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Exploring Day-to-day Variations in the Bus Usage Behavior of Motorcycle Owners in Hanoi

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Abstract

This study attempts to explore the day-to-day variations of motorcycle owners' bus usage behavior and situational factors influencing their mode choice in Hanoi where the motorcycle is a dominant mode. To distinguish which types and how many of the variations can or cannot be captured, we used a multilevel binary logit model which can deal with both observed and unobserved inter-individual and intra-individual variations. In our empirical analysis, we used data from a one-week travel diary of 55 motorcycle owners. The results indicate that the variations of motorcycle owners' bus choice behavior depend much on intra-individual variation which could partly be represented by the variables related to accompany person(s), travel distance, and the complexity of the tour.

Keywords: day-to-day variations; bus usage; motorcycle owner; multilevel binary logit model; intra-individual variations

1. Introduction

In 2007, the motorcycle was the dominant transportation mode in Hanoi which covered 62.7% of travel needs and while the modal share of public transportation (only buses available) was quite small at 8.4% (ALMEC et al. 2007). In September 2011, it was reported that the total motorcycle population in Hanoi was 3.9 million units (Vnmedia). Such a large motorcycle population has caused various transportation problems, such as road congestion, traffic accidents and air pollution. To deal with those

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problems, besides improving the public transportation system (e.g., providing new mass transit modes like metro, light rail transit, bus rapid system, improving the level of service of the existing bus system,. etc) how to encourage people to use public transportation modes, especially motorcycle users, is a very important aspect. Therefore, this study attempts to explore the day-to-day variations in the bus usage behavior of motorcycle owners. The variations are divided into inter-individual and intra-individual variations. Together with *mobility tools* and *individual socio-demographic* attributes which would mainly capture the inter-individual variations, we introduced a set of *situational* attributes which are expected to capture the intra-individual variations. The *situational* attributes include *accompany person(s)*, *travel distance*, *complexity of tour*, *departure time*, *weekdays*, *weather* and *traffic conditions*. In this study, we only select motorcycle owners, since our main focus is to explore the potential shift from motorcycle to bus.

The rest of this paper is organized as follows. It begins with a brief review of previous analysis related to day-to-day variations on activity/travel behavior. Next, the methodology with the multilevel binary logit model is described. Then, an overview of the one-week household travel survey, data preparation and results from the preliminary analysis are presented. That is followed by a presentation of the estimation results and discussions about the results. Finally, the conclusions and directions for future research issues are provided.

2. Literature review

In the last 30 years, the important of day-to-day variations in activity/travel behavior or the similarity of behaviors within the same person have been addressed in a variety of ways. To capture the degree of repetitiousness of behavior, a number of different similarity measures have been proposed by Jones and Clark (1988), Hanson and Huff (1988), and Pas and Koppelman (1987) while Schlich et al. (2001, 2003) compared these measures. A comparison of these results highlight that these studies reached quite different conclusions in terms of the levels of similarity. Focusing on the component of total variations, various studies have shown the significant sharing of intra-individual variations. Early works of Pas (1983, 1988) found that about 50% of the total variations in trip-making could be attributed to intra-individual variations. Pendyala (1999) confirmed the high percentage of variability for travel time, travel distance, trip frequency and departure and arrival time. Susilo and Kitamura (1999) explored day-to-day variation in an individual's action space and concluded that unobserved intra-individual variations may explain about 85% of the total variation of discretionary activities. Kitamura et al. (2006) and Chikaraishi et al. (2009) examined departure time choice and found that depending on the activity type, the intra-individual variations may occupy 35-85% of the total variations.

To the best of our knowledge, there are several studies dealing with day-to-day variations in mode choice over a continuous period of time. Ramadurai and Srinivasan (2006) used a mixed logit model to estimate within-day variability of mode choice with data from a consecutive two-day travel diary. Interestingly, they found an inherent rigidity or inertia, indicating individuals are highly likely to choose a mode they have previously chosen. The inertial effect here is particularly strong for bike and walk modes. Chikaraishi et al. (2011) confirmed that mode choice behavior showed smaller day-to-day variations (compared to other behavioral aspects), meaning that individuals tend to use same mode over time. Cherchi and Cirillo (2008, 2009) studied the effect of repeated tours and investigate the intrinsic day-to-day variability in the individual preferences for mode choices. They found that individual tastes for time and cost are fairly stable but there is a significant systematic and random heterogeneity around these mean values and in the preferences for the different alternatives. They also confirmed that there would be a strong inertia effect in mode choice behavior, and the sequence of mode choice made is influenced by the duration of the activity and the weekly structure of the activities.

