

Chapter 11

Uncertainty in Travel Behavior

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Abstract This chapter gives an overview of uncertainty in travel behavior and its implications for transportation planning. We first address the issue of observation of travel behavior, which provides a foundation for analysis. We then focus on variations of travel behavior that contain information on uncertainties in terms of imperfect model fit to data. After that, changes in travel behavior are addressed, with regard to information on uncertainties in the degree to which the future will resemble the past. Based on the overview of behavioral observation, variations and changes, we discuss the avenues for future research on management of uncertainties from two viewpoints, one emphasizing the improvement of travel behavior analysis and the other the improvement of other components of the transportation planning process. From the former viewpoint, we show the importance of conducting uncertainty analysis to embed improved travel behavior analysis methods in the planning process in an appropriate manner. From the latter viewpoint, we underscore the importance of learning from accumulated experience in diverse countries/cities and learning from experience, particularly in developing countries.

Keywords Behavioral observations • Changes • Travel behavior • Uncertainty • Variations

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11.1 Introduction

11.1.1 *Uncertainties in Transportation Planning*

Transportation planning inevitably involves a number of uncertainties. For example, uncertainties exist in the prediction of travel demand, partly because the prediction is usually made with limited information. Even experts' value judgments involve uncertainties. For example, the value of reducing environmental impact has increased steadily, but the degree of change cannot be known precisely beforehand. Furthermore, we are unsure about how value will be judged in future. It is also difficult to prespecify all benefits and costs of a given project perfectly. Even if this were possible, there would be many unexpected events that affect the estimated benefits and costs, such as delay in construction schedules, political decisions regarding project finance, and lack of human resources to manage the project continuously.

Nevertheless, policy makers and planners must make decisions in the presence of uncertainties, resulting in a number of difficulties and complexities. When decisions are required under such circumstances, two extreme methods of managing uncertainty can be considered. The first method is to plan as if the decision maker understands and can predict the world precisely. Although this method has been widely applied in practice (Morgan and Henrion 1990), Gifford (2003) claims that "the central assumption that travel demand is predictable over a 20-year planning horizon is no longer supportable. Prediction-based analytical planning has been recognized as sharply inadequate". More problematically, because the estimated values are treated as if they were true despite the existence of uncertainties, planners and consultants could integrate political wishes into their forecasting framework, potentially causing implicit appraisal biases (Flyvbjerg et al. 2003) and consequently leading to strong distrust of travel demand prediction (Hyodo 2002). The other extreme method is to regard quantitative demand prediction and policy evaluation as an unnecessary procedure in the planning process, because uncertainties cannot be fully eliminated. Although the latter treatment has not been practiced, especially not in large-scale projects, this type of decision mindset certainly exists. However, this view may also be problematic, because arbitrariness in policy decisions cannot be avoided. A single collective decision on planning must be reached even when people have a wide range of opinions. For this purpose, maximum objectivity of judgments should be ensured, and quantitative analysis is expected to play a significant role in this process.

Although the above two methods are attractive because they avoid arguments over uncertainties that make policy decisions difficult, the optimal method may lie between the two extremes. We should neither rely completely on the prediction and quantitative policy evaluation nor ignore the importance of quantitative analysis. It is important to understand the uncertainties in the transportation planning process as much as possible and to make appropriate use of quantitative analysis (especially travel demand prediction). In this sense, although the question of what remains unknown is an open-ended one, more attention should be paid to answering it.

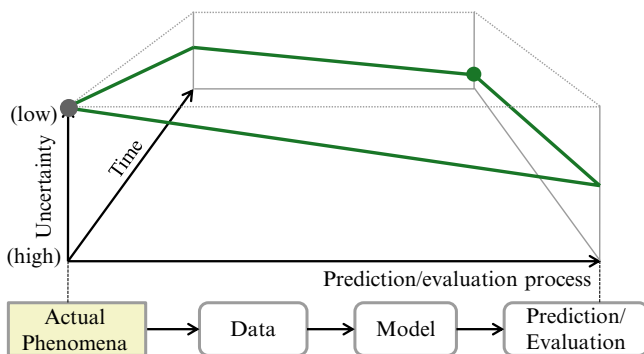


Fig. 11.1 Uncertainties in future prediction and the subsequent policy evaluation

11.1.2 The Focus of This Chapter

In this chapter, we limit our focus to uncertainty regarding travel behavior, which is one of the main sources of uncertainty in travel demand prediction and subsequent policy evaluation. In general, travel demand predictions and policy evaluations are made by eliciting and consolidating information regarding variations in, and changes to, travel behavior, and then using this information to infer the future state and policy impacts, given certain assumptions and conditions. More specifically, data are usually collected from the actual phenomena and used to develop a model to predict future demand and to evaluate policy. Researchers often focus on several indicators, such as value of travel time and price elasticities of travel demand, to transform complex data from actual transport phenomena into manageable and intuitively understandable information. Moreover, they make predictions and evaluations, usually under the assumption that behavioral mechanisms do not change over time.

Uncertainties in the above typical prediction/evaluation process can be graphically represented as shown in Fig. 11.1, where two types of uncertainties are illustrated: those in the prediction/evaluation process and those in the projection of future states. The difference between these two types of uncertainty is that, in essence, the former is procedural uncertainty while the latter arises from actual phenomena.

The remainder of this chapter is organized according to the above perspectives. After defining the terms used in this study, Sect. 11.2 discusses the observation of travel behavior on which the analysis is based. Section 11.3 focuses on the uncertainties that arise during the prediction/evaluation process by examining variations in travel behavior. We then investigate changes in travel behavior, exploring the uncertainties arising from projections of future states. In Sect. 11.5, we discuss the implications for transportation planning of knowing uncertainties.

11.1.3 Terminology

The term “uncertainty” has different meanings depending on context, and researchers have used it in different ways. Knight (1921) distinguished uncertainty from risk: uncertainty indicates that both outcome and the occurrence probability are unknown, while risk indicates that the outcome is unknown but the occurrence probability is known. On the other hand, in practice, a number of researchers use the term “uncertainty” to express what Knight calls risk. For example, a probabilistic treatment of input data is sometimes called uncertainty (Morgan and Henrion 1990). On the other hand, some researchers use the term “risk” even when the probability is unknown (Flyvbjerg et al. 2003). Actually, while it is not difficult to distinguish between uncertainty and risk in theory, it is often difficult in practice. This is because in some cases, “uncertainty” can be converted into “risk” by accumulating knowledge, and thus there are ambiguous relationships between uncertainty and risk in a practical sense. Therefore, this study uses the term “uncertainty” to represent both the uncertainty defined by Knight and risk.

As mentioned above, this study explores uncertainties in two areas: variations and changes in travel behavior. *Variations* are defined here as fluctuations in, or dispersions of, behavior observed over a given period that is sufficiently short to assume stability in the causal structure of behavior (i.e., relations between the target behavior and its determinants). Variations may arise from various sources, including interindividual variations (such as differences in age or gender) and intraindividual variations (such as differences in time pressure or travel party). Some of these can be observed from explanatory information, while the rest cannot. *Changes* are defined as structural changes in behavioral mechanisms over time (i.e., a causal structure of behavior creates different states over time). Here an intrinsic practical difficulty in clearly distinguishing between variations and changes similar to the ecological fallacy should be noted (Robinson 1950). How close together in time must two observations be in order to regard differences between them as variations rather than actual changes in behavior? Can temporal averages in behavior be regarded as typical? This temporal version of the ecological fallacy arises when attempting to distinguish between variation and change empirically. In the following analyses, differences between observations are basically regarded as a source of variation when the observations are made within a year. Otherwise, we regard the difference as a source of changes. These distinctions may be intuitively reasonable, but exploring this temporal version of the ecological fallacy remains as an important future task.

