Exploring Variation Properties of Time Use Behavior Based on a Multilevel Multiple Discrete-Continuous Extreme Value Model[1]

Makoto Chikaraishi
Ph.D. Candidate
Graduate School for International Development and Cooperation, Hiroshima University
1-5-1, Kagamiyama, Higashi-Hiroshima 739-8529, Japan
Tel/Fax: +81-82-424-6957; E-mail: chikaraishi@hiroshima-u.ac.jp

Junyi Zhang
Associate Professor
Graduate School for International Development and Cooperation, Hiroshima University
1-5-1, Kagamiyama, Higashi-Hiroshima 739-8529, Japan
Tel/Fax: +81-82-424-6919; E-mail: zjy@hiroshima-u.ac.jp

Akimasa Fujiwara
Professor
Graduate School for International Development and Cooperation, Hiroshima University
1-5-1, Kagamiyama, Higashi-Hiroshima 739-8529, Japan
Tel/Fax: +81-82-424-6921; E-mail: afujiw@hiroshima-u.ac.jp

Kay W. Axhausen
Professor
Swiss Federal Institute of Technology, Zurich, Switzerland
Tel.: +41-44-633 3943; Fax: +41-44-633 1057
E-mail: axhausen@ivt.baug.ethz.ch

Word Count: 6,654 words + 3 tables/figures = 7,404 equivalent words (max. = 7,500)

Key Words: Behavioral variations, Time use behavior, Multilevel MDCEV model, Mobi*drive* data

Submission date: February 25, 2010

---

[1] Paper submitted to the 89th Annual Meeting of the Transportation Research Board, January 10-14, 2010, Washington D. C.

Please send any correspondence to Mr. Chikaraishi, Tel./fax: +81-824-24-6957;
e-mail: chikaraishi@hiroshima-u.ac.jp

ABSTRACT

This paper attempts to examine the variation properties of time use behavior based on a multilevel MDCEV model, which describes both activity participation and time allocation behavior by incorporating various variance components. In this study, five major variation components are dealt with, including inter-individual, inter-household, temporal, spatial, and intra-individual variations. The Mobi*drive* data, a continuous six-week travel daily data allows us to identify these variations at the same time. Two types of models are empirically examined: one is the model without considering the influences of explanatory variables (*Null* model), and the other is the model by introducing explanatory variables (*Full* model). Based on the estimation results from the *Null* model, it is confirmed that the intra-individual variation still accounts for more than 50% of the total variation (except for mandatory activities) even after incorporating the aforementioned four other types of variations jointly. On the other hand, the results from the *Full* model reveal that most types of unobserved variations (especially the intra-individual variation) are still dominating in the total variation even after introducing the relevant observed information. These findings would provide useful insights into both model development and data collection methods as well as the understanding the mechanisms of time use decisions.

1. INTRODUCTION

Decisions related to activity-travel behavior are influenced by various kinds of factors at various levels, such as socio-demographic, locational, and other contextual attributes. The development of behavioral models mostly aims to acquire a good understanding of such behavioral phenomenon, through uncovering the relationship between a target behavior and influential factors based on some plausible behavioral assumption(s). At the same time, mainly because of the limited information, some influential factors may not be embedded in a model, and as a result, the variations caused by these omitted factors have to be treated as unobserved variations. There are probably several kinds of unobserved variations. Considering that an individual decides his/her behavior with the constraints of time and space as well as his/her own situations at a moment (*1*), the dominant variation types would be intra-individual, inter-individual, inter-household, temporal (i.e., systematic day-to-day variation), and spatial variations. In fact, the existence of such different types of variations has been recognized by researchers, and the importance of discriminating these variations has been intensively discussed (e.g., *2-8*).

Broadly speaking, explaining these behavioral variations based on some observed elements is what a model usually does. It is further expected that increasing the number of the observed elements might reduce the rest of the unobserved variations. For example, if household income variable is not available but has some effects on the behavior, the unobserved inter-household variation would be bigger than that with considering the income effects. Lack of situational attributes (e.g., “with whom” and “for whom”), for example, might lead to a bigger unobserved intra-individual variation than that with considering those attributes.

Although the impacts of such observed elements on a target behavior are substantially important and can be directly connected with policy discussions, this study especially focuses on the unobserved variations in behavior, which cannot be captured by introduced elements. There are at least two reasons why understanding such unobserved variations is needed.

First, before representing the behavioral variations by the observed elements, it is necessary to understand what kinds of variations actually exist by exploring the fundamental variation properties in the behavior. There are many cases, in reality, where analysts have to narrow down the target of analysis to limited variation types, mainly due to the available data and/or analysis methods. For example, it is intrinsically impossible to capture the temporal variations by using a survey data on a single day (*2*), but multi-day surveys are costly and it is often impossible to conduct such surveys in practice. In another instance, the inter-individual variation is automatically lost in traditional 4-step models, in which spatial aggregate data is used, but such a model is still often used, partly because alternative methods are obscure. Because we cannot avoid such limitations especially in practice as of now, at least we have to understand the meaning of focusing on limited variation types. In other words, it is needed to quantitatively identify the loss of information caused by ignoring some kinds of variations.

Second, it might be useful to clarify what kinds of variations cannot be captured even after introducing some observed elements into models. This is because the remaining unobserved variations might indicate that there could be “niches” to be further exploited, probably along with additional observations. In line with this, Kitamura (*3*) pointed out that, even if we could grasp a “stable” relationship in actual phenomena, it would be impossible to understand the phenomena themselves without analyzing how they vary around the stable relationship. The remaining variations could offer useful information to understand how the behavior varies around the discovered stable relationship, and what kinds of factors we should further observe.

On the basis of the above-mentioned considerations, this study attempts to explore the variation properties of time use behavior which is one of the core aspects of the activity-based approach (e.g., *9, 10*). Since some of activities might not be performed at a given period, it becomes necessary to describe whether an activity is performed or not, together with the time allocation in case of participating in the activity. To represent activity participation and time allocation simultaneously, a multiple discrete-continuous extreme value (MDCEV) model, originally proposed by Bhat (*11, 12*), is adopted. The MDCEV model is further extended to incorporate various kinds of variation types by integrating with the multilevel modeling approach (called multilevel MDCEV model). In an empirical analysis, first, this paper attempts to decompose the total variation of time use behavior into five variance components: intra-individual, inter-individual, inter-household, temporal, and spatial variations. This is to understand the above-mentioned first point, i.e., what kinds of variations actually exist. In addition, how much of these variations can be explained by observed variables and how much of the variance still remains are also examined. This is to understand the above-mentioned second point, i.e., how the behavior varies around the stable relationship, and what kinds of factors we should further observe. The empirical analysis is conducted by using a continuous six-week travel survey data (called Mobi*drive* data) collected in the cities of Karlsruhe and Halle in Germany in 1999 (*13*), which is one of the few data sets allowing us to address variation properties in the activity and travel behavior in greater details.

