A DYNAMIC BIVARIATE ORDERED-RESPONSE PROBIT MODEL SYSTEM TO EVALUATE THE EFFECTS OF INTRODUCING FLEXIBLE WORKING HOUR SYSTEM

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Abstract

Flexible working hour system (FWHS) is expected to cost-effectively mitigate traffic congestion because of its influences on individuals' multi-faceted choice behavior over time. This paper attempts to develop a new dynamic model system to evaluate the effects of introducing the FWHS based on an activity-based panel data. The system can simultaneously incorporate the interaction between departure time from home to work and the one from work to home, the interaction between departure time from home and travel time to work, and the interaction between departure time from work to home and travel time to home. A bivariate ordered-response probit model (called BOP model, henceforth) is used to represent each of the interactions. The BOP model assumes that the error terms follow a bivariate normal distribution. Because of individuals' learning, adaptation and adjustment behavior under the FWHS, the above-mentioned behavioral aspects are not independent over time. Therefore, three BOP models are unified to simultaneously represent these three kinds of interactions. Empirical analysis results based on the data collected from a private company in Japan show that the proposed dynamic BOP model system has a sufficiently high goodness-of-fit index and is valid to evaluate the effects of introducing the FWHS.

Keywords: Bivariate ordered-response probit model; Dynamic model; Learning mechanism; Habit persistence; Flexible working hour system
Topic Area: D6 Travel and Shipper Behavior Research

1. Introduction

With the growth of urbanization and the widespread availability of cars, the distance between work and home has increased, although time between work and home remains constant (Brewer, 1998). As a result, many cities around the world, regardless of developed and developing world, are experiencing serious traffic congestion along main traffic corridors and city centers, especially during rush hours. The traffic congestion not only results in the worsening traffic environments (e.g., air pollution and noise), but also torments the commuters by longer travel time, which deteriorates their working conditions and efficiencies. Under such circumstances, flexible work arrangements have been attracting many companies. For example, in recent years, the number of firms introducing flexible working hours system is increasing in Japan. Among the firms with more than 1,000 employees, 35.9% of their departments have introduced the system (Sugie *et al*, 2002). One can also observe the rapid progress of other types of flexible work arrangements like telecommuting around the developed world (Brewster *et al*, 1997).

As mentioned by Brewster *et al* (1997), the policy debates on this kind of labor flexibility have been extremely influenced by the work of Atkinson (1985a, 1985b, 1987; Atkinson and Gregory, 1986). Atkinson (1985a, 1987) argues that economic difficulties experienced by the advanced economies in recent times and technological change have contributed to moves to greater flexibility. Uncertainty about the labor demand has forced the employers to seek ways to make labor both cheaper and more easily variable in quantity (Atkinson, 1985a). These days, technology is changing more quickly then ever before. Furthermore, technology is characterized by computer controlled production systems. Therefore, general effect of technological change has been increased the need for a workforce, which can be redeployed to new and/or more complex jobs as necessary. Another reason is that nowadays, there are a significant number of people who have deliberately, with more or less enthusiasm, chosen to adopt these flexible work patterns (Wareing, 1992). This is argued to be caused by, 1) workers' decisions about balancing work, income and other aspects of their lives in a less typical way, 2) their unwillingness to tie themselves to organizations for long periods of time, or 3) their behavior of combining one job with other, perhaps unpaid, work (Brewster *et al*, 1997). On the other hand, Brewer (1998) shows that place, distance and time, when translated into work practice choices, are perceived by workers as constraints on flexible work arrangements (including flexible working hour system) in terms of job suitability and access to facilities to work from home. The place, distance and time form major travel barriers in selecting travel mode and time of travel to and from work in terms of promptness, routing, queuing, safety, proximity, crowding etc.

This paper focuses on the flexible working hour system, which was originally proposed to improve workers' working efficiency, and meet the unstable and unprecedented market conditions experienced in recent years (Atkinson, 1987) on one hand, it is also expected to contribute to the reduction of traffic congestion because of its influence on individuals' multi-facets choice behavior (e.g., departure time choice for going-to-work and going-home trip, and mode choice behavior and so on) on the other. Because of these potential traffic effects, for example, in order to cost-effectively mitigate traffic congestion, Japanese government has been promoting off-peak commutation policies including flexible working hour system and staggered commuting hour system since the late 1990s. Comparing with staggered commuting hour system, flexible working hour system is characterized by less-constrained office hour (Suto *et al*, 1998).

To evaluate the effects of introducing flexible working hour system, single-faceted and static modeling approaches are not desirable. For example, under flexible working hour system, workers can choose their departure time from home considering their own convenience. As a result, this choice result will influence travel time to work (e.g., shorter travel time by car or taking less crowded train) and also have some impacts on the departure time from work to home considering the required working hours per day/week. On the other hand, after the introduction of flexible working hour system, workers' choice behaviors might be changing over some periods of time due to their learning, adaptation and adjustment behavior under the stimulus caused by the new working system. Careful reviews on existing literature suggest there have not been proposed such multi-faceted and dynamic modeling methodologies focusing on the interactions between different behavior facets under the introduction of flexible working hour system.

Considering the above-mentioned matters, this paper aims at developing a new dynamic model system incorporating the multi-faceted interactions in order to evaluate the effects of introducing flexible working hour system based on a four-wave activity and travel panel data. The data was collected at a construction consultant company, located in the center of Hiroshima City, Japan, from the year of 1996 to 1999.

2. Modeling framework

The flexible working hour system in the target company was introduced in October 1996. After introducing the system, the fixed opening hour (08:40) and closing hour (17:30) was abolished. Instead, the core-opening hour (10:00) and core-closing hour (16:00) was introduced. Under such system, employees can come to and leave from office at any time before the core-opening hour and after the core-closing hour. The change of the working system before and after the introduction of flexible working hour system can be described in Figure 1.

