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Chikaraishi, Makoto; Zhang, Junyi; Fujiwara, Akimasa; [Axhausen, Kay W.](#) 

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## **Exploring Variation Properties of Time Use Behavior Based on a Multilevel Multiple Discrete-Continuous Extreme Value Model<sup>1</sup>**

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

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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 *Mobidrive* 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 ( $I$ ), 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 too 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 model is still often used, partly because alternative methods are obscure. Because we could not avoid such limitations especially in practice as of now, at least we may 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

1 understand the phenomena themselves without analyzing how they vary around the stable  
2 relationship. The remaining variations could offer useful information to understand how the  
3 behavior varies around the discovered stable relationship, and what kinds of factors we  
4 should further observe.

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

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

## 30 31 32 **2. LITERATURE REVIEW**

### 33 34 **2.1. Studies on Time Use Behavior**

35  
36 The analysis of time use behavior has received much attention from many researchers. This is  
37 mainly for a better understanding of activity-travel behavior with the development of  
38 well-founded practice models in mind, or more directly towards the development of new  
39 transportation planning methodologies that reflect people's desires and needs to assess the  
40 impacts of transportation on, for example, their quality of life (e.g., 9, 14-17). Accordingly, a  
41 number of time use models have been developed from both theoretical and practical  
42 perspectives. One of the most fundamental time use models in transportation field was  
43 proposed by Kitamura (18). He modeled individual time use behavior within a given day on  
44 the basis of the law of diminishing marginal utilities (represented based on a logarithm utility  
45 function), incorporating both discrete activity choice and continuous time allocation between  
46 two activity types based on the type-II Tobit model specification. The model (and its

1 concepts) has been extended in various ways. For example, Zhang et al. (19, 20) proposed the  
2 time use models with intra-household interactions. Supernak (21) and Timmermans et al. (22)  
3 doubted the assumption of diminishing marginal utilities and reconsider the shape of the  
4 utility function. Kitamura (23) focused on time use patterns on multiple days and its historical  
5 dependencies. Bhat and Misra (24) attempted to reveal the weekly time allocation behavior  
6 between in-home and out-of-home activities and between weekdays and weekends. Bhat (11,  
7 12) proposed a multiple discrete-continuous extreme value (MDCEV) model which can  
8 represent that individuals choose the multiple types of activities from the whole choice set,  
9 and allocate their time to these activities.

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

## 18 **2.2. Studies on Behavioral Variations**

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

25 There are several studies focusing on intra-individual and inter-individual variations  
26 in time use behavior. As an early research, Jones and Clarke (28) proposed the time-use-based  
27 measure of intra-individual variability (or similarity). They found out the differences in the  
28 degree of intra-individual variability between lifecycle stages as well as gender. Bhat et al.  
29 (29) examined the duration between successive non-maintenance shopping activities by using  
30 a mixed hazard-based duration model. They distinguished intra-individual and  
31 inter-individual variations, and found that around 70% in total unobserved variations are  
32 derived from unobserved intra-individual variations. Bhat et al. (30) also examined the  
33 duration between successive participations of five activity types (maintenance shopping,  
34 non-maintenance shopping, social activities, recreation, and personal business) by using a  
35 multivariate hazard model. They pointed out that, except for non-maintenance shopping,  
36 individuals have well-established rhythms for all activity participations. Their results also  
37 indicate that, while such rhythms substantially vary across individuals, it seems to be difficult  
38 to put the rhythms into the observed elements (i.e., capture the source of rhythms). Spissu et  
39 al. (26) figured out the variations in out-of-home discretionary activities by using the mixed  
40 MDCEV model with unobserved inter-individual and intra-individual variations. Their results  
41 also confirmed large unobserved intra-individual variations for all discretionary activities  
42 (44.8~76.8% in total unobserved variations) and also clarified the difficulties of capturing  
43 such variations by introduced explanatory variables (only 2.9~45.8% of total variations can  
44 be captured). Goulias (31) developed a time use model accounting for not only  
45 inter-individual and intra-individual variations, but also inter-household variations. The  
46 results of his analysis show that inter-household variations for all activities are more than 1/3

1 of the inter-personal variations, and the inter-household variations cannot be ignored.