11.2 Observations of Travel Behavior

The observation of travel behavior plays a fundamental role in travel behavior analysis, because the qualities of the subsequent steps (such as modeling of travel behavior and policy evaluation) are conditional on data quality. In general, the fewer the data that are available, the stronger the assumptions needed to infer a future state.

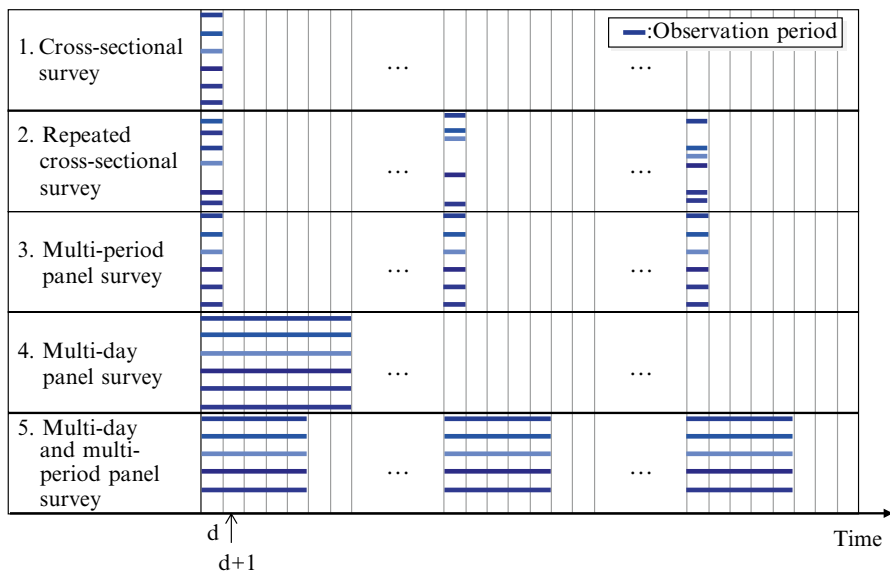


Fig. 11.2 Surveys for observing behavioral variations and changes

Thus, obtaining richer data at lower cost is an important aspect of behavioral observations in practice. In this section, we first introduce types of survey methods for observing changes and variations in travel behavior, and then we discuss sampling designs under budget constraints.

11.2.1 Behavioral Observation: Types of Surveys

Figure 11.2 shows five types of surveys differentiated by richness of information on changes and variations in travel behavior. A traditional survey of travel behavior is cross-sectional. In a typical cross-sectional survey (such as a traditional person–trip or travel diary survey), respondents are asked to report their travel behavior on a given day. Future travel demand can be predicted by assuming that (1) the travel behavior observed on the survey day is typical of all other days, that is, that travel behavior is highly repetitious in the short run, and (2) the behavior elicited from the data does not change over time. However, we can easily imagine situations in which actual behavior does not support these two assumptions. For example, travel behavior certainly varies between weekdays and weekends because activity needs are different. It can also be expected that sensitivity to travel cost may decrease with economic development. Efforts have been made to overcome these limitations. One simple method is to apply repeated cross-sectional surveys, which can partially support the validity of the above assumptions, such as changes in behavior that occur with changes in socioeconomic circumstances. On the other hand, although

repeated cross-sectional data may be suitable for measuring behavioral changes at the macroscopic level, they cannot provide information on behavioral changes at the microscopic level, such as the impacts of life-shock events (Clarke et al. 1982). In addition, Hanson and Huff (1988) pointed out the following.

Say, 10% of a sample group rode the bus on the survey day. One interpretation is that 10% of the population always rides the bus (thereby attributing all of the observed variance to inter-personal variability); at the other extreme is the interpretation that everyone in the population rides the bus 10% of the time (thereby attributing all the variance to intrapersonal variability). Clearly a mixture of these two sources of variability gives rise to the observed outcome, but we cannot ascertain the relative importance of each with cross-sectional data.

Importantly, this indicates that some policy questions, such as the equity of accessibility to bus services, cannot be properly answered with cross-sectional and repeated cross-sectional data. To overcome such limitations, longitudinal information is needed (Hanson and Huff 1988). On the other hand, it has also been pointed out that in some cases, repeated cross-sectional data can be superior to panel data (Yee and Niemeier 1996). For example, for long-term behavioral changes (e.g., changes over 20 years), panel data cannot represent the overall patterns of a population's activity/travel because data from younger generations are usually not included. Additionally, long-term observation of the same individuals is quite difficult for various reasons—for example, because of changes in residence. Repeated cross-sectional data may be suitable for measuring long-term behavioral changes, although they cannot provide information on behavioral changes at the microscopic level. In brief, repeated cross-sectional data have both advantages and disadvantages compared with panel data, and they may be a useful source of information on macroscopic changes.

Regarding longitudinal surveys, there are three types of survey: multiperiod panel surveys, multiday panel surveys, and multiday and multiperiod panel surveys. In all of these, variables are measured in the same units over time. Multiperiod panel survey data are collected to observe travel behavior repeatedly at discrete points of time. The basic purpose of this type of survey is to capture changes in activity/travel behavior. Unlike repeated cross-sectional surveys, the data contain information on changes at the microscopic level. On the other hand, it is usually difficult to identify whether the difference between behaviors observed at two points in time actually comes from changes in behavior; that is, the problem of separating changes and variations may emerge. For example, the difference in departure time choices between two points in time may be caused not only by changes in a person's job but also simply by variations in daily behavior because of physical conditions. In the latter situation, the observed differences should be understood as variations, not as changes.

The second type of longitudinal survey, a multiday panel survey, is used to observe travel behavior on multiple consecutive days. From this type of data, the source of variations can be distinguished. Specifically, intra- and interindividual variations can be distinguished, allowing us to respond to Hanson and Huff's (1988) criticism mentioned above. Moreover, this type of data has contributed greatly to the sophistication of travel behavior models such as that in the activity-based approach (e.g., Kitamura 1988). Commonly cited case studies of multiday panel surveys are the Uppsala Household Travel Survey (Hanson and Huff 1988), the Reading

Activity Diary Survey (Pas 1986), Mobidrive (Axhausen et al. 2002), the REACT! Survey (McNally and Lee 2002), the Twelve Week Leisure Travel Survey (Stauffacher et al. 2005), and the Swiss Longitudinal Travel Survey (Axhausen et al. 2007). In Japan, this type of survey has also been widely implemented in the form of the probe-person survey.¹

Although both multiperiod and multiday panel surveys are important sources of information on changes and variations in travel behavior, they cannot simultaneously capture both. Simultaneous observation is especially important for capturing changes in travel behavior at the microscopic level while avoiding the problem of separating changes and variations mentioned above. For this purpose, a multiday and multiperiod panel survey may be needed. Commonly cited examples are the Dutch Mobility Panel (Van Wissen and Meurs 1989), the Puget Sound Travel Panel (Goulias et al. 2003), the Toronto and Quebec Travel Activity Panel Survey (Roorda et al. 2005), and the German Mobility Panel.² Importantly, researchers cannot know how much they do not know about travel behavior changes at the microscopic level without rich data. Therefore, although implementing a multiday and multiperiod panel survey is costly, it is useful for confirming or rejecting the assumptions made in the conventional and practical analysis. The cost effectiveness of sampling designs will be discussed briefly in the next subsection.

11.2.2 *Sampling Designs*

Although multiday and multiperiod panel data are useful, as discussed in the previous subsection, they are costly and require good institutional organization (e.g., Zumkeller 2009). Thus, multiday and multiperiod panel surveys are seldom implemented in practice. On the other hand, there are several pieces of evidence for the importance of collecting panel data, even from the viewpoint of cost effectiveness. For example, Pas (1986) examined the optimal length (in days) for multiday panel surveys and underscored the substantial benefits of multiday panel surveys in reducing data collection costs and/or improving the precision of parameter estimates. Kitamura et al. (2003) focused on the design of multiperiod panel surveys in the context of discrete travel behavior and concluded that continuous behavioral observations are needed to detect changes in behavior. This implies that to identify changes in behavior, short-term variability must be explicitly distinguished from long-term changes (i.e., the separability problem of variations and changes must be dealt with), indicating that multiday and multiperiod panel survey data are required. In line with this view, Chikaraishi et al. (2013) explored the optimal survey designs for multiday and multipanel surveys.