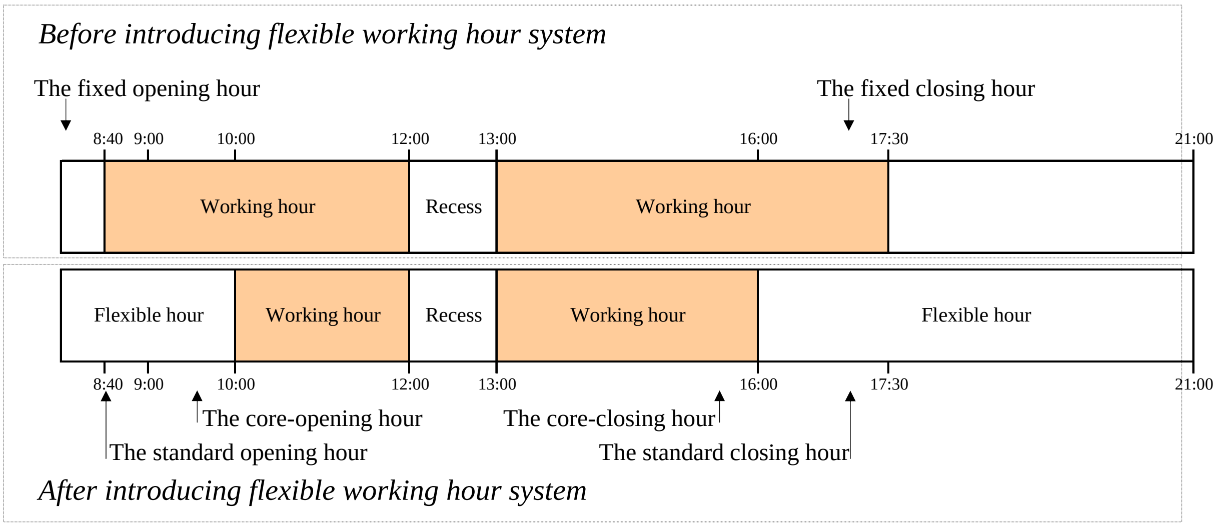

Figure 1. Comparisons Before and After Introducing Flexible Working Hour System

Generally speaking, in response to the change of a system, individuals usually show their learning, adaptation and adjustment behaviors over certain periods of time. Our concern here is how the employees adjust their working hours after the introduction of flexible working hour system. Therefore, this paper attempts to develop a dynamic model system to evaluate the effects of introducing flexible working hour system and capture individuals' learning, adaptation and adjustment behavior.

One can expect various effects of introducing flexible working hour system from different perspectives. Here, this paper only deals with the effects on the choice of departure time and consequently the effects on the travel time, by explicitly considering the interactions among the target behavior aspects (see Figure 2). This is because that departure time and travel time are extremely important factors from the perspective of transportation policies.

2.1 Conceptual discussions

Since people usually need some time to adjust their behaviors after the introduction of flexible working hour system, dynamic characteristics of people's choice behaviors should be represented in the model system. To reflect the above-mentioned matters, the following behavioral aspects will be introduced in the evaluation model system.

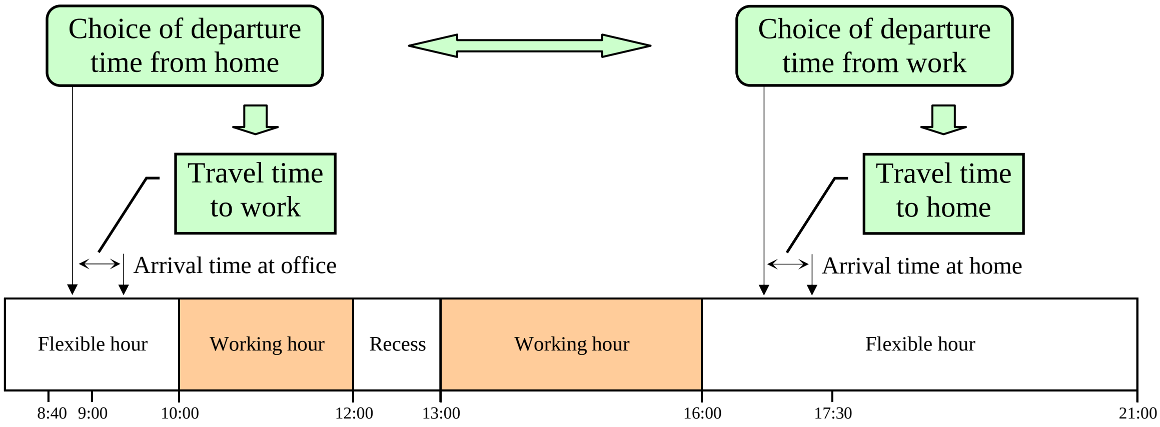

Figure 2. Target Behavior Aspects

1) The system first simultaneously incorporates the interaction between departure time from home to work and from work to home, the interaction between departure time and travel time from home to work, and the interaction between departure time and travel time from work to home. In addition, the influence of departure time choice on travel time is represented by introducing the choice utility of departure time as one of explanatory variables in the sub-model of travel time. This can be used to reflect the temporal characteristics of travel time over a day. Figure 3 conceptually explains the inter-dependency among these behavioral aspects, where “E” indicates the unobserved factor influencing each behavior aspect.

2) Learning mechanism is incorporated into the model system by weighing previous preferences (i.e., utility) in the corresponding sub-model at each wave. The weighted previous preferences are used to represent the influence of habit persistence. The representation of learning mechanism is conceptually shown in Figure 4 along with the above-mentioned interactions.

3) Influence of margin time for being in time for work, taken before the introduction of flexible working hour system, is also introduced into the model system to examine the influence of habitual behavior.

4) The influence of performing on-the-way-work and on-the-way-home activities is incorporated in the utility function for choices of departure time from and to home, respectively. This is used to examine the influence of additional activities during the trip-making process.

2.2 Kernel model structure: Bivariate ordered-response probit model

Since preliminary analysis based on the collected panel data shows that departure time and travel time does not change over time of a day continuously, these time variables are converted to discrete scale in order to effectively capture non-linear behavior mechanisms. To represent these discrete ordered time variables, an ordered-response probit model is suitable as the kernel model structure.