This paper is organized as follows. Section 2 reviews existing studies focusing on the time use behavior and variation properties of activity-travel behavior. In Section 3, the multilevel MDCEV model and the calculation method of variation properties in time use behavior are described. After that, the data used in this study is summarized and the results of model estimations are shown as well as the variation properties. In the final section, some major findings are summarized along with a discussion about future research issues.

2. LITERATURE REVIEW

2.1. Studies on Time Use Behavior

The analysis of time use behavior has received much attention from many researchers. This is mainly for a better understanding of activity-travel behavior with the development of well-founded practice models in mind, or more directly towards the development of new transportation planning methodologies that reflect people’s desires and needs to assess the impacts of transportation on, for example, their quality of life (e.g., *9, 14-17*). Accordingly, a number of time use models have been developed from both theoretical and practical perspectives. One of the most fundamental time use models in transportation field was proposed by Kitamura (*18*). He modeled individual time use behavior within a given day on the basis of the law of diminishing marginal utilities (represented based on a logarithm utility function), incorporating both discrete activity choice and continuous time allocation between two activity types based on the type-II Tobit model specification. The model (and its concepts) has been extended in various ways. For example, Zhang et al. (*19, 20*) proposed time use models with intra-household interactions. Supernak (*21*) and Timmermans et al. (*22*) doubt the assumption of diminishing marginal utilities and reconsider the shape of the utility function. Kitamura (*23*) focused on time use patterns on multiple days and its historical dependencies. Bhat and Misra (*24*) attempted to reveal the weekly time allocation behavior between in-home and out-of -home activities and between weekdays and weekends. Bhat (*11*, *12*) proposed a multiple discrete-continuous extreme value (MDCEV) model which can represent that individuals choose the multiple types of activities from the whole choice set, and allocate their time to these activities.

As described above, various types of time use models have been proposed, and they have different advantages on different aspects. Since the MDCEV model can be easily extended to accommodate various heterogeneous variances of unobserved random components, it is adopted in this study. Note that the scalability of the MDECV model is very similar to the multinomial logit model: mixed logit type extension (*11*, *12*), nested logit (*25*), and panel mixed logit (*26*). In this study, the MDCEV model is further extended to incorporate various kinds of variation types by integrating with multilevel modeling approach (*27*) (called multilevel MDCEV model).

2.2. Studies on Behavioral Variations

Reviews of existing studies on the five variation components (i.e., intra-individual, inter-individual, inter-household, temporal, and spatial variations) are already given in Chikaraishi et al. (*8*). Therefore, here we focus on studies about variation in time use behavior (activity participation, time allocation or both).

There are several studies focusing on intra-individual and inter-individual variations in time use behavior. As an early research, Jones and Clarke (*28*) proposed the time-use-based measure of intra-individual variability (or similarity). They found the differences in the degree of intra-individual variability between lifecycle stages as well as gender. Bhat et al. (*29*) examined the duration between successive non-maintenance shopping activities by using a mixed hazard-based duration model. They distinguished intra-individual and inter-individual variations, and found that around 70% in total unobserved variations are derived from unobserved intra-individual variations. Bhat et al. (*30*) also examined the duration between successive participations of five activity types (maintenance shopping, non-maintenance shopping, social activities, recreation, and personal business) by using a multivariate hazard model. They pointed out that, except for non-maintenance shopping, individuals have well-established rhythms for activity participation. Their results also indicate that, while such rhythms substantially vary across individuals, it seems to be difficult to put the rhythms into the observed elements (i.e., capture the source of rhythms). Spissu et al. (*26*) figured out the variations in out-of-home discretionary activities by using the mixed MDCEV model with unobserved inter-individual and intra-individual variations. Their results also confirmed large unobserved intra-individual variations for all discretionary activities (44.8~76.8% in total unobserved variations) and also clarified the difficulties of capturing such variations by introduced explanatory variables (only 2.9~45.8% of total variations can be captured). Goulias (*31*) developed a time use model accounting for not only inter-individual and intra-individual variations, but also inter-household variations. The results of his analysis show that inter-household variations for all activities are more than 1/3 of the inter-personal variations, and the inter-household variations cannot be ignored.

As presented above, although some existing studies have explored the variation properties, to the authors' knowledge, multiple variation components, including five major components (intra-individual, inter-individual, inter-household, temporal, and spatial variations), have not been examined simultaneously with respect to time use behavior. In the next section, the multilevel MDCEV model, which can capture the above mentioned five variation components, is developed.

3. METHODOLOGY

3.1. Model Formulation

Suppose there are J types of activities, and some of them might be pursued by individual i of household h on day d at action space s. It is assumed that an individual makes a decision conditional on his/her available time budget by maximizing his/her total utility within a given time period. The total utility U_{ihds} is defined as the sum of utilities obtained from each type of activity as follows:

$$\begin{aligned} &\text{maximize} \quad U_{ihds} = \sum_{j=1}^{J} u_{ihds}^{j}\left(t_{ihds}^{j}\right) \\ &\text{subject to} \quad \sum_{j=1}^{J} t_{ihds}^{j} = T\,, t_{ihds}^{j} \geq 0 \left(j = 1,2,...,J \right) \end{aligned} \tag{1}$$

where, $u_{ihds}^{j}(t_{ihds}^{j})$ is the utility derived from activity j given the allocated time t_{ihds}^{j}. T is the total amount of time to be allocated (in this study, T represents 24 hours). For the utility $u_{ihds}^{j}(t_{ihds}^{j})$, we defined the following simple logarithmic function with respect to the allocated time t_{ihds}^{j}, which is one of the most frequently used functions in literature (e.g., *10*, *18*).

$$u_{ihds}^{j}\left(t_{ihds}^{j}\right) = \psi_{ihds}^{j}\, ln\left(t_{ihds}^{j} + 1\right) \tag{2}$$

$$\psi_{ihds}^{j} = exp\left(\beta^{j} x_{ihds}^{j} + \gamma_{ih}^{j} + \gamma_{h}^{j} + \gamma_{d}^{j} + \gamma_{s}^{j} + \eta_{ihds}^{j} + e_{ihds}^{j}\right) \tag{3}$$

Here, ψ_{ihds}^{j} represents the degree of baseline preference of activity j pursued by individual i of household h on day d at action space s. β^{j} represents parameter vector, x_{ihds}^{j} represents explanatory variables. γ_{ih}^{j}, γ_{h}^{j}, γ_{d}^{j}, γ_{s}^{j} and η_{ihds}^{j} represent the random components which indicate inter-individual variation, inter-household variation, temporal variation (date-specific error component), spatial variation (error component specific to action space) and intra-individual variation, respectively. Note that temporal variation is introduced to capture the unobserved effects common to the d'th day (i.e., day effects at an aggregate level), and temporal rhythms for an individual would be captured in the intra-individual variation. e_{ihds}^{j} represents intra-individual variation, and it is assumed to be independently and identically Gumbel-distributed with variance $\sigma^2\pi^2/6$. The parameter σ is fixed as 0.2 because the error components of η_{ihds}^{j} and e_{ihds}^{j} will capture the same inter-individual variation, and the rest of inter-individual variation will be captured by η_{ihds}^{j} (the detailed discussions related to the normalization and specification of the variance can be found in Bhat (*12*) or Ben-Akiva et al. (*32*)). e_{ihds}^{j} is introduced to derive a closed-form model structure conditional on random components in analogy with a mixed logit model (see eq. (6)). Let random components γ^j_{ih}, γ^j_h, γ^j_d, γ^j_s and η^j_{ihds} be normally distributed as follows, where these random components are all assumed to be uncorrelated with each other.