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

### 10 3. METHODOLOGY

#### 12 3.1. Model Formulation

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

$$19 \begin{aligned} & \text{maximize } U_{ihds} = \sum_{j=1}^J u_{ihds}^j(t_{ihds}^j) \\ & \text{subject to } \sum_{j=1}^J t_{ihds}^j = T, t_{ihds}^j \geq 0 (j = 1, 2, \dots, J) \end{aligned} \quad (1)$$

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

$$25 \begin{aligned} 26 & u_{ihds}^j(t_{ihds}^j) = \psi_{ihds}^j \ln(t_{ihds}^j + 1) \quad (2) \\ 27 & \psi_{ihds}^j = \exp(\beta^j x_{ihds}^j + \gamma_{ih}^j + \gamma_h^j + \gamma_d^j + \gamma_s^j + \eta_{ihds}^j + e_{ihds}^j) \quad (3) \end{aligned}$$

28 Here,  $\psi_{ihds}^j$  represents the degree of baseline preference of activity  $j$  pursued by individual  $i$   
29 of household  $h$  on day  $d$  at action space  $s$ .  $\beta^j$  represents parameter vector,  $x_{ihds}^j$  represents  
30 explanatory variables.  $\gamma_{ih}^j$ ,  $\gamma_h^j$ ,  $\gamma_d^j$ ,  $\gamma_s^j$  and  $\eta_{ihds}^j$  represent the random components which  
31 indicate inter-individual variation, inter-household variation, temporal variation (date-specific  
32 error component), spatial variation (error component specific to action space) and  
33 intra-individual variation, respectively.  $e_{ihds}^j$  represents intra-individual variation, and it is  
34 assumed to be independently and identically Gumbel-distributed with variance  $\sigma^2 \pi^2 / 6$ . The  
35 parameter  $\sigma$  is fixed as 0.2 because the error components of  $\eta_{ihds}^j$  and  $e_{ihds}^j$  will capture the  
36 same inter-individual variation, and the rest of inter-individual variation will be captured by  
37  $\eta_{ihds}^j$ . Let random components  $\gamma_{ih}^j$ ,  $\gamma_h^j$ ,  $\gamma_d^j$ ,  $\gamma_s^j$  and  $\eta_{ihds}^j$  be normally distributed as follows,  
38 where these random components are all assumed to be uncorrelated with each other.

41

$$\begin{aligned} \gamma_{ih}^j &\sim N(0, \sigma_{ih/j}^2), \gamma_h^j \sim N(0, \sigma_{h/j}^2), \gamma_d^j \sim N(0, \sigma_{d/j}^2), \\ \gamma_{id}^j &\sim N(0, \sigma_{s/j}^2), \eta_{ihds}^j \sim N(0, \sigma_{0/j}^2) \end{aligned} \quad (4)$$

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 (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.

$$\begin{cases} V_{ihds}^j + e_{ihds}^j = V_{ihds}^1 + e_{ihds}^1 & \text{if } t_{ihds}^{j*} > 0 \\ V_{ihds}^j + e_{ihds}^j < V_{ihds}^1 + e_{ihds}^1 & \text{if } t_{ihds}^{j*} = 0 \end{cases} \quad j = 2, 3, \dots, J \quad (5)$$

where,  $V_{ihds}^j = \beta^j x_{ihds}^j + \gamma_{ih}^j + \gamma_h^j + \gamma_d^j + \gamma_s^j + \eta_{ihds}^j - \ln(t_{ihds}^{j*} + 1)$ .

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

$$\begin{aligned} &P(t_{ihds}^* / \beta, \gamma_{ih}, \gamma_h, \gamma_d, \gamma_s, \eta_{ihds}) \\ &= \frac{(M_{ihds} - 1)!}{\sigma^{M_{ihds} - 1}} \left[ \prod_{m_{ihds}=1}^{M_{ihds}} \frac{1}{(t_{ihds}^{m_{ihds}*} + 1)} \right] \left[ \sum_{m_{ihds}=1}^{M_{ihds}} (t_{ihds}^{m_{ihds}*} + 1) \right] \left[ \frac{\prod_{m_{ihds}=1}^{M_{ihds}} \exp(V_{ihds}^{m_{ihds}} / \sigma)}{(\sum_{j=1}^J \exp(V_{ihds}^j / \sigma))^{M_{ihds}}} \right] \end{aligned} \quad (6)$$

Here,  $t_{ihds}^* = \{t_{ihds}^{1*}, t_{ihds}^{2*}, \dots, t_{ihds}^{M_{ihds}*}, 0, 0, \dots, 0\}$ .  $m_{ihds}$  ( $m_{ihds}=1, 2, \dots, M_{ihds} \mid M_{ihds} \in J$ ) 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 posterior distribution 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:



$$\begin{aligned}
& \pi(\beta, \sigma_{ih}, \sigma_h, \sigma_d, \sigma_s, \sigma_0 / t^*, x) \\
& \propto \prod_{N_{ihds}} P(t_{ihds}^* / \beta, \gamma_{ih}, \gamma_h, \gamma_d, \gamma_s, \eta_{ihds}) \\
& \quad \times f(\gamma_{ih} / \sigma_{ih}) f(\gamma_h / \sigma_h) f(\gamma_d / \sigma_d) f(\gamma_s / \sigma_s) f(\eta_{ihds} / \sigma_0) \\
& \quad \times \phi(\sigma_{ih}) \phi(\sigma_h) \phi(\sigma_d) \phi(\sigma_s) \phi(\sigma_0) \phi(\beta)
\end{aligned} \tag{7}$$