Studies on the day-to-day variations of travel behavior have been summarized as mentioned above and researchers have obtained different conclusions from different contexts for levels of similarity, component of variations and variations in mode choice. Almost all of these studies have focused on cities in developed countries in Europe or United States. However, the characteristics of economic level, household/individual socio-demographics, travel attributes in Hanoi city are all different from developed countries; especially in the context of mixed flow traffic where the motorcycle is the dominant mode. Therefore, the findings of this paper will deepen the understanding of mode choice behavior, find out the potential reasons for motorcycle owners shifting to bus usage and contribute to the comparison of mode choice variations between Hanoi and other developed cities.

3. Methodology

In existing studies, the sources of inter-individual variations have extensively been explored, including motorcycle ownership, gender, age, personal income, and educational level. For example, Hsu et al. (2007) and Lai and Lu (2007) showed that the number of vehicles in the household can be used to indicate the household travel demand while Tuan and Shimizu (2005), Hsu et al. (2007), Lai and Lu (2007) and Senbil et al. (2007) agreed that income is one of the greatest factors influencing both vehicle ownership and mode choice behavior and other social-demographic factors also affect mode choice behavior. Additionally, it can also be expected that the *situational* attributes such as travel purposes, time of day, weather condition, etc., may be important influential factors on mode choice decisions. Since these situational influential factors can easily change even within an individual, these would be reflected in intra-individual variations. In fact, it is usually difficult to capture such *situational* attributes so that many of them would remain as unobserved variations (Chikaraishi et al. 2009, 2010).

As we could imagine, the sources of mode choice variations do not only differ in macro levels (i.e. household, zone) but also vary within micro levels (i.e. individual) and their interaction is following hierarchical or cross-classification structures. To deal with these complex variation patterns, the multilevel modeling may be one of the best approaches (Hox et al. 1995 and Kreft et al. 1998). This method treats hierarchical and cross-classification structures as unobserved heterogeneities and allow for decomposition of total variation into the variations from various sources. In this study, we decompose the total variations of motorcycle owners' bus choice into two variation components that include inter-individual and intra-individual variations with regard to both observed (non-random) and unobserved (random) effects as shown in Fig.1 below.

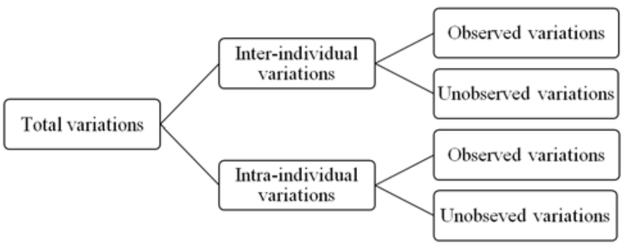

Fig. 1. The variation structure assumed in this study

3.1. Multilevel binary logit model

In this study, a multilevel binary logit model is developed in the context of transportation mode choice behavior (whether they choose bus or not). Consider the situation that an individual *i* chooses an alternative *d*, the individual's utility function could be written as:

$$U_{id} = \beta_0 + \beta' x_{id} + \gamma_i + \varepsilon_{id} \tag{1}$$

where β_0 is constant, x_{id} indicates a set of explanatory variables including both individual/household attributes and situational/contextual factors. β is a coefficient vector associated with x_{id}. Let γ_i be an unobserved component at the individual level which represents inter-individual variations. Here, γ_i is assumed to be normally distributed with a mean of zero and variance σ_i^2, let ε_{id} be an unobserved component at the situational level which reflects the intra-individual variations. Here, ε_{id} is assumed to follow a logistic distribution with a variance of $\pi^2/3$ (the scale parameter is fixed as one, since the utility is unitless). Based on the above mentioned definition, the probability of choosing bus P_{id}^{bus} can be written as follows:

$$P_{id}^{bus} = \exp(U_{id}) / \{\exp(U_{id}) + 1\} \tag{2}$$

3.2. The variation properties of utility difference

Here we shall mention a way to describe behavioral variations in the above-mentioned model, which we used in the empirical study mentioned in the next section. Usually, other researchers have often focused only on observed variations which can be directly connected to policy discussions. This study follows a somewhat different approach (Chikaraishi et al. 2011). That is, all behavioral variations are first treated as unobserved variations in order to determine what kinds of variations really exist. Using the symbol "~" to represent the model estimation results without any explanatory variables (called the *Null model*), the total variance of the utility can be calculated as follows:

$$Var(\widetilde{U}_{id}) = \widetilde{\sigma}_i^2 + \pi^2/3 \tag{3}$$

In the next step, we shall introduce a set of explanatory variables to provide reasons for the behavioral variations measured in the *Null model*. Using the symbol "^" to represent model estimation results with a set of explanatory variables, the total variance of the utility can be calculated as follows:

$$Var(\widetilde{U}_{id}) = Var(\beta' x_{id}) + \sigma_i^2 + \pi^2/3 \tag{4}$$

Introducing explanatory variables could put behavioral variations into observed variations while the rest remain unobserved variations. Our purpose here is to evaluate what types and how many of the variations can be captured by introducing explanatory variables. To do this, we compare the variation components in Eq. (3) against those in Eq. (4). Here, although the absolute expected value of $Var(\widehat{U}_{id})$ may change depending on how many intra-individual variations can be captured by introducing explanatory variables, the component ratio for each variation can be compared between the different models as long as the existence of the same "true" utility can be expected. This is because the scale of $Var(\widehat{U}_{id})$ is strictly defined by the rest of the unobserved intra-individual variations, and also because the other fixed and random parameters are automatically rescaled. Thus, we can compare the component ratio for each variation between Eq. (3) and Eq. (4). This comparison shows which types and how many of the variations can or cannot be captured by introducing a certain set of explanatory variables, as follows:

For observed inter-individual variations (%):

$$\left[\widetilde{\sigma}_i^2 / Var(\widetilde{U}_{id}) - \widehat{\sigma}_i^2 / Var(\widehat{U}_{id})\right] \times 10 \tag{5}$$

For unobserved (or remaining) inter-individual variation (%):

$$\left[\widehat{\sigma}_i^2 / Var(\widehat{U}_{id})\right] \times 100 \tag{6}$$

For observed intra-individual variations (%):

$$\left[3^{-1}\pi^2 / Var(\widetilde{U}_{id}) - 3^{-1}\pi^2 / Var(\widehat{U}_{id})\right] \times 10 \tag{7}$$

For unobserved (or remaining) intra-individual variations (%):

$$\left[3^{-1}\pi^2 / Var\left(\widehat{U}_{id}\right)\right]\times 100 \qquad (8)$$

The variation properties derived from Eqs. (5) to (8) could evaluate the model's performance more precisely for each type of variation. Based on the ratio of them, we shall try to reduce the remaining of variations as much as possible for a better result. In other words, this could bring many implications for not only model improvement but also for data collection.

4. Data and preliminary analysis

The survey was launched from December 2010 to collect 150 households' one-week travel diaries as well as their socio-economic information. We conducted this survey as a part of a series of researches focusing on the promotion of public transport in Hanoi. Thus, the following sampling strategy is used for this survey; 1) finding a person who use buses, and 2) asking them to see if their household members would join the survey. Most of the respondents were recruited at the several main bus stations so that the residential locations of the respondents were spread out throughout in Hanoi city. All household members who are over 15 years old (it is assumed that these people can manage their own activity-travel behavior) were asked to answer the questions regarding household/individual attributes and to fill in a trip diary for all trips that they made during one week.

- Household attributes: number of household members, number of vehicles owned, total income, residential characteristics, etc.
- Individual attributes: age, gender, occupation, education level, driving license, motorcycle for own use, bus monthly ticket, etc.
- Trip attributes: trip purpose, accompanying person(s), mode, departure/arrival time, origin/destination place, etc.