$$\begin{aligned}&\gamma^j_{ih} \sim N\left(0,\sigma^2_{ih|j}\right), \gamma^j_h \sim N\left(0,\sigma^2_{h|j}\right), \gamma^j_d \sim N\left(0,\sigma^2_{d|j}\right),\\ &\gamma^j_s \sim N\left(0,\sigma^2_{s|j}\right), \eta^j_{ihds} \sim N\left(0,\sigma^2_{0|j}\right)\end{aligned} \tag{4}$$

Here, note that Bhat (*12*) proposed a more general utility function, which incorporates different levels of "satiation effects" among activity types, and it seems better than the simple logarithm function in eq. (2) in terms of the goodness-of-fit of the model. Nevertheless, we employ the simple logarithm function because the satiation effects might be closely related to the unobserved variations in the baseline preferences (The details of relevant discussions can be found in Bhat (*12*)). In other words, this paper attempts to capture the total variations in time use behavior by looking at unobserved variations in baseline preferences, rather than by considering the different levels of satiation effects. The variation properties of baseline preferences described in eq. (3) are the most interesting part in this study as discussed in the next subsection.

Applying Kuhn-Tucker conditions to eq. (1), we can obtain the following equations.

$$\begin{cases} V^j_{ihds} + e^j_{ihds} = V^1_{ihds} + e^1_{ihds} & \text{if } t^{j*}_{ihds} > 0 \\ V^j_{ihds} + e^j_{ihds} < V^1_{ihds} + e^1_{ihds} & \text{if } t^{j*}_{ihds} = 0 \end{cases} \quad j = 2,3,\ldots,J \tag{5}$$

where, $V^j_{ihds} = \beta^j \mathrm{x}^j_{\mathrm{ihds}} + \gamma^j_{ih} + \gamma^j_h + \gamma^j_d + \gamma^j_s + \eta^j_{ihds} - ln\left(t^{j*}_{ihds} + 1\right)$.

As we can confirm from eq. (5), mechanism of activity participation can be endogenously represented by applying Kuhn-Tucker conditions. Given values of $\beta^j, \gamma^j_{ih}, \gamma^j_h, \gamma^j_d, \gamma^j_s$, and η^j_{ihds}, the following conditional probability is derived (model derivation processes are given by Bhat (*11*, *12*)).

$$\begin{aligned}&P\left(\mathrm{t}^*_{\mathrm{ihds}} \mid \beta, \gamma_{\mathrm{ih}}, \gamma_{\mathrm{h}}, \gamma_{\mathrm{d}}, \gamma_{\mathrm{s}}, \eta_{\mathrm{ihds}}\right)\\ &\quad = \frac{\left(M_{ihds}-1\right)!}{\sigma^{M_{ihds}-1}} \left[\prod_{m_{ihds}=1}^{M_{ihds}} \frac{1}{\left(t^{m_{ihds}*}_{ihds}+1\right)}\right] \left[\sum_{m_{ihds}=1}^{M_{ihds}} \left(t^{m_{ihds}*}_{ihds}+1\right)\right] \left[\frac{\prod_{m_{ihds}=1}^{M_{ihds}} exp\left(V^{m_{ihds}}_{ihds}/\sigma\right)}{\left(\sum_{j=1}^{J} exp\left(V^j_{ihds}/\sigma\right)\right)^{M_{ihds}}}\right]\end{aligned} \tag{6}$$

Here, $\mathrm{t}^*_{\mathrm{ihds}}=\{t^{1*}_{ihds}, t^{2*}_{ihds}, \ldots, t^{M*}_{ihds}, 0, 0, \ldots, 0\}$. m_{ihds} ($m_{ihds}=1,2,\ldots,M_{ihds}$ | $M_{ihds} \in J$) represents activity types pursued by individual i of household h on day d at action space s. The unconditional probability of eq. (6) involves a number of integrations, and cannot be solved analytically. To estimate such model, some simulation methods are usually adopted, such as a series of Monte Carlo methods and numerical quadrature methods. In this study, we use a hierarchical Bayesian procedure based on Markov Chain Monte Carlo (MCMC) method which has become popular recently and is one of the promising methods to estimate multilevel models with complicated random effects. The method incorporates prior distribution assumptions and, based upon successive sampling from the posterior distributions of the model parameters, yield a chain which is then used for making point and interval estimations. In particular, introducing N_{ihds} as the number of samples, the posterior distribution can be written as follows:

$$\begin{aligned}
&\pi\left(\beta, \sigma_{ih}, \sigma_{h}, \sigma_{d}, \sigma_{s}, \sigma_{0} \mid t^{*}, x\right) \\
&\quad \propto \prod_{N_{ihds}} P\left(t^{*}_{ihds} \mid \beta, \gamma_{ih}, \gamma_{h}, \gamma_{d}, \gamma_{s}, \eta_{ihds}\right) \\
&\quad \times f\left(\gamma_{ih} \mid \sigma_{ih}\right) f\left(\gamma_{h} \mid \sigma_{h}\right) f\left(\gamma_{d} \mid \sigma_{d}\right) f\left(\gamma_{s} \mid \sigma_{s}\right) f\left(\eta_{ihds} \mid \sigma_{0}\right) \\
&\quad \times \phi\left(\sigma_{ih}\right) \phi\left(\sigma_{h}\right) \phi\left(\sigma_{d}\right) \phi\left(\sigma_{s}\right) \phi\left(\sigma_{0}\right) \phi(\beta)
\end{aligned} \tag{7}$$

where, we assume an inverted Gamma distribution for $\phi(\sigma_{ih}), \phi(\sigma_{h}), \phi(\sigma_{d}), \phi(\sigma_{s})$ and $\phi(\sigma_{0})$, and a normal distribution for $\phi(\beta)$, as prior distributions. Besides, by introducing the unobserved random components $\gamma_{ih}, \gamma_{h}, \gamma_{d}, \gamma_{s}$ and η_{ihds} along with their variances into the sampling procedure, $f(\gamma_{ih} \mid \sigma_{ih}), f(\gamma_{h} \mid \sigma_{h}), f(\gamma_{d} \mid \sigma_{d}), f(\gamma_{s} \mid \sigma_{s})$ and $f(\eta_{ihds} \mid \sigma_{0})$, which are assumed to be normally distributed as described in eq.(4), create the so-called “hierarchical” sampling procedure (*33*). In this study, non-informative prior densities are assumed for all parameters. In this case, estimated parameters are asymptotically equivalent to the parameters obtained through a simulated maximum likelihood method (*33*).