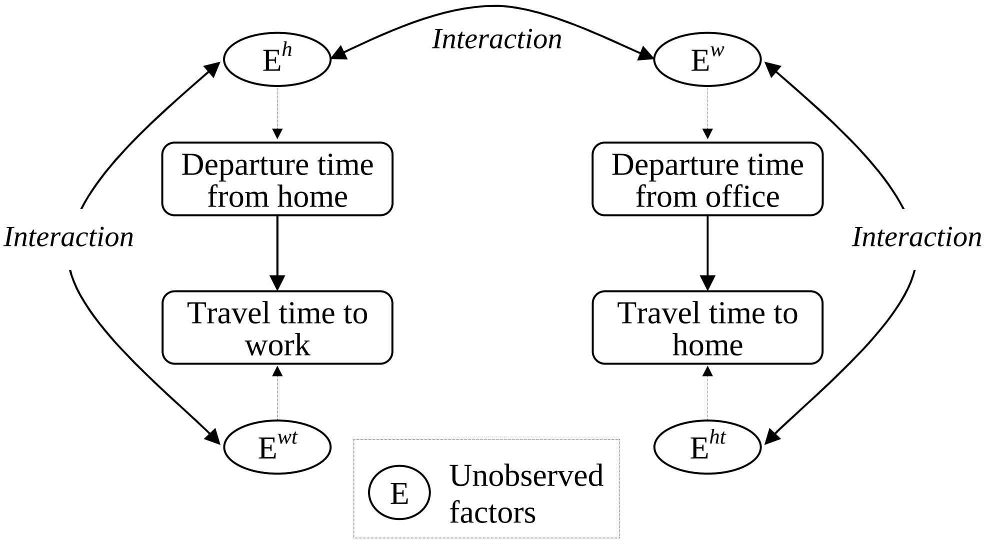

Figure 3. Conceptual Structure of Interactions under Flexible Working Hour System

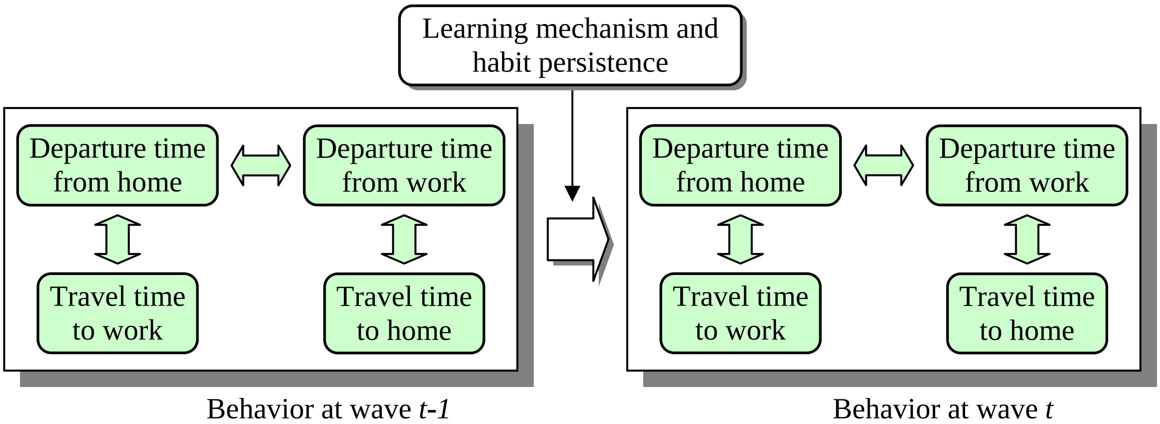

Figure 4. Interactions and Learning Mechanism Incorporated in the Dynamic Model

Let U_i be the latent preference function for individual *i*'s time variable π_i with *J* categories, and define U_i as follows:

$$U_i = V_i + \varepsilon_i, \quad V_i = \sum_q \beta_q x_{iq} \tag{1}$$

where

V_i is deterministic term,

x_{iq} is *q*th explanatory variable,

β_q is parameter of x_{iq}, and

ε_i is error term.

It is assumed that if U_i satisfies the condition shown in equation (2), then individual *i* belongs to category *j* with probability P_i expressed in equation (3).

$$\textit{if } \delta_{j-1} \leq U_i \leq \delta_j \textit{ then } \pi_i = 1, j = \{1,...,J\} \tag{2}$$

$$P_i = \prod_j \left[\int_{\delta_{j-1}-V_i}^{\delta_j - V_i} f(\varepsilon) d\varepsilon \right]^{y_{ij}} = \prod_j \left[\Phi(\delta_j - V_i) - \Phi(\delta_{j-1} - V_i) \right]^{y_{ij}} \tag{3}$$

where
δ_{j-1} and δ_j are unknown threshold values,
y_{ij} is dummy variable (y_{ij} =1 if individual *i* belongs to category *j*, y_{ij} =0 otherwise),
$f(\cdot)$ is standard normal density function, and
$\Phi(\cdot)$ is standard normal distribution function.

Since this paper will represent the interaction between pair of time variables (here defined as π_{ij}^1 and π_{ik}^2), equations (1) and (2) are rewritten as follows:

$$U_i^1 = V_i^1 + \eta_i , \quad V_i^1 = \sum_q \beta_q x_{iq}^1 \tag{1a}$$

$$if \ \delta_{j-1}^1 \le U_i^1 \le \delta_j^1 \ then \ \pi_{ij}^1 = 1, \ j = \{1,...,J\} \tag{2a}$$

$$U_i^2 = V_i^2 + \varepsilon_i , \quad V_i^2 = \sum_r \beta_r x_{ir}^2 \tag{1b}$$

$$if \ \delta_{k-1}^2 \le U_i^2 \le \delta_k^2 \ then \ \pi_{ik}^2 = 1, k = \{1,...,K\} \tag{2b}$$

As discussed in section (2.1), there might exist some interactions between departure time and/or travel time. It can be therefore expected that the error terms η_i and ε_i may be correlated each other. To reflect this point, it is assumed that η_i and ε_i follow a bivariate normal distribution, which joint probability density function $g(\eta,\varepsilon)$ can be expressed as follows:

$$g(\eta,\varepsilon) = \frac{exp\left\{ -\frac{1}{2(1-\rho^2)} \left[\left(\frac{\eta}{\sigma_\eta} \right)^2 - 2\rho \frac{\eta}{\sigma_\eta} \frac{\varepsilon}{\sigma_\varepsilon} + \left(\frac{\varepsilon}{\sigma_\varepsilon} \right)^2 \right] \right\}}{2\pi\sigma_\eta\sigma_\varepsilon\sqrt{1-\rho^2}} \tag{4}$$

where ρ is correlation between error terms η_i and ε_i , and $\sigma_\eta, \sigma_\varepsilon$ are standard deviations of η_i and ε_i .