As a result, a total of 451 valid responses were collected, in which 242 respondents were motorcycle owners. It is observed that 55 motorcycle owners (who belong to 47 households) use buses during the survey period. Since our study focuses on modal shift from motorcycle to buses, we used the information from these 55 respondents for this study.

Our primarily analysis has shown that 85 % of households (47) have 2 or more motorcycles. This result confirms the fact that people's mobility in Hanoi is highly dependent on the motorcycle. The percentage of medium income households (from 5 million Vietnam Dong (VND) to 9 million VND) is about 50%, high income households (from 10 million VND and above) is 35 % and the remaining share belong to low income households (under 5 million VND). Among the 55 motorcycle owners who used bus, 61.8% are male and young people from the ages of 15 to 24 year old are dominant at 76.4%. The percentage of student is highest at 58.2%, work people is 36.4% and the remaining 5.5% is non-workers i.e., retired, jobless people. Thus, the ratio of respondents with high education level (university level or above) is relatively high by 54.5% compared to that of the whole population of Vietnam. The number of students also affects on the high ratio of monthly bus ticket ownership at 43.6%. During a period of 7 days, these 55 motorcycle owners made a total of 859 trips in which the trips made by bus are the highest at 44.0%. The share by motorcycle was 35.5% and the remaining share of 22.5% was by all other modes. *Commuting trips*, i.e., going to work and study, occupied 30.4%, while *non-mandatory trips*, i.e., shopping, leisure, and personal needs, took 23.3% of total trips. Other trips mainly consisted of return home purpose.

To look at the day-to-day variations in mode choice, we firstly use a simple cross-tabulation analysis. Respondents are divided into three categories: bus *captive users*, motorcycle *captive users*, and *non-captive users*. Here, *captive users* include people who use only one mode at least 3 times for a certain purpose, and *non-captive users* include people who use both bus and motorcycle. These three categories are further categorized by trip purposes. The first category is *commuting trips*, and the second is *non-mandatory trips*. The results are shown in the Table 1.

Table 1. The percentage of user by travel mode and trip purpose

	Non-mandatory trips (n)	Commuting trips (n)
Bus captive user(s)	2.5% (1)	24.5% (12)
Motorcycle captive users	5% (2)	8.2% (4)
Non-captive users (mix use)	92.5% (37)	67.3% (33)

Note) the total number of samples shown in this table is not equal to 55, since the remaining respondents did not make a trip for the corresponding trip purpose.

The ratio of *non-captive users* in *non-mandatory trips* is very high at 92.5%, compared to that in *commuting trips*. This is because *commuting trips* usually have fixed schedules and origin-destinations, while *non-mandatory trips* do not have. The interesting point here is the difficulty to explain about mode choice behavior for *commuting trips* in which 67.3% of them are *non-captive users*. In other words, why did people use both bus and motorcycle even when making trips with a fixed schedule and origin-destination? Such intra-individual variation may come from the situational or contextual attributes and we shall try to find the causal factors in the next section.

5. Model estimation and discussion

In this section, we shall first report the estimation results of the multilevel binary logit model in Null model to detect the ratio of intra-individual variations from total variations. Explanatory variables are then introduced in a sequential manner with mobility tools and individual socio-demographic attributes in what we called here as the Halfway model. We then add the set of situational attributes in the Full model. The reasons for taking this procedure are not only to provide the behavioral variation information in greater details, but also to identify the degree of impacts of the situational attributes on the model performance. We develop two different models of mode choice for non-mandatory trips and commuting trips, respectively. All explanatory variables are defined in Table 2.

The estimation results are shown in Table 3. Here, it can be affirmed that the goodness-of-fit of the model (i.e., final log likelihood) improves as more explanatory variables are added in a sequential manner. Concretely speaking, for non-mandatory trip purposes, an increase of about 7.1 points increase in the goodness-of-fit of the Halfway model can be observed compared to that of the Null model, which is actually caused by introducing mobility tools and individual socio-demographic attributes. Moreover, the goodness-of-fit of the Full model shows an increase of around 27.3 points from that of the Halfway model. In other words, introducing situational attributes significantly improves the performance of the model. This implies that motorcycle owners' bus usage behavior varies from day to day or from context to context. Such context dependencies of bus usage behavior are also confirmed for commuting trips: the goodness-of-fit of the model increases sequentially from 6.2 to 29.2, meaning that the variations of motorcycle owners' bus choice behavior depends much on intra-individual variations which could partly be represented by situational attributes.