Figure 11.3 shows the basic concept of survey designs for multiday and multiperiod panel surveys. In this type of survey design, there are three aspects of

¹<http://www.probe-data.jp/eng/index.html> (accessed on November 2, 2012).

²<http://mobilitaetspanel.ifv.uni-karlsruhe.de/en/index.html> (accessed on November 2, 2012).

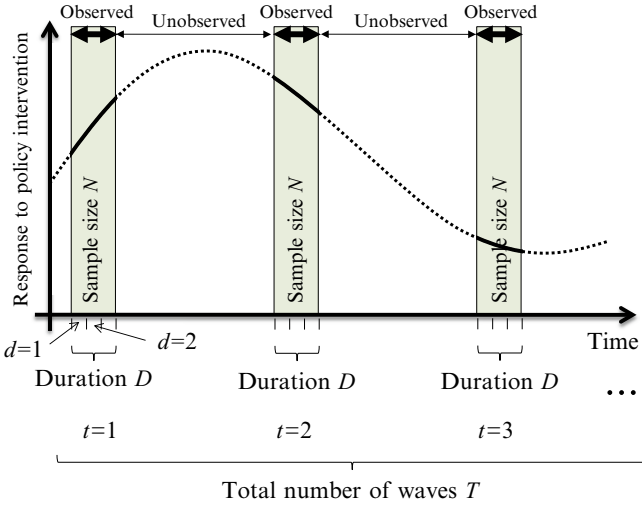


Fig. 11.3 Survey designs for multiday and multiperiod panel survey (Chikaraishi et al. 2013)

behavioral observation: (1) the observed duration of each wave, denoted by D [day/wave], (2) the total number of waves conducted in a certain survey period, denoted by T [wave], and (3) the sample size, denoted by N [people]. Practical examples include the fourth person–trip survey in the Tokyo metropolitan area, in which $\{N, T, D\} = \{883044, 1, 1\}$, the Mobidrive survey (Axhausen et al. 2002), with $\{361, 1, 42\}$, and the German Mobility Panel (Zumkeller 2009) with $\{1800, 17, 7\}$. Thus, survey designs vary. Moreover, because of budget constraints, the trade-off between the observed duration of each wave, the interval between successive waves, and the sample size in the survey designs must be considered, depending on the purpose of the survey. On this subject, Chikaraishi et al. (2013) showed that with an increase in the complexity of behavioral changes, not only shorter intervals between waves but also longer multiday behavioral observations per wave are necessary.

11.3 Variations in Travel Behavior

11.3.1 The Importance of Exploring Behavioral Variations

Variations of travel behavior reveal information on uncertainties in terms of imperfect fit of models to data. Decisions related to travel behavior are influenced by different factors at various levels, such as sociodemographic, locational, and other contextual attributes. Considering that an individual decides his or her behavior according to the constraints of time and space as well as his or her own current situation (Hägerstrand 1970), the dominant types of variation could be intraindividual, interindividual, interhousehold, temporal (i.e., systematic day-to-day variation), or spatial.

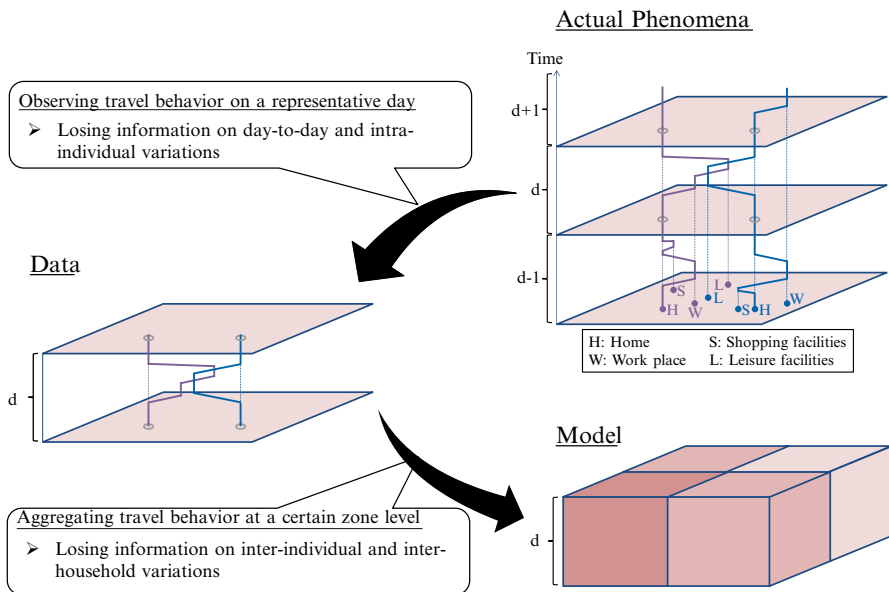


Fig. 11.4 A traditional travel demand prediction process

In fact, the existence of such types of variations is recognized by researchers, and the importance of discriminating among them has been discussed extensively (e.g., Pas 1987; Hanson and Huff 1988; Pas and Sundar 1995; Kitamura et al. 2006; Schlich and Axhausen 2003).

In general, explaining these behavioral variations based on observed elements is what an empirical model usually does. In addition, mainly because of data limitations, some sources of unobserved variation remain even after explanatory information is introduced. For example, if household income is not available but has some effect on behavior, the unobserved interhousehold variation would be greater than that with income effects considered. A lack of situational attributes (e.g., “with whom” and “for whom”) may lead to greater unobserved intraindividual variation than with those attributes considered. Moreover, when a travel demand model, such as a traditional four-step model, is developed based on spatial aggregation data, information on day-to-day variations and intraindividual variations is lost at the data collection step, as is information on interindividual and intraindividual variations at the model development step (Fig. 11.4).

In this study, we attempt to identify sources of variations in various aspects of behavior and assess the possibility of explaining these variations with further information. There are at least three reasons why understanding the properties of variation is important.

First, before attributing behavioral variations to observed elements, it is necessary to understand what kinds of variations exist by exploring the fundamental properties of the behavior. In reality, analysts must narrow the target of analysis to limited variation types in many cases. This is mainly because of the available data, analysis

methods, or both. For example, it is intrinsically impossible to capture temporal variations using survey data from a single day (Pas 1987), but multiday surveys are costly and often impossible to conduct in practice. In other instances, interindividual variation is automatically lost in traditional four-step models using spatial aggregate data, but such models are still often employed, partly because alternative methods are obscure. Because such limitations cannot be avoided in certain situations, especially in current practice, the focus on limited variation types should be understood. In other words, it is necessary to quantify the loss of information caused by ignoring some kinds of variations.

Second, it may be useful to clarify what kinds of variations are difficult to capture even after observed elements are introduced into models. The remaining unobserved variations may indicate niches to be exploited further, probably along with additional observations. In line with this, Kitamura (2003) pointed out that even if one could grasp an actual “stable” relationship between 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 reveal variation in the behavior around the stable relationship and to suggest what kinds of factors should be further observed.