Then, the joint probability $Prob(\pi_{ij}^1 = 1, \pi_{ik}^2 = 1)$ of random events $\pi_{ij}^1 = 1$ and $\pi_{ik}^2 = 1$ can be expressed below.

$$Prob(\pi_{ij}^1 = 1, \pi_{ik}^2 = 1) = \int_{\delta_{j-1}^1 - V_i^1}^{\delta_j^1 - V_i^1} \int_{\delta_{k-1}^2 - V_i^2}^{\delta_k^2 - V_i^2} g(\eta,\varepsilon) d\eta \, d\varepsilon \tag{5}$$

Equation (5) with double integral can be further transformed into the following equation with single integral based on coordinate rotation (Sugie *et al.*, 2003).

$$
\begin{aligned}
&Prob\left(\pi_{ij}^{1}=1,\pi_{ik}^{2}=1\right)\\
&=\left\{\Phi\left(\frac{\delta_{j}^{1}-V_{i}^{1}}{\sqrt{1-\rho^{2}}}\right)-\Phi\left(\frac{\delta_{j-1}^{1}-V_{i}^{1}}{\sqrt{1-\rho^{2}}}\right)\right\}\cdot\left\{\Phi\left(\frac{\delta_{k}^{2}-V_{i}^{2}}{\sqrt{1-\rho^{2}}}\right)-\Phi\left(\frac{\delta_{k-1}^{2}-V_{i}^{2}}{\sqrt{1-\rho^{2}}}\right)\right\}
\end{aligned}
\tag{6}
$$

Based on the above-mentioned equations, individual *i*'s logarithm likelihood function can be defined as follows.

$$
\begin{aligned}
\log L_i &= \sum_j y_{ij}^{1}\log\left\{\Phi\left(\frac{\delta_{j}^{1}-V_{i}^{1}}{\sqrt{1-\rho^{2}}}\right)-\Phi\left(\frac{\delta_{j-1}^{1}-V_{i}^{1}}{\sqrt{1-\rho^{2}}}\right)\right\}\\
&+\sum_k y_{ik}^{2}\log\left\{\Phi\left(\frac{\delta_{k}^{2}-V_{i}^{2}}{\sqrt{1-\rho^{2}}}\right)-\Phi\left(\frac{\delta_{k-1}^{2}-V_{i}^{2}}{\sqrt{1-\rho^{2}}}\right)\right\}
\end{aligned}
\tag{7}
$$

Henceforth, equation (6) is called bivariate ordered-response probit (BOP for short) model.

2.3 Representing behavioral dynamics

To represent the behavioral dynamics discussed in section (3.2), equation (1) is rewritten as follows:

$$U_{it}=V_{it}+\mu_t\sum_{s=1}^{t-1}\theta_s V_{is}+\varepsilon_{it} \tag{8}$$

$$0\le\theta_s\le 1,\sum_s\theta_s=1 \tag{9}$$

where μ_t, θ_s are the newly introduced parameters.

Here, careful interpretation of μ_t suggests that μ_t is nothing but the cumulative effects of previous behavior on current behavior. Positive value of μ_t implies habit persistence and negative value supports variety-seeking behavior. Since commuting travel behavior is compulsory unlike other choice behaviors like recreational activities, it can be expected that μ_t might show the positive value. θ_s is a non-negative normalized weight parameter. The weight describes the relative influence of recent and more distant past behavior on current behavior. Weights increasing over time describe the situation where behavior in the more distant past tends to be forgotten. Conversely, if travelers develop habits early in their experiences, the weights will be decreasing over time. There have been proposed several sophisticated approaches till now (Timmermans *et al*, 2003), however, this paper adopts equations (8) and (9), and leaves the refinement of model structure as a future research issue.

This paper will simultaneously represent the interaction between departure time from home to work and from work to home, the interaction between departure time and travel time from home to work, and the interaction between departure time and travel time from work to home. To reflect these matters in the same modeling framework, it is necessary to combine equations (6), (8) and (9) together. In other words, three BOP models need to be unified over time. The unified three BOP models over time results in a new dynamic model system to evaluate the effects of introducing flexible working hour system. The resultant joint probability over time can be defined in equation (10) and the logarithm likelihood function of the dynamic model system can be expressed in equation (11).

$$P_i = \prod_t \prod_j \prod_k Prob\left(\pi^1_{ijt} = 1, \pi^2_{ikt} = 1\right)$$
$$= \prod_t \left\{ \begin{array}{l} \prod_j \left[\Phi\left(\frac{\delta^1_j - V^1_{it}}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{\delta^1_{j-1} - V^1_{it}}{\sqrt{1-\rho^2}}\right) \right] \\ \cdot \prod_k \left[\Phi\left(\frac{\delta^2_k - V^2_{it}}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{\delta^2_{k-1} - V^2_{it}}{\sqrt{1-\rho^2}}\right) \right] \end{array} \right\} \quad (10)$$

$$log\, L = \sum_i \sum_t \left\{ \begin{array}{l} \sum_j y^1_{ijt}\, log\left[\Phi\left(\frac{\delta^1_j - V^1_{it}}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{\delta^1_{j-1} - V^1_{it}}{\sqrt{1-\rho^2}}\right) \right] \\ + \sum_k y^2_{ik}\, log\left\{ \Phi\left(\frac{\delta^2_k - V^2_{it}}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{\delta^2_{k-1} - V^2_{it}}{\sqrt{1-\rho^2}}\right) \right\} \end{array} \right\} \quad (11)$$

This is called dynamic bivariate ordered-response probit model system, which can be estimated based on conventional maximum likelihood method.