Looking at the details of the estimation results of non-mandatory trips, it can be found that university education level shows a significant and positive impact on bus usage behavior, while household income has a negative impact on it. This implies that university educated motorcycle owners with low household incomes tend to choose the bus for non-mandatory trip purposes. For commuting trips, only work shows a significant and negative impact on bus usage. This implies that motorcycle owners who work may not choose the bus for their commuting trips.

On the other hand, several situational attributes show significant impacts on mode choice behavior. Concretely, the accompany person(s) including both accompanying with household member(s) and with other person(s) have significant and negative impacts, while people tend to use buses when they have a longer travel distance. These results may imply that motorcycle owners choose buses when they go alone and for long distances (at least from 5 km) for both non-mandatory trips and commuting trips purposes. Another significant situational attribute in commuting trips is the complexity of tour: its negative sign may imply that, if motorcycle owners intend to visit somewhere else before/after work/school, they tend to avoid using buses. Other situational attributes including departure time categories, week days, rain and traffic jam show no significant impacts on the bus usage of motorcycle owners.

Table 2. Explanatory variables use for model estimations

Explanatory variables	Definition
Mobility tools	
HH_MC	Number of motorcycle in household
MC_license	Motorcycle driving license (1 = yes; 0 = no)
B_ ticket	Bus monthly ticket (1 = yes; 0 = no)
Individual socio-demographic attributes	
Male	Male (1 = yes; 0 = no)
Age 24	15 – 24 years of age (1 = yes; 0 = no)
Age 25 - 40	25 – 40 years of age (1 = yes; 0 = no)
Age 41 - 60	41 – 60 years of age (1 = yes; 0 = no)
Work	Have a work (1 = yes; 0 = no)
Student	Student (1 = yes; 0 = no)
Edu_uni_ level	University level or above (1 = yes; 0 = no)
HH_income	Household income (in VND)
Situational attributes	
Acc_HH	Accompany with household member (1 = yes; 0 = no)
Acc_OT	Accompany with other people (1 = yes; 0 = no)
Comp_tour	Complexity of tour (number of stop during Home to Home tour)
DT_Morn	Departure time in morning from 5AM to 9:59AM
DT_Noon	Departure time in noon from 10AM to 13:59PM
DT_Aft	Departure time in afternoon from 14PM to 18PM
D 5- 10	Dummy for travel distance (1 = 5km to 10 km, 0 = otherwise)
D 11- 15	Dummy for travel distance (1=10km to 15 km, 0 = otherwise)
D 16	Dummy for travel distance (1 = 15km or over, 0 = otherwise)
W_day	Weekday (1 = yes; 0 = no)
Rain	Rain (1 = yes; 0 = no)
Traffic jam	Traffic jam (1 = yes; 0 = no)

So far, this section has mainly focused on observed behavioral variations without mention of unobserved variations. To evaluate the variation properties of utility difference, we use the variation decomposition technique mentioned in subsection 3.2. The results are shown in Table 4.

Table 3. Estimation results

Variable	Non_mandatory trips					
	Null model		Halfway model		Full model	
	Parameter	t-value	Parameter	t-value	Parameter	t-value
Constant	-0.981	-4.967***	-1.126	-0.516	-1.265	-0.341
Mobility tools						
HH_MC	---	---	0.094	0.468	0.227	0.680
MC_license	---	---	0.456	0.369	-0.444	-0.177
B_ticket	---	---	-0.405	-0.983	-0.500	-0.693
Individual socio-demographic attributes						
Male	---	---	0.012	0.028	-0.242	-0.340
Age 24	---	---	-16.881	-0.009	-17.712	-0.017
Age 25 - 40	---	---	-18.527	-0.01	-21.017	-0.020
Age 41 - 60	---	---	-16.531	-0.009	-14.281	-0.014
Work	---	---	18.433	0.01	20.661	0.020
Student	---	---	16.474	0.009	15.650	0.015
Edu_uni_ level	---	---	0.724	1.449	1.991	2.324 *
HH_income	---	---	-0.259	-0.953	-0.743	-1.648 .
Situational attributes						
Acc_HH	---	---	---	---	-2.979	-3.099 **
Acc_OT	---	---	---	---	-2.410	-3.678 ***
Comp_tour	---	---	---	---	0.104	0.692
DT_Morn	---	---	---	---	1.694	1.874 .
DT_Noon	---	---	---	---	0.218	0.262
DT_Aft	---	---	---	---	0.687	0.856
D 5-10	---	---	---	---	1.828	3.137 **
D 11-15	---	---	---	---	2.332	2.344 *
D 16>	---	---	---	---	3.684	3.996 ***
W_day	---	---	---	---	1.038	1.489
Rain	---	---	---	---	-1.233	-1.225
Traffic jam	---	---	---	---	0.295	0.314