Draws from the posterior are obtained using software WinBUGS (Bayesian inference Using Gibbs Sampling (*34*)). In the Gibbs sampling, draws of each parameter are obtained from its posterior conditional on the other parameters (details refer to Gill (*35*) or Train (*33*)).

3.2. Variation Properties in Time Use Behavior

After developing the model of time use behavior, we further attempt to examine the variation properties of baseline preferences in eq. (3), which is the most interesting part in this study. Since the baseline preference has no absolute reference or zero point, we have to consider the relative value of baseline preference. In this study, the first alternative (in empirical analysis, home activities) is treated as a benchmark for obtaining variation properties of other activities as follows:

$$\frac{\psi^{j}_{ihds}}{\psi^{1}_{ihds}} = exp\left(\beta^{j} x^{j}_{ihds} + \gamma^{j}_{ih} + \gamma^{j}_{h} + \gamma^{j}_{d} + \gamma^{j}_{s} + \varepsilon^{j}_{ihds} + e^{j}_{ihds} - e^{1}_{ihds}\right) \tag{8}$$

Note that parameters and random variables for the first alternative are fixed as zero in order to avoid identification issues. The variation for activity *j* can be calculated as follows:

$$\mathrm{var}\left[ln\left(\frac{\psi^{j}_{ihds}}{\psi^{1}_{ihds}}\right)\right] = \mathrm{var}\left(\beta^{j} x^{j}_{ihds}\right) + \sigma^{2}_{ih|j} + \sigma^{2}_{h|j} + \sigma^{2}_{d|j} + \sigma^{2}_{s|j} + \left(\sigma^{2}_{0|j} + \frac{\sigma^{2}\pi^{2}}{3}\right) \tag{9}$$

where, the first component represents observed variation captured by introduced explanatory variables; the second to fifth components are unobserved variations which indicate unobserved inter-individual variation, unobserved inter-household variation, unobserved temporal variation, and unobserved spatial variation, respectively. The final component represents unobserved intra-individual variation.

In the case of the model without explanatory variables (called *Null* model), eq. (9) represents fundamental variation properties which indicate what kinds of variations actually exist in time use behavior. When the model includes explanatory variables (called *Full* model), all the estimated unobserved variation components will be smaller than those in the *Null* model theoretically because var($\beta^j x^j_{tihds}$) explains a part of the total variation. If we could obtain perfect information on the factors determining time use behavior, unobserved variation components would be nearly zeros, but usually some unobserved variations would still remain. We focus on these remaining unobserved variations which offer information about what kinds of explanatory variables are still lacking to describe time use behavior. This would be substantially important especially when we consider the relationship between data collection and model development which constrain and condition each other (*36*). For example, even if there is a certain level of spatial variation, we may not need to search for further influential factors related to spatial differences when we could capture the variation very well (i.e., unobserved spatial variation are almost explained by introduced observed variables). On the other hand, if substantial unobserved variations still remain at high levels even after introducing all available explanatory variables, there would be "niches" to be exploited along with additional "observation". In the same manner, exploring variation properties described in eq. (9) can provide useful information to search such "niches" for each type of variation. To examine how much each variation can be captured by introduced explanatory variables, this study compares unobserved variations without considering explanatory variables (*Null* model) with those variances with explanatory variables (*Full* model).

4. EMPIRICAL ANALYSIS

4.1. Data

The Mobi*drive* data set (*13*) is used in the empirical analysis. It includes a six-week (42 days) travel diary survey data conducted in Karlsruhe (West Germany) and Halle (East Germany), in the fall of 1999. Including the pilot survey, a total of 361 persons from 162 households participated in this survey. The total recorded days are 119 days, including 56 days from the pilot survey (May 31 through July 25) and 63 days from the main survey (September 13 through November 14). Here, the original data include persons who could not report on their behaviors in some days, for example, due to extended vacations. After data cleaning, a total of 294 persons from 141 households were selected for the empirical analysis in this study, and the total number of samples used in model estimations is 10,290 (= 294[person] × 35[day]). Note that the model estimations will be conducted by using five-week behavior data, and one-week behavior data are just used for introducing the variables of previous activity participation (t-1, t-2, t-3, and t-7). Additionally, for the definition of action space, we took the following steps: 1) classifying the whole space into 4 zones (CBD, inner city, suburb, and elsewhere) for each city, and 2) identifying (non-) active zones in which a person (didn't) conduct any activity on a given day. As a result, 30 action spaces (= (2^4 [active or non-active for 4 zones] - 1 [excluding all non-active case]) × 2 [cities]) are obtained in total. Note that this definition of action space does not reflect that the impacts of action space can differ from individual to individual, i.e., if individuals take same action space, the impacts of action space on their time use are the same across individuals in the employed definition. We could capture individual-specific space effects by introducing a co-variation term which indicates combination effects of individual and spatial variations (*37*), but here we do not introduce such term for simplifying the discussions. At the same time, there are many ways to define the action space (e.g., *38*, *39*). In fact, an action space could be continuous in essence. However, our employed definition of action space assumes discrete action spaces (i.e., when an activity engagement at a certain zone is canceled, the action space is recognized as being completely different from original action space even though other activities remain unchanged). This is because the random effects approach used in this study requires discrete or categorical definitions about action space. How to define the continuous effects of action space and how to incorporate these effects into the analysis of time use behavior remain as an issue to be solved. In summary, we will deal with time use behaviors of 10,290 [person-day] pursued by individual i (=1,...,294) from household h (=1,...,141) on day d (=1,...,105) along with action space s (=1,...,30).

As for activity classification, we employ seven activity types: 1) *home activities* (base alternative); 2) *pick up/drop off*; 3) *private business*; 4) *mandatory activities* (including school, work, and work-related activities in the original activity classification); 5) *daily shopping*; 6) *non-daily shopping*; and 7) *leisure* (including leisure and other activities in the original classification). For the sake of simplifying the discussion, we grouped several activities, by considering the degree of the flexibility (or essentiality) of activities in the decision making. In addition, the number of other activities is only 0.46% in total and we assume that these are kinds of leisure activities although some of them would not hold similar properties with leisure activities. It is expected that this will not bringing any significant influence on analysis results. The time allocated to travel is considered as a part of the next activity.

4.2. Model estimation and Discussion

In this study, the hierarchical Bayesian procedure based on MCMC method is used for estimating the multilevel MDCEV model described in Section 3. For this estimation, the non-informative prior distributions are given for all parameters, and a total of 450,000 iterations are done in order to obtain 10,000 draws: the first 150,000 for burn-in to mitigate start-up effects and 300,000 after convergence, of which every 30th sample is retained. The estimation results are quite stable for both *Null* and *Full* models. Even when we reduce the number of draws to 350,000 (150,000 is for burn-in, and every 20th sample in the rest of draws is used) or change the initial values, the estimated values and its standard deviations are asymptotically equivalent to the reported estimation results. We also checked the convergence of the model by using the Geweke diagnostic (*40*) as well as trace plots of the parameter chains, and found that all parameters are well converged.