3. Data

To measure the effects of introducing flexible working hour system and capture individuals' learning, adaptation and adjustment behavior, a four-wave activity and travel panel survey was conducted for commuters at a construction consultant company, located in the center of Hiroshima City, Japan. This company holds about 500 employees and introduced the flexible working hour system on Oct. 1, 1996. The 1st wave of survey was done in September 1996 before the introduction of flexible working hour system. The other three after-the-fact waves were done in November 1996, October 1997 and October 1999, respectively.

As a result, 167 valid panelists participated in the survey and reported their actual behavior on one designated weekday in each wave. Each respondent was asked to report his/her individual attributes (e.g., age, gender, household composition), commuting behavior (e.g., departure time from home and office, travel mode choice result, activity participation on the way home and office) etc.

Table 1 shows the means and variances of departure time from/to home and arrival time at office. One can see that after introducing the flexible working hour system, departure time from/to home and arrival time at office gradually become later, and their variances become larger than before the fact. This suggests that commuting behavior has been changing since the introduction of flexible working hour system. Panel analysis also showed that less people changed their travel modes. In addition, car travel time to work decreased by 17% on average, but travel time to home in the 4^{th} wave increased by 18%. The distributions of departure time from/to home are shown in Figures 5 and 6, respectively. After the introduction of flexible working hour system, one can observe the stable distribution of departure time from home. In contrast, departure time to home (i.e., from work) began to largely move backwards three years after the fact. These results suggest complex interactions among departure time from/to home, and their corresponding travel time.

Table 1. Change of Commuting Behavior in Panel Data

Commuting behavior	1st wave	2nd wave	3rd wave	4th wave
Laspe of time after the fact	- 1 month	+ 1 month	+ 1 year	+ 2 year
Departure time from home to work	7:43	8:11	8:19	8:29
	(926)	(1262)	(1450)	(1590)
Arrival time at office	8:27	8:51	8:59	9:06
	(171)	(677)	(783)	(877)
Time that work begins	8:40	9:01	N.A.	9:17
	(42)	(496)		(732)
Departure time from work	19:04	19:01	19:04	19:43
	(4285)	(4735)	(5841)	(6250)
Sample	167			

( ): variance in the squared minute

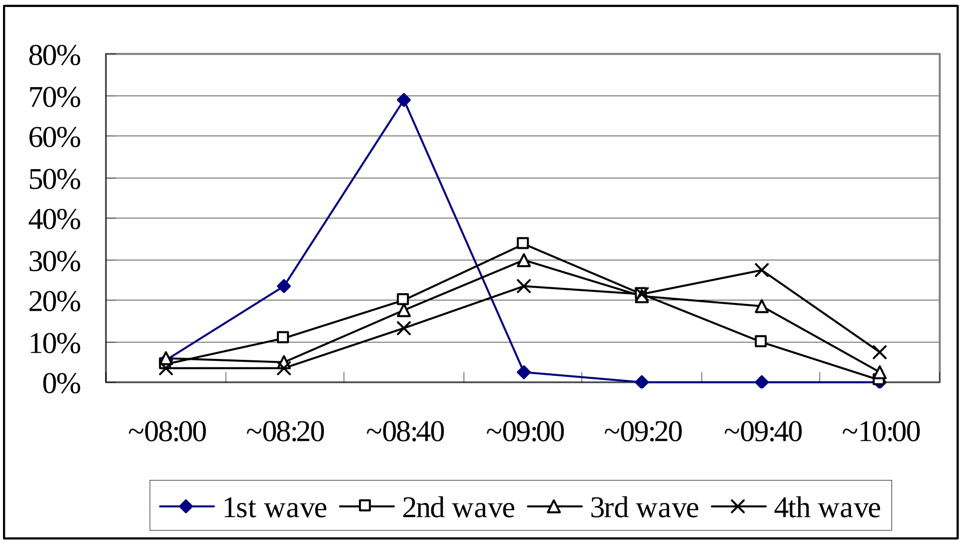

Figure 5. Distribution of Departure Time from Home

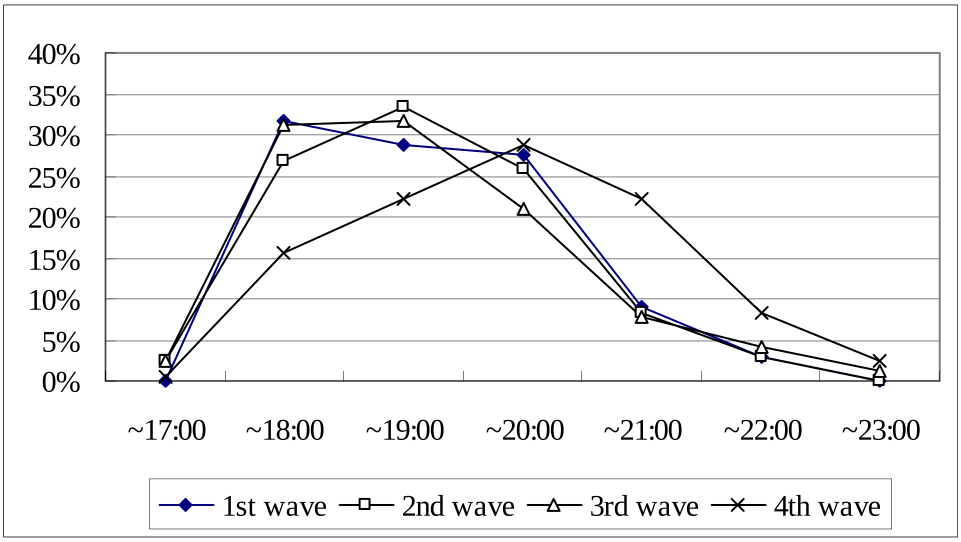

Figure 6. Distribution of Departure Time from Work

4. Model estimations and discussions about policy implications

4.1 Specification of model structure

The adopted common explanatory variables are age, and other six dummy variables: "commuting by car (yes 1, no 0)", "gender (male 1, female 0)", "single (yes 1, no 0): if the worker is single or not", "child (yes 1, no 0): if the worker has a preschool child or not", "elderly (yes 1, no 0): if the household has any elderly people or not", and "wife's job status (yes 1, no 0)". Since these common variables are almost time-independent, if they are simultaneously introduced into each latent preference function U_{it} , multicollinearty will occur due to the interactions explained in section 2.1. To avoid this statistical issue, a common latent variable Ω_t is introduced as a construct that represents the influence of these common explanatory variables. Then the deterministic term V_{it} can be re-defined as,

$$V_{it} = \varphi\,\Omega_t + \sum_m \kappa_m z_{im} \qquad (12)$$

where φ is parameter of common latent variable Ω_t , z_{im} is the aspect-specific explanatory variable with a parameter κ_m (i.e., referred to as "margin time" for departure time to work, "participation to the on-the-way activity" for departure time to both work and home).