Third, related to the first and second points, information on variation properties could contribute to a better understanding of potential fallacies in the analysis. For example, a number of researchers have confirmed the risk of the aggregative (ecological) fallacy (Robinson 1950) in relation to aggregate models (i.e., four-step models) and the representative fallacy in relation to disaggregate models. The representative fallacy can be seen as an issue arising from the assumption that individual behavior varies little from day to day and that the behavior on a typical day can be used to represent almost all behavior on other days. These fallacies indicate that more detailed and microscopic behavioral analysis is needed. On the other hand, microscopic level analysis can also be strongly affected by the “atomistic fallacy” (Diez-Roux 1998), which is the fallacy of modeling behavior exclusively on a given microscopic level unit while ignoring macroscopic level effects. In the transportation literature, the aggregative fallacy has received much more attention than its counterpart, the atomistic fallacy. In the real world, the unit of analysis can be defined at various levels. For example, the macroscopic level could be defined according to a city or a zone, and the microscopic level according to a household, an individual, an activity episode, or a trip. Basically, the more microscopic level units are employed as basic units of analysis, the more likely the research into the effects of macroscopic level variables on behavior should be discouraged, and vice versa. Information on various types of observed and unobserved variation could remind us of these potential fallacies.

11.3.2 Empirical Findings on Behavioral Variations

As mentioned above, there are five main variation types: intraindividual, interindividual, interhousehold, day-to-day (temporal), and spatial variations. In this subsection,

we introduce empirical findings regarding the properties of the five variation types proposed by Chikaraishi et al. (2009, 2010a, 2011a). They explore the properties of these variations using a multilevel modeling approach (Hox 1995; Kreft and de Leeuw 1998; Goldstein 2003):

$$F(y_{t\text{ihds}}) = \beta x_{t\text{ihds}} + \gamma_{ih} + \gamma_h + \gamma_d + \gamma_s + \varepsilon_{t\text{ihds}} \quad (11.1)$$

where $F()$ is the response function in generalized linear models, $y_{t\text{ihds}}$ is the dependent variable of the t th trip made by person i of household h on day d in space s , β is a vector of unknown parameters, $x_{t\text{ihds}}$ is a vector of explanatory variables, and γ_{ih} , γ_h , γ_d , γ_s , and $\varepsilon_{t\text{ihds}}$ are random components that indicate unobserved interindividual, interhousehold, temporal (day-to-day), spatial, and intraindividual variations, respectively. It is also assumed that all random components are normally distributed with a mean of zero and variance σ_{ih}^2 , σ_h^2 , σ_d^2 , σ_s^2 and σ_0^2 , respectively. Equation (11.1) is used when the unit of analysis is “trip” (e.g., departure time and travel mode choice), while suffix t may be omitted from Eq. (11.1) when the unit of analysis is “person-day” (e.g., activity generation and time use for a single day).

In the model without explanatory variables (called the *Null* model), the total variation of $F(E[y_{t\text{ihds}}])$ can be calculated as:

$$\text{Var}(F(y_{t\text{ihds}})) = \tilde{\sigma}_{ih}^2 + \tilde{\sigma}_h^2 + \tilde{\sigma}_d^2 + \tilde{\sigma}_s^2 + \tilde{\sigma}_0^2 \quad (11.2)$$

where “~” indicates the estimated parameters of the *Null* model. Based on the variation properties in the *Null* model, it is possible to clarify which source of variation affects behavior.

When the model includes explanatory variables (called the *Full* model), the total variation of $F(E[y_{t\text{ihds}}])$ can be calculated as:

$$\text{Var}(F(y_{t\text{ihds}})) = \text{Var}(\hat{\beta}x_{t\text{ihds}}) + \hat{\sigma}_{ih}^2 + \hat{\sigma}_h^2 + \hat{\sigma}_d^2 + \hat{\sigma}_s^2 + \hat{\sigma}_0^2 \quad (11.3)$$

where “^” indicates the estimated parameters of the *Full* model.

Theoretically, all estimated variation components of the random components in the *Full* model should be smaller than those in the *Null* model because $\text{Var}(\hat{\beta}x_{t\text{ihds}})$ explains part of the total variation. It is further expected that increasing the number of explanatory variables decreases the variances σ_{ih}^2 , σ_h^2 , σ_d^2 , σ_s^2 and σ_0^2 . As mentioned above, it is interesting to know how much of these variances are explained for several reasons. The main reason is that remaining variation offers information about which types of explanatory variables are still lacking and which direction future research should take. For example, if the specified set of explanatory variables does not reduce spatial variation or if it remains high, more attention should be paid to observing spatial variables. However, determining which explanatory variables reduce the unobserved heterogeneities is less certain because microscopic level variables in particular have cross-level influences, and it is rare to eliminate unobserved variation at one level completely (Teune 1979). For example, the duration of a commute may be categorized as a situational attribute, but it is not difficult to imagine that there are substantial differences between individuals or O–D pairs.

Therefore, a model including duration of commute as an explanatory variable may reduce not only intraindividual variation but also other variation. Thus, in the following discussion of empirical findings, we mainly focus on the variation properties of various behavioral aspects, rather than on which factor is the ultimate source of behavioral variations.

The variation decomposition technique based on the multilevel modeling approach can be applied to a number of behavioral aspects, as long as the behavioral model can be regarded as a generalized linear model such as a linear regression model, binary choice model, multinomial choice model, or some types of discrete-continuous model. In the following discussion on empirical findings, we consider four behavioral aspects: departure time, activity participation, time use, and mode choice.

11.3.2.1 Behavioral Variations Without Explanatory Information

Figure 11.5 shows the variation properties of departure time, activity participation, time use, and mode choice (Chikaraishi et al. 2009, 2010a, 2011a; Chikaraishi 2010). All variation properties were estimated using Mobidrive data, which are continuous 6-week travel survey data collected in the cities of Karlsruhe and Halle, Germany, in 1999 (Axhausen et al. 2002). These data represent one of the longest multiday travel diary panel surveys, and they may be suitable for exploring the variation properties of behavioral aspects.

The major findings from Fig. 11.5 can be summarized as follows:

1. Larger interindividual variations are observed for mandatory activities (school and work) in departure time, activity participation and time use. Thus, it can be expected that variations of mandatory activities mainly arise from differences across individuals. On the other hand, it can also be confirmed that interindividual variations are smaller in recreational activities (nondaily shopping and leisure) for departure time, activity participation, and time use.
2. The proportion of intraindividual variation is substantial in most cases, except for variation properties of mandatory activity participation and time use, and all travel modes. This implies that it may be inappropriate to assume that individual behavior changes little from day to day and behavior on a typical day remains constant. In other words, multiday panel data may be needed to explore the mechanisms of behavioral aspects.
3. On the other hand, the variation properties of mode choices show smaller day-to-day and intraindividual variations, meaning that mode choice behavior is relatively stable from day to day compared with other behavioral aspects.
4. It is confirmed that a substantial amount of variation information may be lost when we use spatial aggregated data in a traditional four-step model.

Although the empirical findings shown here are conditional on the models employed, it may be useful to revisit the validity of the current demand prediction procedure, shown in Fig. 11.4. In other words, knowing about such variation properties informs us about the limitations of the current prediction procedure, which focuses on a limited number of variation types.