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  $\eta_{ihds}$  along with their variances into the sampling procedure,  $f(\gamma_{ih} / \sigma_{ih})$ ,  $f(\gamma_h / \sigma_h)$ ,  $f(\gamma_d / \sigma_d)$ ,  $f(\gamma_s / \sigma_s)$  and  $f(\eta_{ihds} / \sigma_0)$ , which are assumed to be normally distributed as described in eq.(4), create the so-called ‘‘hierarchical’’ sampling procedure (32). 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 (32).

Draws from the posterior are obtained using software WinBUGS (Bayesian inference Using Gibbs Sampling (33)). In the Gibbs sampling, draws of each parameter are obtained from its posterior conditional on the other parameters (details refer to Gill (34) or Train (32)).

### 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:

$$\frac{\Psi_{ihds}^j}{\Psi_{ihds}^1} = \exp(\beta^j x_{ihds}^j + \gamma_{ih}^j + \gamma_h^j + \gamma_d^j + \gamma_s^j + \varepsilon_{ihds}^j + e_{ihds}^j - e_{ihds}^1) \tag{8}$$

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:

$$\text{var} \left[ \ln \left( \frac{\Psi_{ihds}^j}{\Psi_{ihds}^1} \right) \right] = \text{var}(\beta^j x_{ihds}^j) + \sigma_{ih/j}^2 + \sigma_{h/j}^2 + \sigma_{d/j}^2 + \sigma_{s/j}^2 + \left( \sigma_{0/j}^2 + \frac{\sigma^2 \pi^2}{3} \right) \tag{9}$$

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),

1 all the estimated unobserved variation components would be smaller than those in the *Null*  
 2 model theoretically because  $\text{var}(\beta^j x_{\text{thds}}^j)$  explains a part of the total variation. If we could  
 3 obtain perfect information of influential factors determining time use behavior, unobserved  
 4 variation components would be nearly zeros, but usually some unobserved variations would  
 5 still remain. We focus on these remaining unobserved variations which offer information  
 6 about what kinds of explanatory variables are still lacking to describe time use behavior. This  
 7 would be substantially important especially when we consider the relationship between data  
 8 collection and model development which constrain and condition each other (35). For  
 9 example, even if there is a certain level of spatial variation, we may not need to search for  
 10 further influential factors related to spatial differences when we could capture the variation  
 11 very well (i.e., unobserved spatial variation are almost explained by introduced observed  
 12 variables). On the other hand, if substantial unobserved variations still remain at high levels  
 13 even introducing all available explanatory variables, there would be “niches” to be exploited  
 14 along with additional “observation”. In the same manner, exploring variation properties  
 15 described in eq. (9) can provide useful information to search such “niches” for each type of  
 16 variation. To examine how much each variation can be captured by introduced explanatory  
 17 variables, this study compares unobserved variations without considering explanatory  
 18 variables (*Null* model) with those variances with explanatory variables (*Full* model).  
 19  
 20

## 21 4. EMPIRICAL ANALYSIS

### 23 4.1. Data

25 The *Mobidrive* data set (13) is used in the empirical analysis. It includes a six-week (42 days)  
 26 travel diary survey data conducted in Karlsruhe (West Germany) and Halle (East Germany),  
 27 in the fall of 1999. Including the pilot survey, a total of 361 persons from 162 households  
 28 participated in this survey. Here, the original data include persons who could not report on  
 29 their behaviors in some days, for example, due to extended vacations. After data cleaning, a  
 30 total of 294 persons from 141 households were selected for the empirical analysis in this  
 31 study, and the total number of samples is 12,348 (= 294[person]  $\times$  42[day]). The total  
 32 recorded days are 119 days, including 56 days from the pilot survey (May 31 through July 25)  
 33 and 63 days from the main survey (September 13 through November 14). Additionally, for  
 34 the definition of action space, we took the following steps: 1) classifying the whole space into  
 35 4 zones (CBD, inner city, suburb, and elsewhere) for each city, and 2) identifying (non-)  
 36 active zones in which a person (didn't) conduct any activity on a given day. As a result, 30  
 37 action spaces (=  $2^4$  [active or non-active for 4 zones] - 1 [excluding all non-active case])  $\times$  2  
 38 [cities]) are obtained in total. In summary, we will deal with time use behaviors of 12,348  
 39 [person-day] pursued by individual  $i$  (=1,...,294) from household  $h$  (=1,...,141) on day  $d$   
 40 (=1,...,119) along with action space  $s$  (=1,...,30). Here, note that there are so many ways to  
 41 define the action space (e.g., 36, 37). In fact, an action space could be continuous in essence.  
 42 However, our employed definition of action space assumes discrete action spaces (i.e., when  
 43 an activity engagement at a certain zone is canceled, the action space is recognized as being  
 44 completely different from original action space even though other activities remain  
 45 unchanged). This is because the random effects approach used in this study requires discrete  
 46 or categorical definitions about action space. How to define the continuous effects of action

1 space and how to incorporate these effects in the analysis of time use behavior remain as an  
2 issue to be solved.