The bivariate ordered-response probit model is first estimated with respect to the 1st wave data (i.e., the data before the fact), and then the dynamic bivariate ordered-response probit model system is estimated by using the data after the fact (i.e., 2nd, 3rd and 4th waves). For the dynamic model system, the detailed model structure in this study is shown in Figure 7, where ε refers to the error term, ρ indicates the correlation between error terms, and γ represents the influence of departure time on travel time. Other notations are, "w: to work", "h: to home", "DT: departure time", "TT: travel time", "wt: travel time to work", and "ht: travel time to home".

Based on preliminary analysis, departure time from home to work is categorized as "~08:00", "08:00~08:30", "08:30~09:00" and "09:00~", and departure time from work to home as "~18:10", "18:10~18:55", "18:55~19:40" and "19:40~". Travel time to work and to home is classified into four categories, i.e., "within 15 minutes", "from 15 to 30 minutes", "from 30 to 45 minutes", "from 45 to 60 minutes" and "over 60 minutes". The model estimation results are shown in Tables 2 and 3, respectively. McFadden's Rho-squared is 0.2403 for the 1st wave data, and 0.2570 for the panel data of the 2nd, 3rd and 4th waves. This suggests that each of these two models has a sufficiently high goodness-of-fit index.

4.2 Performance of kernel model structure

One can see that all of correlation parameters for the bivariate normal distributions and all of threshold parameters characterizing the ordered-response probit model are statistically significant. This implies that the kernel model structure (bivariate ordered-response probit model structure) is effective to represent the interactions between departure time and/or travel time. Comparing with the model for the 1st wave data, the model for the panel data of the 2nd, 3rd and 4th waves has relatively small values of correlation coefficients. This might be caused by the fact that various temporal factors including habit persistence and learning mechanisms are incorporated in the dynamic model. Considering

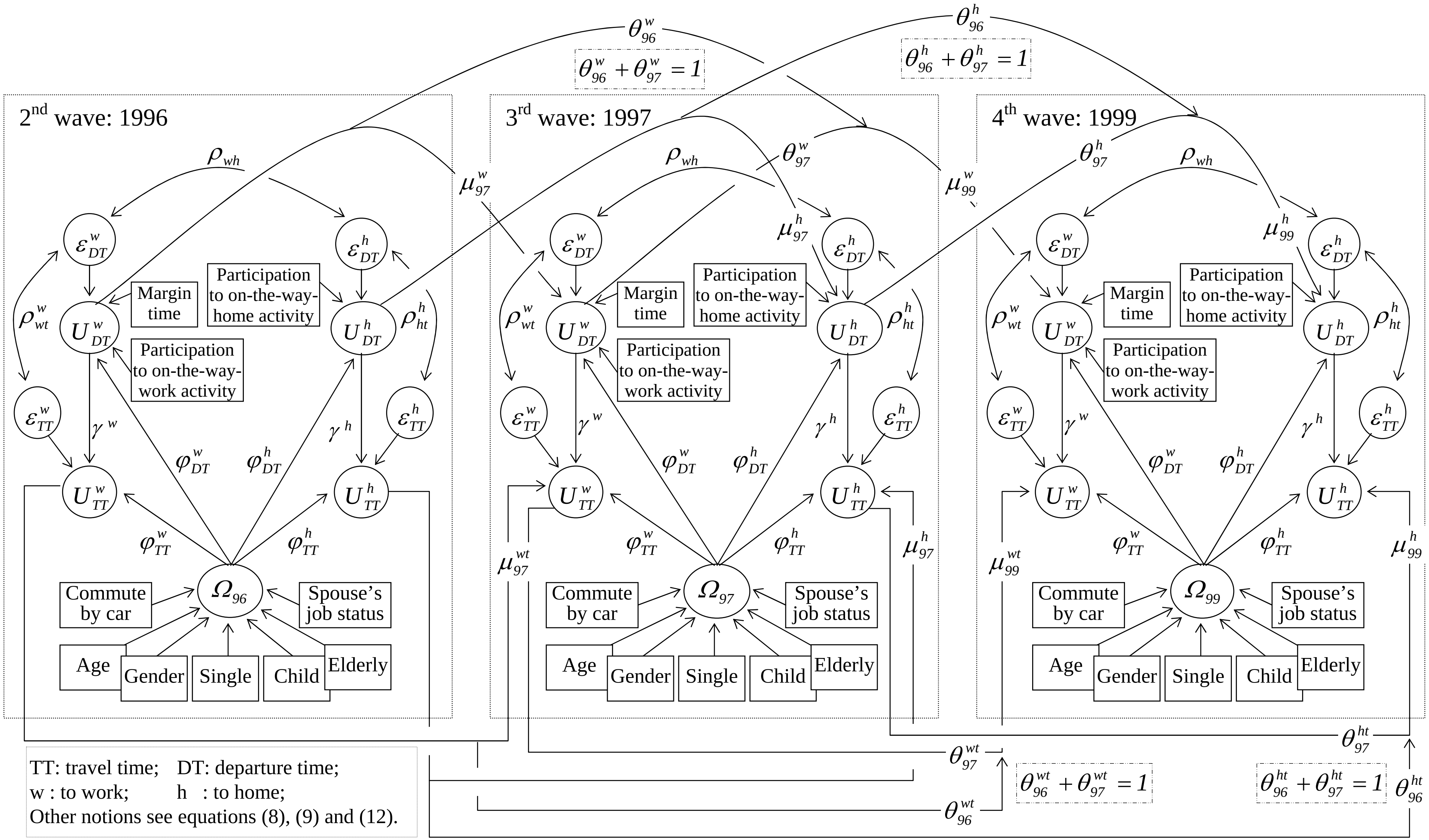

Figure 7. Dynamic Model Structure Adopted in this Study

Table 2. Estimation Results of Bivariate Ordered-Response Probit Model (1st wave)