The estimation results of *Null* model (i.e., the model without explanatory variables) are presented in Table 1. This is intended to first explore actual variations, and then to provide some reference points for evaluating the impacts of explanatory variables by comparing with the *Full* model. Putting the estimated parameters into eq. (9), the proportions of variations in baseline preferences can be obtained (the results are shown in Table 3 with the results of variation proportions of *Full* model). The major findings are described below.

(i) The inter-individual variations in *pick up/drop off*, *mandatory activities*, and *daily* *shopping* account for more than 20% of total variations, while *private business*, *non-daily shopping*, and *leisure* account for around 10%. This is because more task allocations among household members might be observed regarding the former activities compared to the latter activities.

(ii) *Mandatory activities* show the biggest inter-household variation. This might be derived from the differences of lifecycle stages. For example, elderly households rarely participate in *mandatory activities*. On the other hand, *daily shopping* shows non-significant inter-household variation (and we exclude this from the model). This implies that the allocated time and activity participation in *daily shopping* would be almost the same across households.

(iii) The biggest temporal variation (i.e., systematic day-to-day variation) is found in *mandatory activities*, because these might be conducted on most weekdays and rare on some weekends. On the other hand, it is also confirmed that time use for *pick up/drop off* is not dependent on the date.

(iv) Spatial variations vary from 1.2% to 13.6% across activities, but the variations in *mandatory activities* and *daily shopping* are relatively smaller than those in the other activities. This might be because that an individual's action space is usually centered around his/her work location and/or household location, and consequently *daily shopping* is probably conducted within this fundamental action space. Conversely, performing other activities like *leisure* might force the individual to expand his/her action space beyond the fundamental action space.

(v) Except for *mandatory activities*, 54.4~67.1% of total variations are derived from intra-individual variations (the highest proportions among five variation types). To this variation, situational factors (e.g., travel party, weather, health condition, events decided in previous days, mental state, and time pressure) might be significantly influential. The finding here however suggests that such situation-dependent behaviors may not well be captured in travel surveys. On the other hand, the intra-individual variation in *mandatory activities* accounts for only 16.6%, which is the second lowest among the five variation components. This is probably because participation in *mandatory activities* is not affected by, for example, the situational factors.

In summary, the results of *Null* model indicate that time use behavior could be affected by various kinds of factors, and none of the introduced variation types can be ignored. This implies, even though we would not have a rich data like Mobi*drive* data, at least we should pay attention to interpreting the results obtained from the limited data. For example, if only a one-day survey data is available, one should realize that at least the temporal variations (~29.6%) will not be captured in the analysis. In addition, it might also be difficult to capture some of intra-individual variations because some situational attributes affecting the intra-individual variations might belong to the information on other days (e.g., shopping in a day might be decided for a party held on the next day).

The estimation results of *Full* model are shown in Table 2. The introduced explanatory variables are selected from various kinds of factors, such as individual, household, temporal, spatial, and situational attributes like the variables of historical dependencies of the behavior (*23*). These variables are often used in existing literatures, and we take these variables to represent the common case. Here, although we can obtain some more useful information from the estimation results about the explanatory variables (the signs of parameters are quite understandable in general), here we only focus on the variations calculated from *Full* model in comparison with those from *Null* model because of space limitations.

The comparison results of variations between the *Null* and *Full* models are shown in Table 3. The amounts of variation reductions are also described in the lower part of the table. The values in parenthesis represent that to what extent the corresponding variations can be captured by the introduced explanatory variables. This means that the values can be regarded as a quasi R-squared by activity type and variation type, with the assumption that the introduced random effects and explanatory variables are statistically independent with each other. Although the value of intra-individual variation for *non-daily shopping* is negative, meaning the assumption would not be true, the value is quite small. This study thus argues that the values in Table 3 are eligible for evaluating the variation reductions (i.e., the negative value can be assumed as zero). Needless to say, co-variation effects (i.e., combinatorial effects of two or more variation types) should be confirmed in future (*37*). The major findings are summarized below.

(i) The reduction levels in inter-individual, inter-household, and spatial variations vary from activity to activity, but there are probably some “niches” to be further explored in all activity types without inter-household variation in *mandatory activities*. Given more detailed information related to individual, household and action space attributes, it is expected that the model performance could be further improved. For example, habitual preferences for shopping location, leisure type/location, etc. might be needed to describe the behavior in greater details. In this case, it is necessary to further discuss, for example, how we can measure such individual(household)-specific preferences.

(ii) The biggest reduction rate is observed with respect to temporal variations (86.7~99.7%). This implies that some systematic day-to-day variations can be well captured by the introduced explanatory variables (perhaps mainly by day-of-week dummies), and weekly time use behavior would be quite stable at the aggregate level. This point is consistent with the results of Habib et al. (*41*). The remaining variations (i.e., 0.03%-13.3%) might mainly come from the specific day-of-week variations across weeks. Note that these results do not mean that individual-specific temporal rhythms are stable from week to week. Rather, the results indicate that even at an aggregate level, there are some day-to-day variations, and the behavior observed on a certain day could not be assumed as a “representative” day, which has been assumed in traditional modeling approaches.

(iii) The reduction levels in intra-individual variations for all activities are quite small. This may imply that we need some additional information related to, for example, situational attributes that should be further collected. To describe the activity participation behavior by introducing situational attributes, the information from non-participants is also required; however, it is usually difficult to collect the situational information from the non-participants just because they did not participate in the activity. For example, “with whom” information might be one of the important influential factors to perform leisure activities, but this information is only available for those who already participate in it. In this sense, it becomes important how to collect the relevant situational information from non-participants. This might be a very challenging research topic. In addition, from the modeling perspective, because our results indicate that it would be difficult to capture especially intra-individual variations by the linear-in-parameter model with general revealed preference information, recent efforts for describing (re)scheduling *process* of activity-travel behavior could be one of the ways to further explore intra-individual variations (e.g., *42*).

5. CONCLUSIONS

This paper has examined the variation properties of time use behavior by building a multilevel MDCEV model, which simultaneously represents activity participation and time allocation and decomposes the total variation in time use behavior into five major variation components (i.e., inter-individual, inter-household, temporal, spatial, and intra-individual variations). Mobi*drive* data (a continuous six-week travel daily data) were adopted in the empirical analysis. Model estimation results have indicated that time use behavior could be affected by various kinds of factors, and also confirmed that narrowing down the target of an analysis to limited variation types could lose some valuable information. It has been further revealed that most variation types cannot be ignored even after incorporating their influences by using some observed information, except for temporal variations in all activity types and inter-household variation in *mandatory activities*. Furthermore, it has also been found that it is difficult to capture the intra-individual variations in all activities by introduced explanatory variables. These findings could provide useful information to figure out what should be done to improve modeling and/or data observation tasks as well as the understanding of mechanisms of time use behavior.