3 As for activity classification, we employ seven activity types: 1) *home activities* (base  
4 alternative); 2) *pick up/drop off*; 3) *private business*; 4) *mandatory activities*; 5) *daily*  
5 *shopping*; 6) *non-daily shopping*; and 7) *leisure*. The allocated time to travel is considered as  
6 a part of the next activity. Table 1 shows descriptive statistics of activity participation and  
7 duration for each activity type. It is found that that the ratios of participation in *leisure* and  
8 *mandatory activities* are much higher and their durations are also much longer than other  
9 out-of-home activities. Especially when focusing on the activity participation ratio at  
10 individual level, all the respondents participated in *leisure* at least once during the 42 days.  
11 On the other hand, more than 10 percent of respondents had never conducted *pick up/drop off*  
12 and *mandatory activities*. Thus, it is expected that these activities might have relatively higher  
13 inter-individual variations.

## 14 15 **4.2. Model estimation and Discussion**

16  
17 In this study, the hierarchical Bayesian procedure based on MCMC method is used for  
18 estimating the multilevel MDCEV model described in Section 3. For this estimation, the  
19 non-informative prior distributions are given for all parameters, and a total of 450,000  
20 iterations are done in order to obtain 10,000 draws: the first 150,000 for burn-in to mitigate  
21 start-up effects and 300,000 after convergence, of which every 30 samples are retained. The  
22 estimation results are quite stable for both *Null* and *Full* models. Even when we reduce the  
23 number of draws to 350,000 (150,000 is for burn-in, and every 20 samples in the rest of  
24 draws is retained) or change the initial values, the estimated values and its standard deviations  
25 are asymptotically equivalent to the reported estimation results.

26 The estimation results of *Null* model (i.e., the model without explanatory variables)  
27 are presented in Table 2. This is intended to first explore actual variations, and then to provide  
28 some reference points for evaluating the impacts of explanatory variables by comparing with  
29 *Full* model. Putting the estimated parameters into eq. (9), the proportions of variations in  
30 baseline preferences can be obtained, as shown in Figure 1. The major findings are described  
31 below.

- 32 (i) The inter-individual variations in *pick up/drop off*, *mandatory activities*, and *daily*  
33 *shopping* account for more than 20% of total variations, while *private business*, *non-daily*  
34 *shopping*, and *leisure* account for around 10%. This is because more task allocations  
35 among household members might be observed regarding the former activities compared  
36 to the latter activities.
- 37 (ii) *Mandatory activities* show the biggest inter-household variation. This might be derived  
38 from the differences of lifecycle stages. For example, elderly households rarely  
39 participate in *mandatory activities*. On the other hand, *daily shopping* shows  
40 non-significant inter-household variation (and we exclude this from the model). This  
41 implies that the allocated time and activity participation in *daily shopping* would be  
42 almost the same across households.
- 43 (iii) The biggest temporal variation (i.e., systematic day-to-day variation) is found in  
44 *mandatory activities*, because these might be conducted on most weekdays and rare on  
45 some weekends. On the other hand, it is also confirmed that time use for *pick up/drop off*  
46 is not dependent on the date.

- 1 (iv) Spatial variations vary from 1.4% to 14.6% across activities, but the variations in  
2 *mandatory activities* and *daily shopping* are relatively smaller than those in the other  
3 activities. This might be because that an individual's action space is usually centered  
4 around his/her work location and/or household location, and consequently *daily shopping*  
5 is probably conducted within this fundamental action space. Conversely, performing  
6 other activities like *leisure* might force the individual to expand his/her action space  
7 beyond the fundamental action space.
- 8 (v) Except for *mandatory activities*, 55.6~65.6% of total variations are derived from  
9 intra-individual variations (the highest proportions among five variation types). To this  
10 variation, situational factors (e.g., travel party, weather, health condition, events decided  
11 in previous days, mental state, and time pressure) might be significantly influential. The  
12 finding here however suggests that such situation-dependent behaviors may not well be  
13 captured in travel survey. On the other hand, the intra-individual variation in *mandatory*  
14 *activities* account for only 17.0%, which is the second lowest among the five variation  
15 components. This is probably because participation in *mandatory activities* is not affected  
16 by, for example, the situational factors.