Explanatory variables	Estimated parameter	t score
Common latent variable Ω		
Commute by car (Yes 1, No 0)	0.0151	0.037
Age	0.1006	6.603
Gender (Male 1, Female 0)	1.3901	1.951
Single (Yes 1, No 0)	1.6531	2.680
Preschool child (Yes 1, No 0)	0.5736	0.913
Elderly (Yes 1, No 0)	0.1421	0.156
Wife's job status (Yes 1, No 0)	0.2416	0.601
Departure time to work		
Influence of common latent variable φ^{w}_{DT}	0.1768	20.766
Participation of on-the-way-work activity (Yes 1, No 0)	0.2620	3.894
Margin time (minutes)	-0.0186	-12.954
Threshold parameter δ_1	0.1956	9.390
δ_2	0.7552	31.428
Travel time to work		
Influence of common latent variable φ^{w}_{TT}	0.0479	4.415
Influence of departure time on travel time γ^{w}	-0.0678	-0.584
Threshold parameter δ_1	0.1857	5.491
δ_2	0.2266	5.750
δ_3	0.3980	8.011
Departure time to home		
Influence of common latent variable φ^{h}_{DT}	0.0386	5.672
Participation of on-the-way-home activity (Yes 1, No 0)	-0.2373	-3.904
Threshold parameter δ_1	0.0831	4.467
δ_2	0.3968	15.577
Travel time to home		
Influence of common latent variable φ^{w}_{TT}	0.0822	6.245
Influence of departure time on travel time γ^{h}	-0.6232	-3.657
Threshold parameter δ_1	0.3661	10.151
δ_2	0.5039	10.608
δ_3	0.7566	13.057
Correlation coefficient ρ^{h}_{ht}	0.9189	67.925
ρ^{w}_{wt}	0.9570	95.776
ρ_{wh}	0.9456	116.851
Initial logarithm likelihood	-1653.00	
Converged logarithm likelihood	-1255.86	
McFadden's Rho-squared	0.2403	
Sample size	167	

that correlation arises due to the existence of common unobserved and/or omitted information in a pair of error terms, the representation of habit persistence and learning mechanisms can contribute to not only improving model performance, but also mitigating the uncertainty in the model.

4.3 Analysis of behavioral interactions and dynamics

As discussed above, introducing the correlation parameter can represent the behavioral interactions caused by the unobserved and/or omitted information. Here, the interaction caused by observed information will be examined. Concretely speaking, this refers to the influence of departure time on travel time (see γ^w and γ^h). One can see that all the corresponding parameters in the dynamic bivariate ordered-response probit model (Table 3) have negative values and are statistically significant. This also holds regarding travel time to home, but does not hold with respect to that of going-to-work trip, before the introduction of flexible working hour system (Table 2). Negative value means that choice of later departure time results in shorter travel time. It is also obvious that the parameter of travel time to work is larger after the fact than that before the fact. In contrast, the parameter of travel time to home shows an opposite trend. This might result from the fixed opening hour before the fact, because less variation of departure time may lead to less change in travel time during the morning rush hour. Under flexible working hour system, people can choose their departure time considering their own convenience. Large heterogeneity in choice of departure time brings about large variation in travel time. One the other hand, the travel time to home shows the opposite results. This might be because people could adjust their working hours to avoid the traffic congestion when going home, even before the introduction of flexible working hour system.

Under flexible working hour system, the range of threshold values for departure time and travel time from both home and work are larger than before (δs in Tables 2 and 3). This coincides with the observation results that under the fixed working hour system, especially, departure time to work did not change largely. Due to people's adaptive and learning behaviors under the new system, the corresponding variation becomes very large. Travel time also shows a large variation. This might be because there is still a limited number of companies in Hiroshima City, which introduced the new working system. Under such circumstances, people's adaptive and learning behaviors could be constrained.

Estimation results of the proposed dynamic model show that there does exist learning behavior (θs in Table 3) in the choice of departure time to home and in travel time to work. Habit persistence is observed in the choice of departure time (see μs in Table 3). The parameter of the influence of habit persistence on the travel time to home in the 3rd wave (1997) is statistically negative. This implies that in the 3rd wave (i.e., one year after the system introduction), travel time to home was still under the adaptation (or trial-error) process.

4.4 Analysis of the influence of observed factors

Margin time for going-to-work trips shows negative influence on departure time choice even after the fact. This also reflects the influence of habit persistence. Parameters of participation to on-the-way-work/home activities all have negative values after the fact. These results imply that longer margin time and performing additional activities on the way leads to the choice of earlier departure time.

To properly evaluate the influences of common explanatory variables on the choice of departure time and on travel time, it is necessary to calculate a composite parameter, which is the product of common latent variable parameter (Ω) and the parameter of each corresponding explanatory variable. Table 4 shows the values of these composite parameters. Before the introduction of flexible working hour system, the earlier comers to work (consequently leave the office earlier than before) were either the married female young people without children, or the people whose wives were housewives and did not commute by car. In contrast, the young people leave from home and work later after the fact than before the fact. The people who commute by car spend shorter travel time than before. The people who have preschool children and live together with the elderly household member(s), and whose wives have jobs also travel shorter time.