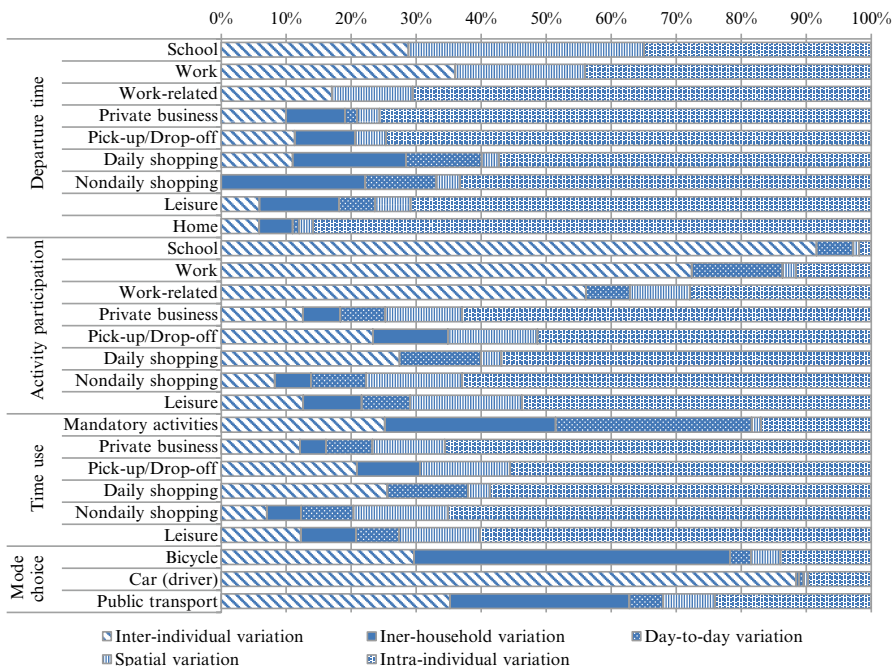


Fig. 11.5 Estimated behavioral variations (without explanatory information). *Notes:* (1) The estimation results of departure time model from Chikaraishi et al. (2009). A multilevel linear regression model was applied to obtain the variation properties. (2) The estimation results of activity participation model from Chikaraishi (2010). A multilevel binary logit model was applied. (3) The estimation results of time use model from Chikaraishi et al. (2010a). A multilevel MDCEV (Multiple Discrete-Continuous Extreme Value) model was applied. (4) The estimation results of mode choice model from Chikaraishi et al. (2011a). A multilevel multinomial logit model was applied. (5) The definitions of spatial variations vary across case studies. See the above cited papers for the details. (6) Since the utility in the MDCEV model and logit model has no absolute reference or zero point, one has to consider the relative value of utility to obtain variation properties. In-home activities (Car Passenger) were treated as a reference alternative for obtaining the variation properties of other alternatives in time use (mode choice) behavior

11.3.2.2 Behavioral Variations with Explanatory Information

Next, we examine how much of the unobserved variances of random components can be explained by observed information. Here we only focus on the results of departure time choice (Chikaraishi et al. 2009). The results of time use and mode choice are also available from Chikaraishi (2010) and Chikaraishi et al. (2011), respectively. The additional data needed to capture variations in departure time include:

- [Individual attributes] gender, marriage status, employment status, age, and vehicle license;
- [Household attributes] number of household members, number of children in household, number of personal vehicles, distance to the nearest bus stop/LRT/ rail station, and household income; [spatial attributes] residential locations;

- [Temporal attributes] day-of-week; and
- [Episode unit attributes] travel time, number of activities per day, size of party, and travel mode.

Explanatory variables were selected based on a preliminary analysis conducted to select statistically significant variables (at least at the 90 % level of significance). The selected variables vary from activity to activity (the details can be found in Chikaraishi et al. 2009). The additional data provide a fair representation of the variables used in practical models.

Figure 11.6 shows the estimated variation properties of departure time. First, it is found that most temporal variation can be explained by the additional data introduced above. More specifically, more than 70 % of temporal variation in private business, daily shopping, nondaily shopping, leisure and home is captured. The reason may be twofold. First, the introduced day-of-week dummy works well to reduce such variations. Second, introducing other types of variables may also reduce such temporal variation. For example, some activities in which two or more household members participate could occur more frequently on holidays. In such cases, introducing the relevant information could reduce temporal variation.

The smallest reduction of unobserved variation is observed in intraindividual variation (4–16 %). Explaining intraindividual variation using variables appears quite difficult for all activity types. This implies that, at least in departure time choice, additional information is needed to capture intraindividual variations. As for other components of variations (interindividual, interhousehold, and spatial variation), the reduction of unobserved variation varies greatly with activity type; interindividual variation ranges from 20 % to 83 %, interhousehold variation from 27 % to 65 %, and spatial variation from 30 % to 82 %. However, for almost all activity types, significant amounts of unobserved interindividual, interhousehold and spatial variation remain, suggesting that it is necessary to introduce further appropriate observed variables to explain it. In this way, this type of analysis can provide a fundamental picture of what we do not know about the mechanisms of travel behavior.

11.4 Changes in Travel Behavior

11.4.1 *Types of Behavioral Changes and Data*

Changes in travel behavior contain information on uncertainty about the similarity of the future to the past. Behavioral changes can occur at both microscopic and macroscopic levels (Pendyala and Pas 2000). The former changes could occur along with changes in areas such as jobs, life cycle stages, or home location. Lifestyle change is another important factor causing microscopic level changes. Macroscopic level changes can occur along with changes in socioeconomic circumstances, such as the development of information technology, an aging population, and a diminishing

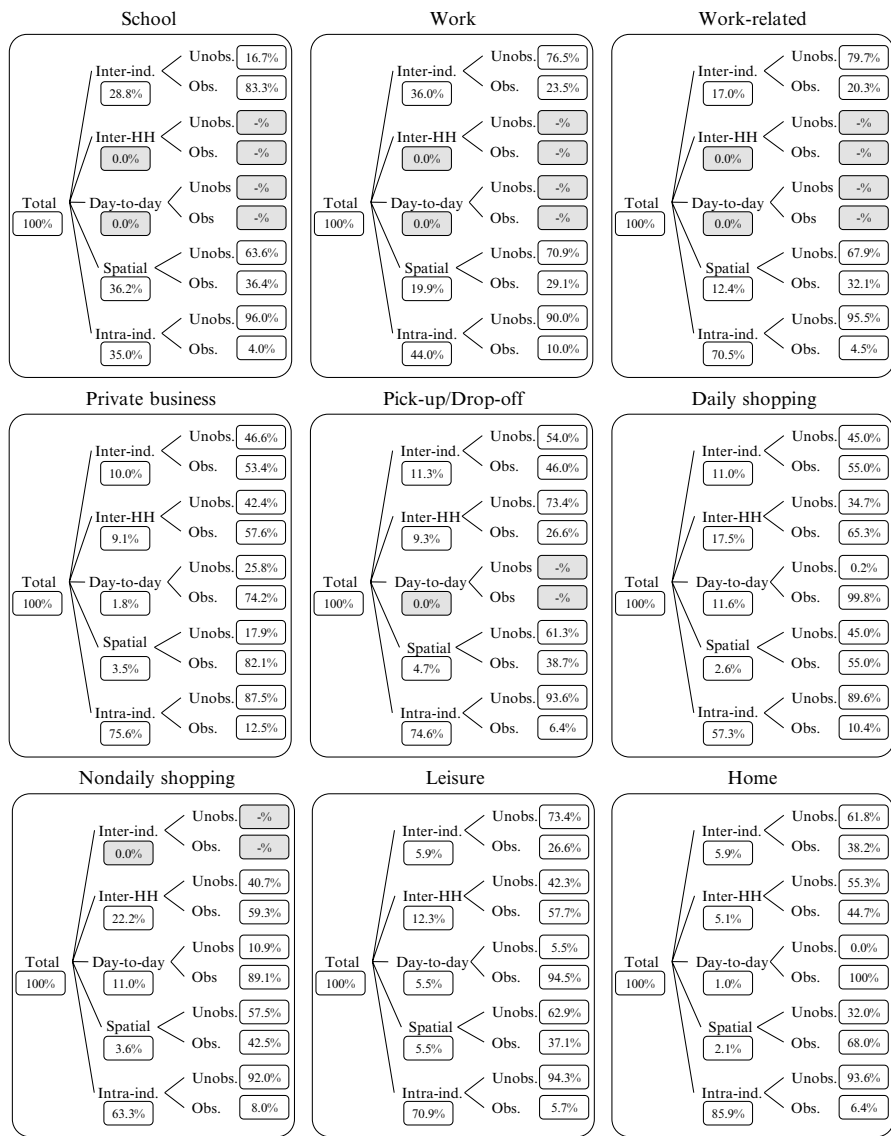


Fig. 11.6 Estimated behavioral variations in departure time (with explanatory information) (Chikaraishi et al. 2009)

number of children. Although it may be expected that the cumulative effects of microscopic changes will cause macroscopic changes, it can also be expected that macroscopic level changes will eventually cause a gradual shift in the degree of changes at the microscopic level. For example, the diminishing number of children may be expected to keep elderly people working longer, and as a result, the impact

and timing of a “life-shock event” could be changed. In addition, changes in technologies can cause changes in individual travel behavior; for example, through telecommuting. Thus, it can naturally be considered that microscopic and macroscopic states typically coevolve (Epstein 2006).