17 In summary, the results of *Null* model indicate that time use behavior could be  
18 affected by various kinds of factors, and all the introduced variation types cannot be ignored.  
19 This implies, even though we do not have a rich data like *Mobidrive* data, at least we should  
20 pay attention to interpreting the results obtained from the limited data. For example, if only a  
21 one-day survey data is available, one should realize that at least the temporal variations  
22 (~30.2%) will not be captured in the analysis. In addition, it might also be difficult to capture  
23 some of intra-individual variations because some situational attributes affecting the  
24 intra-individual variations might belong to the information on other days (e.g., shopping in a  
25 day might be decided for a party held on the next day).

26 The estimation results of *Full* model are shown in Table 3. The introduced  
27 explanatory variables are selected from various kinds of factors, such as individual,  
28 household, temporal, spatial, and situational attributes. These variables are often used in  
29 existing literatures, and we take these variables to represent the common case. Here, although  
30 we can obtain some more useful information from the estimation results about the  
31 explanatory variables (the signs of parameters are quite understandable in general), here we  
32 only focus on the variations calculated from *Full* model in comparison with those from *Null*  
33 model because of space limitations.

34 The comparison results of variations between the *Null* and *Full* models are shown in  
35 Table 4. The amounts of variation reductions are also described in the lower part of the table.  
36 The values in parenthesis represent that to what extent the corresponding variations can be  
37 captured by the introduced explanatory variables. This means that the values can be regarded  
38 as a quasi R-squared by activity type and variation type, with the assumption that the  
39 introduced random effects and explanatory variables are statistically independent with each  
40 other. Although some values are negative, meaning the assumption would not be true, the  
41 values are quite small. In addition, the values of total amount of variation reductions (the  
42 second line from the bottom in Table 4) are also quite similar to the observed variations  
43  $\text{var}(\beta x)$ . This study thus argues that the values in Table 4 are eligible for evaluating the  
44 variation reductions (i.e., the negative values can be assumed as zero). Needless to say,  
45 co-variation effects (i.e., combinatorial effects of two or more variation types) should be  
46 confirmed in future. The major findings are summarized below.

- 1 (i) The reduction levels in inter-individual, inter-household, and spatial variations vary from  
2 activity to activity, but there are probably some “niches” to be further explored in all  
3 activity types without inter-household variation in *mandatory activities*. Given more  
4 detailed information related to individual, household and action space attributes, it is  
5 expected that the model performance could be further improved.
- 6 (ii) The biggest reduction rate is observed with respect to temporal variations (89.0~99.6%).  
7 This implies that some systematic day-to-day variations can be well captured by the  
8 introduced explanatory variables (perhaps mainly by day-of-week dummies), and weekly  
9 time use behavior would be quite stable. This is consistent with the results of Habib et al.  
10 (38).
- 11 (iii) The reduction levels in intra-individual variations for all activities are quite small. This  
12 implies that we need some additional information related to, for example, situational  
13 attributes that should be further collected. However, it has not been clarified what kinds  
14 of situational attributes are really relevant to the time use behavior. In addition, to  
15 describe the activity participation behavior, the information from non-participants is also  
16 required; however, it is usually difficult to collect the situational information from the  
17 non-participants just because they did not participate in the activity. For example, “with  
18 whom” information might be one of the important influential factors to perform leisure  
19 activities, but this information is only available for those who already participate in it. In  
20 this sense, it becomes important how to collect the relevant situational information from  
21 non-participants. This might a very challenging research topic.

## 22 23 24 **5. CONCLUSIONS**

25  
26 This paper has examined the variation properties of time use behavior by building a  
27 multilevel MDCEV model, which simultaneously represents activity participation and time  
28 allocation and decomposes the total variation in time use behavior into five major variation  
29 components (i.e., inter-individual, inter-household, temporal, spatial, and intra-individual  
30 variations). *Mobidrive* data (a continuous six-week travel daily data) were adopted in the  
31 empirical analysis. Model estimation results have indicated that time use behavior could be  
32 affected by various kinds of factors, and also confirmed that narrowing down the target of an  
33 analysis to limited variation types could lose some valuable information. It has been further  
34 revealed that most variation types cannot be ignored even after incorporating their influences  
35 by using some observed information, except for temporal variations in all activity types and  
36 inter-household variation in *mandatory activities*. Furthermore, it has also been found that it  
37 is difficult to capture the intra-individual variations in all activities by introduced explanatory  
38 variables. These findings could provide useful information to figure out what should be done  
39 to improve modeling and/or data observation tasks as well as the understanding of  
40 mechanisms of time use behavior.