However, there are a number of unresolved issues. From the modeling perspective, a continuous representation of action space might be needed to more properly capture spatial variations. In addition, the existence of co-variation effects among variation types should be confirmed along with correlations among activity types. Exploring the meaning and interpretation of intra-individual variations also remains as future tasks. The different behavioral rhythms, habits, and ideologies among individuals might be one of the important influential factors on the decision making of activity-travel behavior. The way to remove white noise and extract such influential factors from behavioral variations might be needed. Another challenge is the analysis of activity generation process, especially focusing on how to incorporate the influence of situational attributes from both modeling and data collection perspectives. Although activity generation process has been examined by some researchers (e.g., *43*), there are still some big “niches” to be explored.

ACKNOWLEDGEMENTS

The authors acknowledge the constructive comments given by anonymous reviewers who significantly aided in improving the quality of the paper.

REFERENCES

1. Hägerstrand, T.: What about people in regional science?, *Papers and Proceedings of the Regional Science Association*, Vol. 24, pp. 7-21, 1970.
2. Pas, E.I.: Intrapersonal variability and model goodness-of-fit, *Transportation Research Part A*, Vol. 21, pp. 431-438, 1987.

3. Kitamura, R.: A Preliminary study on variability, *Invited Paper of Infrastructure Planning Review*, Vol. 20, pp. 1-15, 2003 (in Japanese).
4. Hanson, S., Huff, J.: Repetition and day-to-day variability in individual travel patterns: Implications for classification, in R.G. Golledge and H. Timmermans (eds.) *Behavioural Modelling in Geography and Planning*, Croom Helm, London, pp. 368-398, 1988.
5. Pas, E.I., Sundar, S.: Intrapersonal variability in daily urban travel behavior: Some additional evidence, *Transportation*, Vol. 22, pp. 135-150, 1995.
6. Bhat, C.R.: A multi-level cross-classified model for discrete response variables, *Transportation Research Part B*, Vol. 34, pp. 567-582, 2000.
7. Schlich, R., Axhausen, K.W: Habitual travel behaviour: Evidence from a six-week travel diary, *Transportation*, Vol. 30, pp. 13–36, 2003.
8. Chikaraishi, M., Fujiwara, A., Zhang, J., Axhausen, K.W.: Exploring variation properties of departure time choice behavior using multilevel analysis approach, *Paper presented at the 88th Annual Meeting of the Transportation Research Board*, Washington, D. C., 2009.
9. Bhat, C.R., Koppelman, F.S.: A Retrospective and prospective survey of time-use research, *Transportation*, Vol. 26, pp. 119-139, 1999.
10. Yamamoto, T., Kitamura, R.: An analysis of time allocation to in-home and out-of-home discretionary activities across working days and non-working days, *Transportation*, Vol. 26, pp. 211-230, 1999.
11. Bhat, C. R.: A multiple discrete–continuous extreme value model: Formulation and application to discretionary time-use decisions, *Transportation Research Part B*, Vol. 39, pp. 679-707, 2005.
12. Bhat, C.R.: The multiple discrete-continuous extreme value (MDCEV) model: Role of utility function parameters, identification considerations, and model extensions, *Transportation Research Part B*, Vol. 42, pp. 274-303, 2008.
13. Axhausen, K.W., Zimmermann, A., Schonfelder, S., Rindsfuser, G., Haupt, T.: Observing the rhythms of daily life: A six-week travel diary, *Transportation*, 29, pp. 95-124, 2002.
14. Kitamura, R.: An evaluation of activity-based travel analysis, *Transportation*, Vol. 15, pp.9-34, 1988.
15. Harvey, A.S.: The Measurement of household time allocation: Data Needs, analytical approaches, and standardization, *Journal of Family and Economic Issues*, Vol. 17, pp. 261-280, 1996.
16. Kitamura, R., Fujii, S., Pas, E.I.: Time-use data, analysis and modeling: Toward the next generation of transportation planning methodologies, *Transport Policy*, Vol. 4, pp. 225-235, 1997.
17. Timmermans, H.J.P., Arentze, T.A., Joh, C.-H.: Analysing space-time behaviour: new approaches to old problems, *Progress in Human Geography*, Vol. 26, pp. 175-190, 2002.
18. Kitamura, R.: A model of daily time allocation to discretionary out-of-home activities and trips, *Transportation Research Part B*, Vol. 18, pp. 255-266, 1984.
19. Zhang, J., Timmermans, H.J.P., Borgers, A.: A model of household task allocation and time use, *Transportation Research Part B*, Vol. 39, pp. 81-95, 2005.
20. Zhang, J., Fujiwara, A.: Representing household time allocation by endogenously incorporating diverse intra-household interactions: A case study in the context of elderly couples, *Transportation Research Part B*, Vol. 40, pp. 54-74, 2006.
21. Supernak, J.: Temporal utility profiles of activities and travel: Uncertainty and decision making, *Transportation Research Part B*, Vol. 26, pp. 61-76, 1992.

22. Timmermans, H.J.P., Arentze, T., Joh, C.-H.: Modeling effects of anticipated time pressure on execution of activity programs, *Transportation Research Board*, 1752, pp. 8-15, 2001.
23. Kitamura, R.: An analysis of weekly activity patterns and travel expenditure, in R.G. Golledge and H. Timmermans (eds.) *Behavioural Modelling in Geography and Planning*, Croom Helm, London, pp. 399-423, 1988.
24. Bhat, C.R., Misra, R.: Discretionary activity time allocation of individuals between in-home and out-of-home and between weekdays and weekends, *Transportation*, Vol. 26, pp. 193-209, 1999.
25. Pinjari, A.R., Bhat, C.R.: A Multiple discrete-continuous nested extreme value (MDCNEV) model: Formulation and application to non-worker activity time-use and timing behavior on weekdays, *Technical paper*, Department of Civil, Architectural & Environmental Engineering, The University of Texas at Austin, August 2008, 2008.
26. Spissu, E., Pinjari, A.R., Bhat, C.R., Pendyala, R.M., Axhausen, K.W.: An analysis of weekly out-of-home discretionary activity participation and time-use behavior, *Paper presented at the 87th Annual Meeting of the Transportation Research Board*, Washington, D. C., 2008.
27. Goldstein, H.: *Multilevel Statistical Models*, *Third Edition*, Edward Arnold, London, 2003.
28. Jones, P., Clarke, M.: The significance and measurement of variability in travel behaviour, *Transportation*, 15, pp. 65-87, 1988.
29. Bhat, C.R., Sivakumar, A., Axhausen, K.W.: An analysis of the impact of information and communication technologies on non-maintenance shopping activities, *Transportation Research Part B*, Vol. 37, pp. 857-881, 2003.
30. Bhat, C.R., Srinivasan, S., Axhausen, K.W.: An analysis of multiple interepisode durations using a unifying multivariate hazard model, *Transportation Research Part B*, Vol. 39, pp. 797-823, 2005.
31. Goulias., K.G.: Multilevel analysis of daily time use and time allocation to activity types accounting for complex covariance structures using correlated random effects, *Transportation*, 29, pp. 31-48, 2002.
32. Ben-Akiva, M., Bolduc, D., Walker, J.: Specification, identification, & estimation of the logit kernel (or continuous mixed logit) model, Working Paper, Department of Civil Engineering, MIT, 2001.
33. Train, K.E.: *Discrete Choice Methods with Simulation*, Cambridge University Press, 2003.
34. Lunn, D.J., Thomas, A., Best, N., Spiegelhalter, D.: WinBUGS - a Bayesian modelling framework: concepts, structure, and extensibility, *Statistics and Computing*, Vol. 10, 325-337, 2000.
35. Gill, J: *Bayesian Methods - A Social and Behavioral Sciences Approach*, 2nd edition, Chapman & Hall/CRC, 2008.
36. Axhausen, K.W.: Definition of movement and activity for transport modelling, in D.A. Hensher and K.J. Button (eds.) *Handbook of Transport Modelling*, 2nd edition, Elsevier, Oxford, pp. 329-344, 2008.
37. Chikaraishi, M., Fujiwara, A., Zhang, J., Axhausen, K.W.: Decomposing Variations and Co-Variations in Discrete Travel Choice Behavior with Multilevel Cross-Classified Logit Model, *Submitted to 12th International Conference on Travel Behaviour Research*, Jaipur,