To capture behavioral changes at the microscopic level, panel data are required. For example, developing dynamic behavioral models (Hensher 1988; Kitamura 1990) and exploring individual transitional behavior (Goulias 1999; Thøgersen 2006) are impossible without panel data. On the other hand, to investigate macroscopic level changes in addition to panel data, repeated cross-sectional data in which an independent sample is collected at each time point could be used. For example, aggregated observations of changes and monitoring trends in behavior (Levinson and Kumar 1995) and the temporal (in)stability of a population’s (or macro) activity–travel patterns (Zahavi and Talvitie 1980) could be confirmed using repeated cross-sectional data. Moreover, aggregated time-series data usually contain much longer continuous period information, although these are mostly aggregated data where most variation information is lost because of the aggregation procedure discussed above.

Considering the advantages and disadvantages of different types of data, this section introduces three empirical studies. First, we show changes in traffic demand elasticities (for details refer to Chikaraishi et al. 2010b). This study was conducted using traffic volume data, which are easily accessed time-series data. Second, behavioral variations in time use are introduced (Chikaraishi et al. 2012). This study uses repeated cross-sectional time-use data. Third, we briefly introduce the empirical findings regarding variations in travel time expenditure (Chikaraishi et al. 2011b). In the third case study, multiday and multiperiod data were applied, allowing us to distinguish between interindividual and intraindividual variations.

11.4.2 Changes in the Response to Certain Variables: Traffic Demand Elasticities

First, we examine the spatiotemporal changes of traffic demand elasticities regarding gasoline prices, focusing on the substantial fluctuations that occurred throughout 2008 in Japan. The analysis uses monthly traffic volume data collected on 53 expressways, which are automatically collected by the traffic counter devices installed on roadsides. The elasticities are calculated based on a log-transformed Cobb–Douglas demand function that has been widely used in practice. We directly extend this traditional model to capture the spatial and temporal instability of the elasticities by first building a random coefficient model to represent spatial heterogeneity and then applying a sequential Bayesian updating method to examine monthly changes in these elasticities.

Figure 11.7 shows the spatiotemporal changes in traffic demand elasticities. The results indicate that although most monthly changes in the average elasticities over

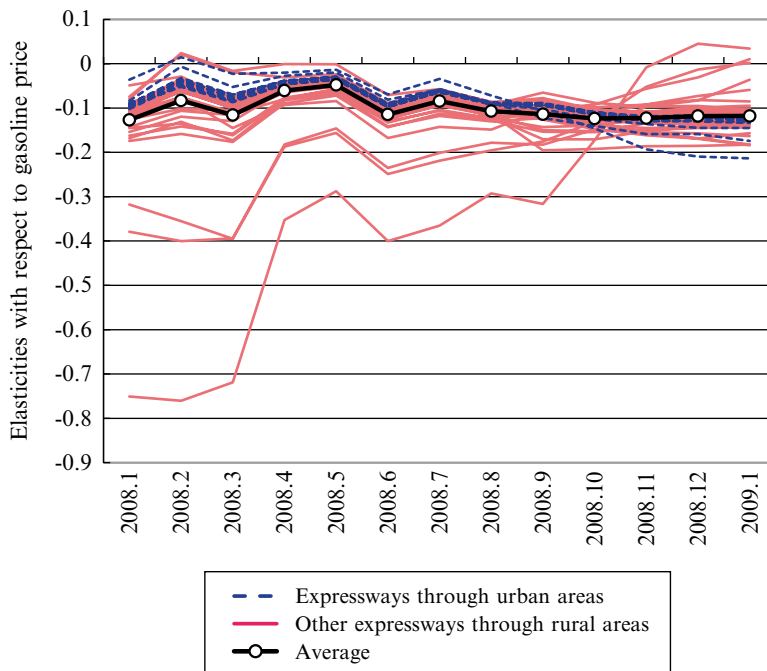


Fig. 11.7 Changes in traffic demand elasticities (Chikaraishi et al. 2010b)

all routes were observed before August 2008, different directions of change across routes were observed after September 2008, when gasoline prices began to fall. The results also indicated that responses to gasoline price changes depend on the causes of price changes. Furthermore, on urban expressways, it was found that once a reduction in traffic demand was attained because of rising gasoline prices, demand did not fully recover even after the actual prices fell again to the original level.

Although this analysis focused on unusually strong fluctuations in gasoline prices, such events often occur. This indicates that even when a plausible parameter value for future demand prediction is obtained, continuous monitoring of parameter changes may be needed, especially when the policy can be adjusted over time. On the other hand, information on behavioral changes based on such aggregated data is still limited because the intraindividual, interindividual, and interhousehold variations have not been taken into account in the aggregated analysis.

11.4.3 Changes in Behavioral Variations: Time-Use Behavior

Compared with aggregated time-series data, repeated cross-sectional data contain more detailed information on travel behavior. This subsection introduces the

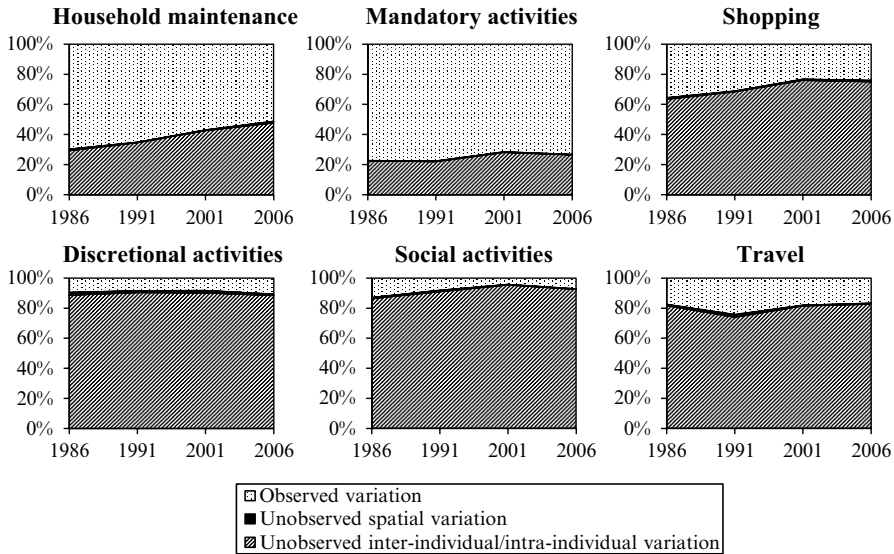


Fig. 11.8 Changes in variations in time use behavior (Chikaraishi et al. 2012)

estimation results of the long-term changes in cross-sectional variations in time-use behavior by Japanese people using a multilevel MDCEV model as in Chikaraishi et al. (2012). The basic methodology is the same as that in the previous section, but the definition of variations is different. Specifically, cross-sectional variations include interindividual/intraindividual variation and spatial variation (at the prefecture level). Here it should be noted that interindividual and intraindividual variation cannot be separated because repeated cross-sectional data cannot distinguish between them. Despite this, this analysis may provide useful information on changes; for example, whether structural changes in time-use behavior have led to diversification (again, we cannot distinguish whether the diversification occurs between or within individuals). The empirical analysis was conducted using national time-use data collected at four points in time (1986, 1991, 1996, and 2001) from the “Survey on Time Use and Leisure Activities” conducted by the Japanese Ministry of Internal Affairs and Communications.