41 However, there are a number of unresolved issues. From the modeling perspective, a  
42 continuous representation of action space might be needed to more properly capture spatial  
43 variations. In addition, the existence of co-variation effects among variation types should be  
44 confirmed along with correlations among activity types. Exploring the meaning and  
45 interpretation of intra-individual variations also remains as future tasks. The different  
46 behavioral rhythms, habits, and ideologies among individuals might be one of the important

1 influential factors on the decision making of activity-travel behavior. The way to remove  
2 white noise and extract such influential factors from behavioral variations might be needed.  
3 Another challenge is the analysis of activity generation process, especially focusing on how  
4 to incorporate the influence of situational attributes from both modeling and data collection  
5 perspectives. Although activity generation process has been examined by some researchers  
6 (e.g., 39), there are still some big “niches” to be explored.

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**TABLE 1 Descriptive Statistics of Activity Participation and Duration**

**TABLE 2 Estimation Results (*Null Model*)**

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**TABLE 4 Comparison of Variations between the *Null* and *Full* Models**

**FIGURE 1 Proportions of variations (*Null model*).**

**TABLE 1 Descriptive Statistics of Activity Participation and Duration**

Activity type	Duration	Number of participants			
	(min)	(person-day)	(%)	(person) <sup>1)</sup>	(%)
Home activities (base)	1021.1	12103 <sup>2)</sup>	98.0%	294	100.0%
Pick up/Drop off	6.7	1153	9.3%	212	72.1%
Private business	19.1	2647	21.4%	286	97.3%
Mandatory activities	216.5	6017	48.7%	255	86.7%
Daily shopping	14.3	3299	26.7%	281	95.6%
Non-daily shopping	9.7	1347	10.9%	271	92.2%
Leisure	152.6	5995	48.6%	294	100.0%
Total	1440.0	12348 (=294individuals×42days)		294	

1) Number of individuals who participate in the corresponding activity at least once during 42 days.

2) 245 samples (=12348-12103), who don't conduct home activities within a given day, conduct: only leisure (around 80%), only mandatory activities (around 10%), and others (mainly multiple activities except for home activities).

**TABLE 2 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	-15.10	(0.58)	-10.64	(0.43)	-7.36	(0.47)	-9.54	(0.34)	-14.71	(0.70)	-5.80	(0.51)	
<b>Random effects</b>													
Inter-individual variation (s.d.)	$\sigma_{ih}$	3.244	(0.26)	2.134	(0.17)	3.595	(0.25)	2.566	(0.13)	2.068	(0.23)	2.179	(0.15)
Inter-household variation (s.d.)	$\sigma_h$	2.219	(0.38)	1.228	(0.27)	3.675	(0.45)	-	-	1.792	(0.30)	1.820	(0.23)
Temporal variation (s.d.)	$\sigma_d$	-	-	1.637	(0.16)	3.938	(0.28)	1.787	(0.15)	2.210	(0.26)	1.599	(0.13)
Spatial variation (s.d.)	$\sigma_s$	2.637	(0.43)	2.044	(0.33)	0.850	(0.16)	0.937	(0.19)	2.978	(0.48)	2.194	(0.34)
Intra-individual variation (s.d.)	$\sigma_0$	5.283	(0.13)	4.952	(0.08)	2.930	(0.03)	3.867	(0.06)	6.278	(0.16)	4.820	(0.05)

$\log[\pi(x|\text{mean}(\theta))] = -88035$ ,  $\log[\text{mean}(\pi(x|\theta))] = -101399$ ,  $pD = 26728$ ,  $DIC = 229526$

Notes: “-” represents non-significant random terms (at the significance level of 90%), and we exclude it from the model. “ $\log[\pi(x|\text{mean}(\theta))]$ ” represents the log likelihood with the posterior means of parameters. “ $\log[\text{mean}(\pi(x|\theta))]$ ” represents the posterior mean of the log likelihood. “pD” is defined as  $2(\log[\text{mean}(\pi(x|\theta))] - \log[\pi(x|\text{mean}(\theta))])$ , which is used as the Bayesian measure of model complexity. “DIC” stands for Deviance Information Criterion which is defined as  $-2(\log[\pi(x|\text{mean}(\theta))] - pD)$ . DIC can be viewed as a Bayesian analogue of AIC (Akaike Information Criterion). For details, please refer to Spiegelhalter et al. (40).