Table 3. Estimation Results for Bivariate Ordered-Response Probit Model (2nd-4th waves)

Explanatory variables	Estimated parameter	t score
Common latent variable Ω_t		
Commute by car (Yes 1, No 0)	-0.3508	-2.009
Age	0.1260	16.854
Gender (Male 1, Female 0)	-2.1598	-8.337
Single (Yes 1, No 0)	-1.0915	-4.014
Preschool child (Yes 1, No 0)	-1.3201	-5.477
Elderly (Yes 1, No 0)	0.2059	0.868
Wife's job status (Yes 1, No 0)	-0.2118	-1.219
Departure time to work		
Constant term	1.6444	20.656
Influence of common latent variable φ_{DT}^{w}	-0.0823	-6.696
Participation of on-the-way-work activity (Yes 1, No 0)	-0.3448	-3.336
Margin time (minutes)	-0.0206	-10.740
Influence of habit persistence on the behavior in 1999 μ_{99}^{w}	0.6478	7.579
Influence of habit persistence on the behavior in 1997 μ_{97}^{w}	0.3412	4.646
Influence of learning behavior in 1997 on the behavior in 1999 θ_{97}^{w}	1.68E-07	0.929
Influence of learning behavior in 1996 on the behavior in 1999 θ_{96}^{w}	1.00E+00	-
Threshold parameter δ_1	0.8307	98.030
δ_2	1.7369	197.335
Travel time to work		
Constant term	0.2309	2.030
Influence of common latent variable φ_{TT}^{w}	0.2082	10.978
Influence of departure time on travel time: γ^{w}	-0.1849	-2.623
Influence of habit persistence on the behavior in 1999 μ_{99}^{wt}	-0.1314	-1.185
Influence of habit persistence on the behavior in 1997 μ_{97}^{wt}	-0.0106	-0.099
Influence of learning behavior in 1997 on the behavior in 1999 θ_{97}^{wt}	0.9989	877.013
Influence of learning behavior in 1996 on the behavior in 1999 θ_{96}^{wt}	0.0011	-
Threshold parameter δ_1	0.5141	10.541
δ_2	0.8204	13.653
δ_3	1.3856	16.371
Departure time to home		
Constant term	1.0343	15.515
Influence of common latent variable φ_{DT}^{h}	-0.2020	-16.193
Participation of on-the-way-home activity (Yes 1, No 0)	-0.4592	-7.897
Influence of habit persistence on the behavior in 1999 μ_{99}^{h}	1.1611	8.129
Influence of habit persistence on the behavior in 1997 μ_{97}^{h}	0.0062	0.063
Influence of learning behavior in 1997 on the behavior in 1999 θ_{97}^{h}	0.4514	4.064
Influence of learning behavior in 1996 on the behavior in 1999 θ_{96}^{h}	0.5486	-
Threshold parameter δ_1	0.2493	10.471
δ_2	0.9003	20.265
Travel time to home		
Constant term	0.2642	2.102
Influence of common latent variable φ_{DT}^{h}	0.1930	5.732
Influence of departure time on travel time γ^{h}	-0.1553	-2.081
Influence of habit persistence on the behavior in 1999 μ_{99}^{ht}	-0.1243	-1.178
Influence of habit persistence on the behavior in 1997 μ_{97}^{ht}	-0.1729	-2.666
Influence of learning behavior in 1997 on the behavior in 1999 θ_{97}^{ht}	0.1094	1.150
Influence of learning behavior in 1996 on the behavior in 1999 θ_{96}^{ht}	0.8907	-
Threshold parameter δ_1	0.6215	11.121
δ_2	0.9159	12.972
δ_3	1.4825	14.920
Correlation coefficient ρ_{ht}^{h}	-0.7359	-20.493
ρ_{wt}^{w}	-0.7261	-23.176
ρ_{wh}	0.7235	24.826
Initial logarithm likelihood	-4948.40	
Converged logarithm likelihood	-3676.89	
McFadden's Rho-squared	0.2570	
Sample size	167	

Table 4. Influence of Explanatory Variables for Departure Time and Travel Time

Explanatory variables	Departure time to work		Departure time to home		Travel time to work		Travel time to home	
	Before-the-fact	After-the-fact	Before-the-fact	After-the-fact	Before-the-fact	After-the-fact	Before-the-fact	After-the-fact
Commute by car (Yes 1, No 0)	0.0027	0.0289	0.0006	0.0708	0.0007	-0.0730	0.0012	-0.0677
Age	0.0178	-0.0104	0.0039	-0.0254	0.0048	0.0262	0.0083	0.0243
Gender (Male 1, Female 0)	0.2458	0.1778	0.0536	0.4362	0.0666	-0.4496	0.1142	-0.4168
Single (Yes 1, No 0)	0.2923	0.0899	0.0638	0.2204	0.0792	-0.2272	0.1359	-0.2107
Child (Yes 1, No 0)	0.1014	0.1087	0.0221	0.2666	0.0275	-0.2748	0.0471	-0.2548
Elderly (Yes 1, No 0)	0.0251	-0.0170	0.0055	-0.0416	0.0068	0.0429	0.0117	0.0397
Wife's job status (Yes 1, No 0)	0.0427	0.0174	0.0093	0.0428	0.0116	-0.0441	0.0199	-0.0409

5. Conclusions and future research issues

Flexible working hour system, as one type of flexible working arrangements, is also expected to contribute to the mitigation of the ever-rising levels of urban transportation issues like traffic congestion. To properly evaluate the effects of introducing flexible working hour system, one need to know how workers' departure time will change and how that change will influence their travel time during the usual rush hours (normally morning and evening) over time. As methodological issues, the interactions between departure time and/or travel time, individuals' learning behaviors and habitual decision-making mechanisms need to be properly represented in the evaluation model system. In addition, as the influential factors for explaining each time variable (departure and/or travel time), it is sure that there exist some time-specific factors, however, most of them are individual and household attributes, which are usually time-independent during a day.

To systematically reflect the influence of the above-mentioned behavioral aspects, this paper developed a new dynamic model system which kernel structure is based on a bivariate ordered-response probit model. This dynamic model system can simultaneously represent the interaction between departure time from home to work and from work to home, the interaction between departure time and travel time from home to work, and the interaction between departure time and travel time from work to home over time. Individuals' learning behavior and habitual decision-making mechanisms were also incorporated into the model system by explicitly introducing the influence of previous behavior. To rationally represent the influence of time-independent factors like individual and household attributes without violating statistical requirements (here refers to multicollinearty), a common latent variable was introduced as a construct of those time-independent factors.

To evaluate the effects of introducing flexible working hour system, a four-wave panel survey was conducted at a middle-scale private company in Hiroshima City, Japan from the year of 1996 to 1999. The data at the first wave was collected before the introduction of the new working system, and the data of the remaining three waves was done after the fact. Empirical analysis results show that the proposed dynamic bivariate ordered-response probit model system has a sufficiently high goodness-of-fit index and is sufficiently valid to capture individuals' learning, adaptation and adjustment behavior.

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