India, December 13-18, 2009.

38. Rai, R.K., Balmer, M., Rieser, M., Vaze, V.S., Schönfelder, S., Axhausen, K. W.: Capturing human activity spaces: New geometries, *Transportation Research Record*, No. 2021, pp. 70-80, 2007.
39. Susilo, Y.O., Kitamura, R.: Analysis of day-to-day variability in an individual's action space: Exploration of 6-week Mobidrive travel diary data, *Transportation Research Record*, 1902, pp. 124-133, 2005.
40. Geweke, J.: Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments, in J.M. Bernardo, J.O. Berger, A.P. Dawid and A.F.M. Smith (eds.), *Bayesian Statistics 4*, Oxford: Oxford University Press, pp. 169-193, 1992.
41. Habib, K.M.N., Miller, E.J., Axhausen, K.W.: Weekly rhythm in joint time expenditure for all at-home and out-of-home activities: Application of Kuhn-Tucker demand system model using multiweek travel diary data, *Transportation Research Record*, No. 2054, pp. 64-73, 2008.
42. Lee-Gosselin, M.E.H., Doherty, S.T.: *Integrated Land-Use and Transportation Models: Behavioural Foundations*, Elsevier, 2005.
43. Habib, K.M.N.: *Modelling Activity Generation Process*, Ph. D Dissertation, University of Toronto, Canada, 2007 (http://www.ualberta.ca/~nurulhab/Final%20PhD%20Thesis_KMNH_SubmittedToIATBR.pdf).
44. Spiegelhalter, D.J., Best, N.G., Carlin, B.P., van der Linde, A.: Bayesian measures of model complexity and fit, *The Journals of the Royal Statistical Society B*, Vol. 64, pp. 583-639, 2002.

List of Tables/Figure

TABLE 1 Estimation Results (*Null* Model)

Items		Pick up/ Drop off		Private business		Mandatory activities		Daily shopping		Non-daily shopping		Leisure	
		mean	(s.d.)	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)
Constant		-15.05	(0.70)	-10.50	(0.49)	-7.30	(0.63)	-9.71	(0.35)	-14.68	(0.70)	-5.73	(0.51)
Random effects													
Inter-individual variation (s.d.)	σ_{ih}	3.213	(0.28)	2.169	(0.18)	3.669	(0.25)	2.564	(0.14)	1.970	(0.25)	2.189	(0.15)
Inter-household variation (s.d.)	σ_h	2.357	(0.41)	1.280	(0.33)	3.721	(0.45)	-	-	1.990	(0.31)	1.861	(0.24)
Temporal variation (s.d.)	σ_d	-	-	1.656	(0.18)	3.920	(0.30)	1.785	(0.17)	1.950	(0.25)	1.579	(0.14)
Spatial variation (s.d.)	σ_s	2.597	(0.43)	2.035	(0.32)	0.790	(0.16)	1.046	(0.21)	2.719	(0.45)	2.156	(0.34)
Intra-individual variation (s.d.)	σ_0	5.186	(0.15)	4.841	(0.09)	2.917	(0.03)	3.877	(0.06)	6.219	(0.17)	4.816	(0.06)

log[π(x| mean(θ))] = -73235, log[mean(π(x|θ))] = -84374, pD = 22278, DIC = 191026

Notes: *"-" represents non-significant random terms (at the significance level of 90%), and we exclude it from the model.* "log[π(x| mean(θ))]" *represents the log likelihood with the posterior means of parameters.* "log[mean(π(x|θ))]" *represents the posterior mean of the log likelihood.* "pD" *is defined as* 2(log[mean(π(x|θ))] - log[π(x| mean(θ))]), *which is used as the Bayesian measure of model complexity.* "DIC" *stands for Deviance Information Criterion which is defined as* -2(log[π(x| mean(θ))] - pD). DIC *can be viewed as a Bayesian analogue of AIC (Akaike Information Criterion). For details, please refer to Spiegelhalter et al. (44).*

TABLE 2 Estimation Results (*Full* Model)

Items	Pick up /Drop off		Private business		Mandatory activities		Daily shopping		Non-daily shopping		Leisure	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Constant	-19.50	(1.11)	-13.73	(0.70)	-5.922	(0.72)	-9.503	(0.69)	-15.43	(1.08)	-8.003	(0.83)
Explanatory variables												
Individual attributes												
Age			0.045	(0.01)	-0.042	(0.01)	0.019	(0.01)	0.039	(0.01)	-0.039	(0.01)
Male [D]	-0.766	(0.42)			0.586	(0.24)	-1.032	(0.27)	-1.664	(0.31)	-0.060	(0.21)
Married [D]							0.199	(0.33)				
Number of fixed commitments											0.332	(0.14)
Full-time worker [D]					2.554	(0.33)	-0.739	(0.34)				
Part-time worker [D]	-1.263	(0.77)	0.608	(0.40)	2.136	(0.44)						
Student [D]					1.165	(0.48)	-1.160	(0.54)			0.938	(0.42)
Retired person [D]	-0.943	(0.71)	1.116	(0.44)	-3.889	(0.55)	0.228	(0.51)			0.565	(0.47)
Vehicle license holder [D]	1.496	(0.52)			-0.428	(0.34)	1.039	(0.38)	-0.453	(0.44)		
Season ticket holder [D]					-0.603	(0.26)			-0.911	(0.42)		
Household attributes												
Number of personal vehicles	-1.838	(0.43)					-1.146	(0.23)	-0.861	(0.40)		
Number of household members	1.082	(0.23)			-0.320	(0.11)					-0.286	(0.15)
Household income (in 1000DM)					0.082	(0.06)			0.177	(0.12)		
Bus stop: Distance (in 100m)									-0.035	(0.02)		
LRT stop: Distance (in 100m)			-3.E-04	(4.E-04)			-9.E-04	(4.E-04)	9.E-05	(6.E-04)	8.E-05	(5.E-04)
Heavy rail stop: Distance (in 100m)	0.017	(8.E-03)					0.010	(5.E-03)	-0.011	(8.E-03)	-0.018	(7.E-03)
Temporal attributes												
Tuesday [D]					-0.137	(0.33)						
Wednesday [D]			-0.371	(0.30)	-0.493	(0.32)						
Thursday [D]											0.324	(0.23)
Friday [D]			-0.779	(0.30)			0.629	(0.15)			0.739	(0.23)
Saturday [D]			-2.567	(0.33)	-6.523	(0.35)	0.796	(0.15)	1.784	(0.34)	2.490	(0.22)
Sunday [D]	0.585	(0.29)	-3.616	(0.36)	-6.406	(0.38)	-4.783	(0.27)	-5.248	(0.57)	3.434	(0.23)