Figure 11.8 shows the changes in variation properties of time-use behavior. The most important finding here is that given the explanatory variables used in the empirical analysis (i.e., work style, car ownership, income, age, and gender), increased effects of unobserved interindividual variations in household maintenance and shopping are evident in Japanese time-use behavior. This implies that patterns in behavior become more evident over time, and it may be difficult to predict activity–travel patterns in the long term. In other words, structural changes in time-use behavior have resulted in diversification.

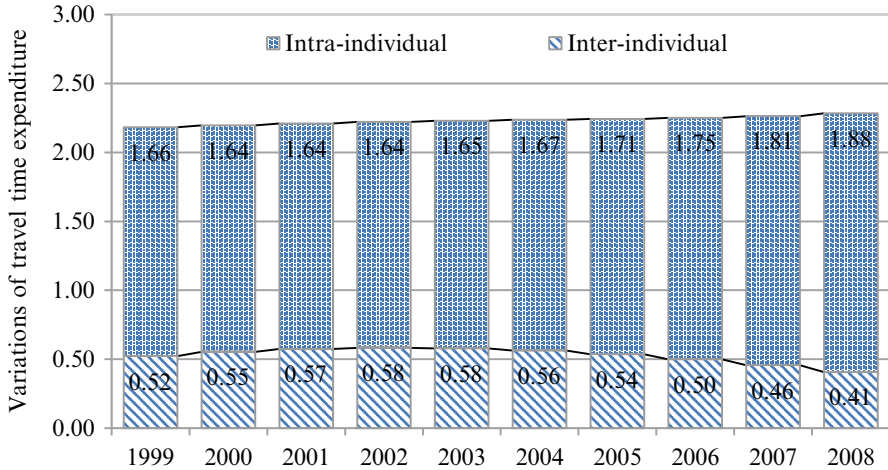


Fig. 11.9 Changes in variations in travel time expenditure (Chikaraishi et al. 2011b)

11.4.4 Changes in Behavioral Variations: Travel Time Expenditure

Although a tendency toward behavioral diversification was shown above, we did not clarify the source; that is, diversification within an individual or diversification between individuals. In this section, we conduct an empirical analysis of changes in travel time expenditure, distinguishing between intraindividual and interindividual variations, following Chikaraishi et al. (2011b). The methodology is a simple extension of the multilevel models introduced in the previous section: all parameters are assumed to be functions of time, including variance parameters; thus, the estimated variation properties can change over time. In the empirical analysis, a multilevel Tobit model was applied to take into account zero travel time expenditure; that is, days when a person is immobile. The analysis considers interindividual and intraindividual variations. Although theoretically we can incorporate other types of variations, such as spatial and temporal, the variation types were restricted to reduce the cost of estimation. The data used in the empirical analysis are from the German Mobility Panel, which is a multiday and multiperiod panel survey.

The empirical results are shown in Fig. 11.9. The empirical results indicate that intraindividual variations increase over time, whereas interindividual variations become smaller. This suggests that over time, people’s travel time expenditures become more dependent on situational attributes than on individual or household attributes. The implication is that travel time expenditure diversifies for an individual; that is, observed travel time expenditure may become sensitive to the immediate situation. This finding means that description of travel behavior based on conventional data for 1 day may become less accurate over time. A longer observation period for each wave may be more important for capturing behavioral changes.

11.4.5 Summary of Behavioral Changes

We have briefly introduced the results of three empirical analyses, focusing on changes in travel behavior. The first empirical study indicates that the transport-related indicator is not truly stable over time. The second empirical study indicates that modeling travel behavior becomes difficult over time given a specific set of explanatory information, implying that more detailed behavioral observation and/or more sophisticated modeling techniques may be required simply to maintain the current level of prediction accuracy. The third empirical study indicates that intra-individual variations become greater over time, implying the need for longer multi-day periods of behavioral observation. Although these are just a small part of the empirical results of changes in travel behavior, the results clearly support Gifford's (2003) assertion: the assumption that travel demand is predictable over a 20-year planning horizon is no longer supportable. Particularly, implications from the empirical findings that activity–travel behavior has diversified over time are critical for travel demand forecasting. If prediction procedures cannot be improved, there is a possibility that uncertainty in demand forecasting will gradually increase. In the next section, we discuss several possible ways to improve transportation planning procedures.

11.5 Implications for Transportation Planning

The proper role of travel behavior analysis (particularly travel demand prediction) in the transportation planning process may depend on the degree of prediction accuracy (or uncertainties in prediction). If we could accurately estimate future travel demand, then we could depend more on travel behavior analysis, and vice versa. Some uncertainties will be reduced by improving behavioral observation and modeling techniques, while some will not. In this section, we first discuss the former aspect; that is, how we can reduce uncertainties by improving travel behavior analysis. We then discuss other components of transportation planning that could compensate for the imperfection of prediction. Finally, the implications for transport planning in developing countries are discussed.

11.5.1 Reducing Uncertainties by Improving Travel Behavior Analysis

The empirical results above indicate several ways to reduce uncertainties in travel behavior analysis. One important implication is that we have overlooked the importance of intraindividual variation (i.e., situational/contextual information) in the modeling of travel behavior analysis. In line with this view, a number of efforts have

been made to collect multiday travel diary data (e.g., Pas 1986; Hanson and Huff 1988; Roorda et al. 2005; Axhausen et al. 2002, 2007; Hato and Kitamura 2008) and to develop more accurate activity–travel behavior models by incorporating a number of new aspects such as activity scheduling, household/social interactions, planned/unplanned activities and the psychological aspects of activity–travel decisions (Kitamura 1988; Axhausen and Gärling 1992; Supernak 1992; Harvey 1996; Kitamura et al. 1997; Bowman and Ben-Akiva 2001; Timmermans et al. 2001, 2002; Miller and Roorda 2003; Bhat et al. 2004; Arentze and Timmermans 2004; Auld and Mohammadian 2009). In addition, the empirical results showed that behavioral changes may occur frequently, implying the need to develop dynamic models to reflect such behavioral changes. Accordingly, several dynamic models have been developed in previous studies (e.g., Hensher 1988; Kitamura 1990; Goulias 1999; Thøgersen 2006). The data required for such dynamic modeling have also been corrected (e.g., Zumkeller 2009). Moreover, data fusion techniques (Stopher and Greaves 2007; Acharya et al. 2011) have some potential to connect detailed behavioral data with other time-series data to shed light on behavioral changes.

There is no doubt about the importance of the above-mentioned improvements in travel behavior analysis. On the other hand, the contributions to the transportation planning process are difficult to capture without knowing the extent to which uncertainties are reduced because of the improvement. In other words, in addition to improving behavioral observation and modeling techniques, researchers need to implement uncertainty analyses to embed the improved travel behavior analysis methods in the transportation planning process in an appropriate manner. For this purpose, Rasouli and Timmermans (2012) reviewed current uncertainty analyses in travel demand models and found a lack of comprehensive uncertainty analysis. Further empirical analysis of uncertainties in travel demand models is an important future research task.

11.5.2 Reducing Uncertainties by Improving Other Components of the Planning Process

Gifford (2003) pointed out several fallacies in current long-term transportation planning. In this section, we first introduce two that may be useful for discovering other techniques for overcoming uncertainty in the planning process. The first is the exogenous goal fallacy: long-term transport planning is often conducted with goals in mind, but these goals do not magically present themselves to planners. Once the goals are fixed, it is difficult to change them, although value judgments may change. Gifford (2003) pointed out that one of the sources of this fallacy is that planning has been conducted as a purely scientific enterprise. Given the social and cultural aspects of cities, regions, and nations, it is clear that planning is a kind of trans-science problem that cannot be fully resolved by a purely scientific approach (Weinberg 1972). In this sense, it may be better to consider planning based not only on the technology of reason (e.g., rational decisions based on cost–benefit analyses)

but also on the technology of foolishness (taking action to learn what is not known) (March 1979). This learning-by-doing strategy may be particularly important in developing countries' planning, where only limited data and model techniques are available. We will discuss this point in detail in the next subsection. The second fallacy is the predictive modeling fallacy, which is the transportation planners' predisposition to rely on medium- to long-range forecasts. Although the degree of this fallacy may depend on improvements in travel behavior analysis, there are several intrinsic difficulties in prediction, such as changes in people's values and decisions on other matters that the planners cannot decide (Friend and Jessop 1976; Hall 1982).