**TABLE 3 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	-20.35	(1.35)	-13.55	(0.76)	-2.627	(1.15)	-9.334	(0.75)	-14.20	(1.22)	-5.997	(1.03)
<b><u>Explanatory variables</u></b>												
<b><i>Individual attributes</i></b>												
Age			0.052	(0.01)	-0.070	(0.02)	0.026	(0.01)	0.032	(0.01)	-0.055	(0.01)
Male [D]	-0.864	(0.48)	-0.184	(0.28)	1.016	(0.37)	-1.126	(0.29)	-1.659	(0.33)	-0.067	(0.26)
Married [D]	-0.461	(0.55)			-0.057	(0.50)	0.304	(0.34)				
Number of fixed commitments							-0.133	(0.16)			0.545	(0.18)
Full-time worker [D]					4.523	(0.51)	-0.746	(0.39)				
Part-time worker [D]	-1.489	(0.89)	0.640	(0.50)	3.780	(0.68)	0.297	(0.54)				
Student [D]					1.807	(0.74)	-0.943	(0.60)			0.807	(0.54)
Retired person [D]	-0.872	(0.83)	1.217	(0.51)	-5.635	(0.83)	0.264	(0.59)			0.951	(0.60)
Vehicle license holder [D]	2.450	(0.67)			-1.141	(0.54)	1.236	(0.41)	-0.485	(0.47)		
Season ticket holder [D]			-0.174	(0.34)	-0.719	(0.40)			-1.023	(0.44)		
<b><i>Household attributes</i></b>												
Number of personal vehicles	-2.004	(0.49)			0.228	(0.33)	-1.156	(0.24)	-1.012	(0.39)	-0.251	(0.39)
Number of household members	1.241	(0.27)			-0.462	(0.19)					-0.287	(0.20)
Household income (in 1000DM)					0.144	(0.10)			0.187	(0.12)	0.018	(0.13)
Bus stop: Distance (in 100m)	-0.005	(0.02)					-2.E-03	(0.01)	-0.043	(0.02)	9.E-04	(0.02)
LRT stop: Distance (in 100m)			-5.E-04	(5.E-04)			-8.E-04	(4.E-04)	-7.E-05	(6.E-04)	2.E-04	(6.E-04)
Heavy rail stop: Distance (in 100m)	0.025	(0.01)			-0.007	(0.01)	0.011	(0.00)	-0.015	(0.01)	-0.025	(0.01)

**TABLE 3 (Cont'd) Estimation Results (Full Model)**

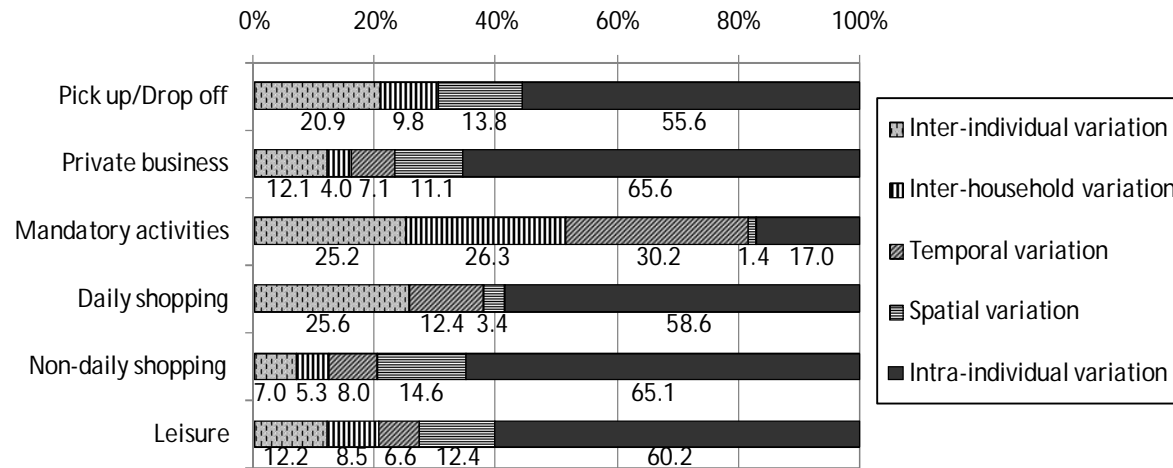
Items	Pick up/ Drop off		Private business		Mandatory activities		Daily shopping		Non-daily shopping		Leisure	
	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)
<b>Temporal attributes</b>												
Tuesday [D]					0.330	(0.17)						
Wednesday [D]			-0.373	(0.28)	0.199	(0.17)					0.150	(0.22)
Thursday [D]			-0.254	(0.28)							0.282	(0.22)
Friday [D]			-0.750	(0.28)			0.616	(0.14)			0.633	(0.22)
Saturday [D]			-2.860	(0.31)	-6.972	(0.19)	0.855	(0.14)	1.981	(0.32)	2.685	(0.22)
Sunday [D]	0.383	(0.28)	-3.904	(0.34)	-8.638	(0.22)	-5.195	(0.24)	-5.909	(0.57)	3.969	(0.22)
<b>Spatial attributes</b>												
Lining in CBD [D]	-1.892	(1.23)	1.319	(0.76)	-2.261	(0.77)			-3.094	(1.00)	-0.339	(0.89)
Lining in Karlsruhe [D]	-0.154	(0.96)	0.956	(0.77)			-0.136	(0.48)	-0.605	(1.17)	2.251	(0.77)
<b>Situational attributes</b>												
Use car on a given day [D]	4.271	(0.31)	1.824	(0.18)	0.344	(0.10)	0.765	(0.13)	2.556	(0.30)	1.905	(0.14)
Use PT on a given day [D]			0.543	(0.22)	1.288	(0.12)	-0.129	(0.16)	1.005	(0.33)	0.338	(0.17)
Var( $\beta_x$ )	7.82		4.89		30.73		6.53		9.41		5.68	
<b>Random effects</b>												
Inter-individual variation (s.d.) $\sigma_{ih}$	3.057	(0.28)	1.694	(0.16)	2.733	(0.15)	2.034	(0.11)	1.972	(0.26)	1.821	(0.14)
Inter-household variation (s.d.) $\sigma_h$	1.356	(0.65)	1.317	(0.23)	0.281	(0.25)	-		1.231	(0.49)	1.863	(0.21)
Temporal variation (s.d.) $\sigma_d$	-		0.543	(0.14)	0.419	(0.07)	0.117	(0.07)	0.497	(0.25)	0.387	(0.10)
Spatial variation (s.d.) $\sigma_s$	2.053	(0.36)	1.805	(0.30)	0.651	(0.13)	0.924	(0.19)	2.770	(0.47)	1.613	(0.27)
Intra-individual variation (s.d.) $\sigma_0$	5.191	(0.14)	4.936	(0.08)	2.923	(0.03)	3.871	(0.06)	6.299	(0.16)	4.793	(0.05)