TABLE 2 (Cont'd) Estimation Results (*Full* Model)

Items	Pick up /Drop off		Private business		Mandatory activities		Daily shopping		Non-daily shopping		Leisure	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Spatial attributes												
Lining in CBD [D]	-1.630	(1.10)	1.254	(0.68)	-1.218	(0.51)			-2.589	(1.02)		
Lining in Karlsruhe [D]			0.738	(0.76)							1.868	(0.69)
Situational attributes												
Use car on a given day [D]	4.255	(0.32)	1.799	(0.19)	0.333	(0.10)	0.859	(0.14)	2.280	(0.31)	1.776	(0.15)
Use PT on a given day [D]			0.464	(0.22)	1.141	(0.12)			1.060	(0.35)	0.296	(0.18)
Previous participation in a corresponding activity on t-1 day [D]	1.266	(0.28)	0.760	(0.17)	2.746	(0.12)	-0.196	(0.13)	0.856	(0.34)	1.582	(0.12)
Previous participation in a corresponding activity on t-2 day [D]	0.188	(0.29)	0.293	(0.18)	0.432	(0.12)	-0.080	(0.13)	0.614	(0.33)	0.372	(0.13)
Previous participation in a corresponding activity on t-3 day [D]	-0.384	(0.30)	0.323	(0.18)	0.177	(0.11)	-0.042	(0.13)	-0.037	(0.33)	0.015	(0.13)
Previous participation in a corresponding activity on t-7 day [D]	2.004	(0.28)	1.051	(0.17)	1.842	(0.11)	1.151	(0.12)	1.381	(0.31)	1.208	(0.13)
Random effects												
Inter-individual variation (s.d.) σ_{ih}	2.541	(0.27)	1.334	(0.17)	1.675	(0.11)	1.883	(0.12)	1.325	(0.31)	1.283	(0.13)
Inter-household variation(s.d.) σ_h	1.167	(0.54)	1.152	(0.21)	0.198	(0.16)	-		1.627	(0.30)	1.505	(0.17)
Temporal variation (s.d.) σ_d	-		0.604	(0.14)	0.914	(0.09)	0.090	(0.06)	0.394	(0.24)	0.394	(0.10)
Spatial variation (s.d.) σ_s	1.951	(0.34)	1.774	(0.30)	0.528	(0.11)	0.988	(0.20)	2.461	(0.43)	1.524	(0.25)
Intra-individual variation (s.d.) σ_0	5.060	(0.14)	4.836	(0.09)	2.734	(0.03)	3.856	(0.06)	6.296	(0.17)	4.746	(0.06)
$\log[\pi(x \mid mean(\theta))] = -73245$, $\log[mean(\pi(x \mid \theta))] = -84364$, pD = 22238, DIC = 190965												

Notes: *The value of* $\log[\pi(x \mid mean(\theta))]$ *is not so different from that in Null model. This is because the log likelihood value in Null model also accounts for the effects of introduced explanatory variables by unobserved random effects.*

TABLE 3 Comparison of Variations between the *Null* and *Full* Models

		Pick up/ Drop off	Private business	Mandatory activities	Daily shopping	Non-daily shopping	Leisure
Null model	Inter-individual variation	10.32 (20.8%)	4.70 (12.8%)	13.46 (25.9%)	6.57 (25.3%)	3.88 (6.7%)	4.79 (12.4%)
	Inter-household variation	5.56 (11.2%)	1.64 (4.5%)	13.85 (26.7%)	-	3.96 (6.8%)	3.46 (8.9%)
	Temporal variation	-	2.74 (7.5%)	15.37 (29.6%)	3.19 (12.2%)	3.80 (6.6%)	2.49 (6.4%)
	Spatial variation	6.74 (13.6%)	4.14 (11.3%)	0.62 (1.2%)	1.09 (4.2%)	7.39 (12.8%)	4.65 (12.0%)
	Intra-individual variation	27.03 (54.4%)	23.57 (64.1%)	8.64 (16.6%)	15.16 (58.3%)	38.81 (67.1%)	23.33 (60.2%)
	Total	**49.65**	**36.79**	**51.94**	**26.02**	**57.84**	**38.72**
Full model	Inter-individual variation	6.46	1.78	2.81	3.55	1.76	1.65
	Inter-household variation	1.36	1.33	0.04	0.0	2.65	2.27
	Temporal variation	0.0	0.36	0.83	0.01	0.15	0.16
	Spatial variation	3.81	3.15	0.28	0.98	6.06	2.32
	Intra-individual variation	25.74	23.52	7.61	15.00	39.77	22.66
	Total	**37.36**	**30.14**	**11.56**	**19.53**	**50.39**	**29.05**
The amount of variation reductions (%)	Inter-individual variation	3.87 (37.5%)	2.93 (62.2%)	10.66 (79.2%)	3.03 (46.1%)	2.13 (54.8%)	3.15 (65.6%)
	Inter-household variation	4.19 (75.5%)	0.31 (19.0%)	13.81 (99.7%)	-	1.31 (33.2%)	1.20 (34.6%)
	Temporal variation	-	2.38 (86.7%)	14.53 (94.6%)	3.18 (99.7%)	3.65 (95.9%)	2.34 (93.8%)
	Spatial variation	2.94 (43.6%)	0.99 (24.0%)	0.35 (55.3%)	0.12 (10.8%)	1.34 (18.1%)	2.33 (50.0%)
	Intra-individual variation	1.29 (4.8%)	0.05 (0.2%)	1.03 (12.0%)	0.16 (1.1%)	-0.96 *(-2.5%)*	0.67 (2.9%)
	Total	**12.29 (24.8%)**	**6.66 (18.1%)**	**40.37 (77.7%)**	**6.49 (24.9%)**	**7.46 (12.9%)**	**9.68 (25.0%)**
Var(βx) in the *Full* model		8.20	5.19	29.00	6.47	8.59	7.00