To avoid these fallacies, Gifford (2003) had three ideas: control, flexibility, and adaptive discovery. Control is a technique that turns an unpredictable environment into a predictable one. For example, laws and regulations are the main methods of control. If a prediction is different from the actual outcome, we can modify the degree of regulation to reach a certain level. Flexibility is a technique that is pliable or responsive to (unexpected) changes. For example, bus may be a more flexible option than light rail transit, because it is easier to open, close and reroute the service. Adaptive discovery is a kind of learning by doing as mentioned above. Findings from previous projects can be embedded in the current project, findings from the current project can be reflected in the next project, and so forth. Actually, this third idea can be regarded as a governing system of the two former ideas: the idea of adaptive discovery provides a platform for adjusting control and flexibility measures sequentially through the learning process.

Although control and flexibility are important ideas, they should be applied in an appropriate way. Of course, excessive control (for example regulating people's mobility too much) may be impractical because of the difficulty in justifying the possible negative impacts on economic condition. Excessive flexibility may reduce the cost efficiency of investments. Thus, careful institutional arrangements are needed to manage the learning process properly, as a number of previous studies have mentioned (Friend and Jessop 1976; Flyvbjerg et al. 2003; Gifford 2003). On the other hand, although a number of studies have pointed out the conceptual importance of institutional arrangements, the methods, findings and lessons of previous projects are retained only by the people involved and have not been collected and sorted in a practical manner. In this sense, learning from other projects implemented even in other cities/countries may be crucial, as recent studies have mentioned (e.g., Dolowitz and Marsh 2000; Bulmer and Padgett 2004; Ison et al. 2011; Marsden et al. 2012). In this regard, Dolowitz and Marsh (2000) underscore the importance of looking at "the process by which knowledge of policies, administrative arrangements, institutions and ideas in one political system (past or present) is used in the development of policies, administrative arrangements, institutions and ideas in another political system". Furthermore, transportation researchers have recently discussed learning from other cities/countries' experiences; for example, in a special journal issue focusing on "Transferability of urban transport policy" (Ison et al. 2011). Enhancing such learning processes may be crucial for better transportation planning decisions under uncertainty.

11.5.3 Implications for Planning in Developing Countries

Although advanced modeling techniques can be applied in developing countries, there are several intrinsic limitations. First, data have not been gathered in developing countries. Advanced surveys such as longitudinal surveys could be conducted, but the low literacy rate of poor people, for example, makes such complicated surveys difficult. Moreover, even if there were sufficient data, the lack of human resources may cause difficulties in using the advanced prediction techniques. In addition, many developing countries have a unique public transit system—paratransit. Because paratransit provides a huge number of jobs as well as mobility for poor people, more care may be needed in interventions in public transit systems. In this sense, those transferring the planning techniques in developed countries to developing countries should consider paratransit as well as the different institutional arrangements. Thus, uncertainties in transportation planning in developing countries are expected to be greater than in developed countries.

Considering these aspects, it may be worth applying the concept of single- and double-loop learning, proposed by Argyris and Schon (1978). Single-loop learning may correspond to a learning process where control and flexibility measures are sequentially adjusted to developing countries' situations. For example, because the results of regulating paratransit are uncertain, such actions may require repeated modification based on the results of previous actions. On the other hand, double-loop learning may correspond to the process of learning about the planning organization itself (i.e., altering its governing values) and the development of people's ability to make better choices in the face of complexity and uncertainty. For example, after repeated modification of regulations for paratransit, the organization may learn the pros and cons of the regulations, reexamine and finally alter its governing values. These learning processes may be important, but we do not have sufficient knowledge of them in the context of transport planning. There are a number of discussions in other fields, including public sector management (e.g., Argyris 1992; Common 2004; Vare and Scott 2007; Krasny et al. 2010; Lundholm and Plummer 2010; Sterling 2010). Learning from these existing studies for better capacity building may be important for improving transportation planning processes in developing countries.

11.6 Conclusions

This chapter has investigated uncertainty in travel behavior and its implications for transportation planning. Based on our empirical studies, we pointed out the intrinsic limitations and the importance of uncertainty analysis in transportation demand forecasting. In particular, developing more sophisticated demand models often only emphasizes the improvement of the existing models, and the extent to which uncertainty can be reduced using the refined model has not been well examined. For example, although a more sophisticated model may produce better goodness of fit,

sometimes it may also reduce the temporal stability of the model. Thus, a comprehensive uncertainty analysis is needed before replacing an existing model with a newly developed model. Additionally, the proper role of demand forecasting in the transportation planning process may depend on the degree of prediction accuracy. If we could accurately estimate future travel demand, then we could depend more on travel behavior analysis, and vice versa. For this reason, uncertainty analysis in demand prediction is also crucial when we attempt to embed demand forecasting in the transportation planning process.

Considering the difficulty of completely eliminating uncertainties, we have also discussed other ways to improve transportation planning. Although control and flexibility could be significant measures in transportation planning under the existence of uncertainty, we have underscored the importance of learning mechanisms, partly because it could play a significant role in adjusting control and flexibility measures sequentially. In general, there are two types of learning mechanism: learning from experience accumulated in other countries/cities, and learning by doing; that is, learning from one's own experience. Recently, the importance of learning from other countries/cities has been underscored, mainly in Western countries. This type of learning may be effective partly because Western countries/cities tend to have similar attributes such as social and physical infrastructure, cultures, politics, societies and economies. Because a number of transportation policies lead to irreversible consequences, there are certain limitations on the implementation of trial and error experiments in some countries or cities. Thus, it would be better to learn from accumulated experience in other countries/cities. On the other hand, there is some difficulty in doing so, especially regarding some developing countries/cities, mainly for the following reasons. First, developing countries often have a unique public transit system, and thus it may be less efficient for them to learn from Western countries' experiences than it is for Western countries to learn from each other. Second, even where countries/cities have similar properties in terms of features such as their social and physical infrastructure and economies, information about their experiences is not well organized. Under such conditions, learning-by-doing processes may play a significant role in developing countries' transportation planning process.

Research on uncertainties in transportation planning may not be just a theoretical or conceptual research theme but also quite a practical one. For example, it should address the possibility of the failure of assumptions in demand forecasting and the extent to which we should believe that prediction results are important practical issues affecting administrative and institutional arrangements for planning. Kouvelis and Yu (1997) noted that the best way to handle uncertainty is "to accept uncertainty, make a strong effort to structure it and understand it, and finally, make it part of the decision making". To do this, experiences in various countries/cities should be described and shared, including the failure of demand predictions and policy implementation. Experiences of failure, in particular, may be shared less frequently, presumably because people may fear blame. In such cases, however, we lose opportunities to learn from the failure and to avoid repeating it in another context, resulting in an inefficient learning cycle. The underlying cause of this may be a lack of understanding of the nature of uncertainty in transportation planning: it

cannot be eliminated perfectly, and thus there is always a possibility of failure. For this reason, it would be beneficial to understand the danger of criticisms such as “demand forecasting should never fail,” and as a first step, we may have to accept that inescapable uncertainties exist in the planning process, at least in current practical planning procedures. Further conceptual, theoretical, and empirical studies are certainly needed to deepen our understanding of the nature of uncertainties in transportation planning.

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