$\log[\pi(x|\text{mean}(\theta))] = -88030$ ,  $\log[\text{mean}(\pi(x|\theta))] = -101391$ ,  $pD = 26722$ ,  $DIC = 229503$

*Notes: The value of  $\log[\pi(x|\text{mean}(\theta))]$  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 4 Comparison of Variations between the *Null* and *Full* Models**

	Pick up/ Drop off	Private business	Mandatory activities	Daily shopping	Non-daily shopping	Leisure	
<i>Null</i> model	Inter-individual variation	10.52	4.55	12.92	6.58	4.28	4.75
	Inter-household variation	4.92	1.51	13.51	-	3.21	3.31
	Temporal variation	-	2.68	15.51	3.19	4.88	2.56
	Spatial variation	6.95	4.18	0.72	0.88	8.87	4.81
	Intra-individual variation	28.04	24.65	8.72	15.09	39.54	23.36
	<b>Total</b>	<b>50.44</b>	<b>37.57</b>	<b>51.38</b>	<b>25.74</b>	<b>60.79</b>	<b>38.79</b>
<i>Full</i> model	Inter-individual variation	9.35	2.87	7.47	4.14	3.89	3.32
	Inter-household variation	1.84	1.73	0.08	-	1.52	3.47
	Temporal variation	-	0.29	0.18	0.01	0.25	0.15
	Spatial variation	4.21	3.26	0.42	0.85	7.67	2.60
	Intra-individual variation	27.08	24.50	8.68	15.12	39.81	23.10
	<b>Total</b>	<b>42.48</b>	<b>32.65</b>	<b>16.82</b>	<b>20.12</b>	<b>53.13</b>	<b>32.64</b>
The amount of variation reductions (%)	Inter-individual variation	1.18 (11.2%)	1.68 (37.0%)	5.45 (42.2%)	2.45 (37.2%)	0.39 (9.1%)	1.43 (30.2%)
	Inter-household variation	3.09 (62.7%)	-0.23 (-15.0%)	13.43 (99.4%)	-	1.70 (52.8%)	-0.16 (-4.8%)
	Temporal variation	-	2.38 (89.0%)	15.33 (98.9%)	3.18 (99.6%)	4.64 (94.9%)	2.41 (94.1%)
	Spatial variation	2.74 (39.4%)	0.92 (22.0%)	0.30 (41.4%)	0.02 (2.7%)	1.20 (13.5%)	2.21 (46.0%)
	Intra-individual variation	0.96 (3.4%)	0.16 (0.6%)	0.04 (0.5%)	-0.03 (-0.2%)	-0.26 (-0.7%)	0.26 (1.1%)
	<b>Total</b>	<b>7.97 (15.8%)</b>	<b>4.92 (13.1%)</b>	<b>34.55 (67.3%)</b>	<b>5.62 (21.8%)</b>	<b>7.65 (12.6%)</b>	<b>6.15 (15.9%)</b>
Var( $\beta_x$ ) in the <i>Full</i> model	7.82	4.89	30.73	6.53	9.41	5.68	



*Note: The figures in the table represent the percentage of a corresponding variation in total.*

**FIGURE 1 Proportions of variations (Null model).**