model. Transportation Research Record, 637, 39-46.


<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>MPRI model (Simulated Best)</th>
<th>MPRI model</th>
<th>RURI model</th>
<th>RRM model</th>
<th>RAM model</th>
<th>RRM_RI model</th>
<th>RAM_RI model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>t-statistic</td>
<td>Parameter</td>
<td>t-statistic</td>
<td>Parameter</td>
<td>t-statistic</td>
<td>Parameter</td>
<td>t-statistic</td>
</tr>
<tr>
<td>Constant term (1~3) (reference: off-peak hours - trunk road)</td>
<td>0.7724</td>
<td>1.454</td>
<td>-1.4625</td>
<td>**</td>
<td>-3.326</td>
<td>-1.3783</td>
<td>*</td>
</tr>
<tr>
<td>Individual attributes</td>
<td>Gender (1: male; 0: female) (1)</td>
<td>-1.0846</td>
<td>-0.776</td>
<td>-0.1716</td>
<td>-0.429</td>
<td>-0.2521</td>
<td>-0.564</td>
</tr>
<tr>
<td></td>
<td>Age (1)</td>
<td>-0.0915</td>
<td>-1.002</td>
<td>-0.0017</td>
<td>-0.053</td>
<td>-0.0829</td>
<td>-0.401</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SP attributes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Trip purpose (1: Business; 0: Recreation) (6)</td>
<td>1.6018 **</td>
<td>2.811</td>
<td>1.1873</td>
<td>*</td>
<td>1.780</td>
<td>1.1970 **</td>
</tr>
<tr>
<td></td>
<td>Timing constraint of arrival (1: Being late is permitted; 0: not permitted) (1)</td>
<td>5.0542 *</td>
<td>2.555</td>
<td>1.4517 **</td>
<td>3.145</td>
<td>1.5991 *</td>
<td>3.142</td>
</tr>
<tr>
<td></td>
<td>Error of travel time prediction (two levels: 10% and 30%) (3)</td>
<td>-10.7376 **</td>
<td>-2.293</td>
<td>-4.7750</td>
<td>-1.403</td>
<td>-4.3298</td>
<td>-1.495</td>
</tr>
<tr>
<td>Travel time</td>
<td>(α = 1.0, β = 0.1, λ = 1.0) (α = β = 0.88, λ = 2.25)</td>
<td>-0.0373 **</td>
<td>-5.770</td>
<td>-0.0182 **</td>
<td>-6.452</td>
<td>-0.0934 **</td>
<td>-5.141</td>
</tr>
<tr>
<td></td>
<td>Relative advantage</td>
<td>0.1116 **</td>
<td>7.308</td>
<td>0.0333 **</td>
<td>5.998</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Other attributes</td>
<td>Ownership of car navigation system (1: Yes; 0: No) (3)</td>
<td>-1.8742 *</td>
<td>-2.041</td>
<td>-0.8129</td>
<td>-1.037</td>
<td>-0.6472</td>
</tr>
<tr>
<td></td>
<td>Familiarity of road network in Beijing (2)</td>
<td>-0.0947 *</td>
<td>-1.690</td>
<td>-0.2092</td>
<td>-0.872</td>
<td>-0.1261</td>
<td>-0.636</td>
</tr>
<tr>
<td>Relative interest parameter</td>
<td>(1) Peak hours - Ring road</td>
<td>0.0902 **</td>
<td>3.560</td>
<td>0.3343 **</td>
<td>3.926</td>
<td>0.3000 **</td>
<td>3.964</td>
</tr>
<tr>
<td></td>
<td>(2) Peak hours - Trunk road</td>
<td>0.3026 **</td>
<td>6.828</td>
<td>0.1188 *</td>
<td>2.509</td>
<td>0.1348</td>
<td>2.313</td>
</tr>
<tr>
<td></td>
<td>(3) Peak hours - Branch road</td>
<td>0.1709 *</td>
<td>2.345</td>
<td>0.2518 **</td>
<td>3.610</td>
<td>0.2816 *</td>
<td>3.496</td>
</tr>
<tr>
<td></td>
<td>(4) Off-peak hours - Trunk road</td>
<td>0.2363 **</td>
<td>6.059</td>
<td>0.2951 *</td>
<td>2.297</td>
<td>0.2833 **</td>
<td>2.721</td>
</tr>
<tr>
<td>Converged log-likelihood</td>
<td>-2334.61</td>
<td>-2340.99</td>
<td>-2341.1</td>
<td>-2346.46</td>
<td>-2344.46</td>
<td>-2339.96</td>
<td>-2240.36</td>
</tr>
<tr>
<td>Adjusted McFaddan’s Rho-squared</td>
<td>0.0958</td>
<td>0.0953</td>
<td>0.0953</td>
<td>0.0924</td>
<td>0.0931</td>
<td>0.0937</td>
<td>0.0836</td>
</tr>
<tr>
<td>χ² test (critical value = 7.82; degree of freedom: 3)</td>
<td>23.70 **, 10.94 **, 10.72 **</td>
<td>19.70 **, 6.94 **, 6.72 **</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample size (SP responses)</td>
<td>1872</td>
<td>1872</td>
<td>1872</td>
<td>1872</td>
<td>1872</td>
<td>1872</td>
<td>1872</td>
</tr>
</tbody>
</table>

(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) χ² 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