	Null model	Halfway model	Full model
Inter_individual variations	0.402	0.149	1.170
LL0	-138.629	-138.629	-138.629
LL1	-119.2	-112.1	-84.82
Rho	0.140	0.191	0.388
Number of observation		200	

Table 3. Estimation results (continued)

Variable	Commuting trips					
	Null model		Halfway model		Full model	
	Parameter	t-value	Parameter	t-value	Parameter	t-value
Constant	0.480	1.565	1.251	0.515	-1.250	-0.459
Mobility tools						
HH_MC	---	---	0.273	0.874	0.244	0.792
MC_license	---	---	0.544	0.528	0.459	0.467
B_ticket	---	---	0.850	1.265	1.230	1.773 .
Individual socio-demographic attributes						
Male	---	---	0.081	0.138	-0.017	-0.029
Age 24	---	---	-2.190	-0.966	-0.599	-0.271
Age 25 - 40	---	---	0.176	0.07	2.345	0.938
Age 41 - 60	---	---	-3.474	-1.362	-1.143	-0.444
Work	---	---	-1.750	-1.159	-3.300	-2.037 *
Student	---	---	0.830	0.556	0.086	0.053
Edu_uni_ level	---	---	-1.265	-2.001 *	-0.888	-1.428
HH_income	---	---	0.146	0.776	0.178	0.891
Situational attributes						
Acc_HH	---	---	---	---	-2.878	-2.363 *
Acc_OT	---	---	---	---	-0.598	-0.960
Comp_tour	---	---	---	---	-0.359	-2.603**
DT_Morn	---	---	---	---	0.765	0.728
DT_Noon	---	---	---	---	0.434	0.397
DT_Aft	---	---	---	---	0.321	0.275
D 5-10	---	---	---	---	1.494	2.526 *
D 11-15	---	---	---	---	3.114	4.577 ***
D 16>	---	---	---	---	2.354	3.717 ***
W_day	---	---	---	---	-0.125	-0.195
Rain	---	---	---	---	0.845	1.314
Traffic jam	---	---	---	---	1.272	1.316

	Null model	Halfway model	Full model
Inter_individual variations	3.217	2.146	1.531
LL0	-180.911	-180.911	-180.911
LL1	-152.1	-145.9	-116.7
Rho	0.159	0.194	0.355
Number of observation		261	

(.) significant at the 90% level, (*)significant at the 95% level, (**)significant at the 99% level, (***) significant at the 99,9% level

Table 4. The ratio of variations

	Non-mandatory trips	Commuting trips
Inter-individual variation	10.89 %	49.44 %
Observed inter-individual variation	*5.22 %*	*31.81 %*
Unobserved inter-individual variation	*5.67 %*	*17.63 %*
Intra-individual variation	89.11 %	50.56 %
Observed intra-individual variation	*73.17 %*	*12.69 %*
Unobserved intra-individual variation	*15.94 %*	*37.87 %*
Total	100%	100%

It is confirmed that *non-mandatory trips* have higher intra-individual variations compared to *commuting trips*, while the impacts of introduced *situational* attributes on intra-individual variations are much higher in *non-mandatory trips*: about 82% (calculated by dividing 73.17 by 89.11) of intra-individual variations in *non-mandatory trips* can be captured by the introduced *situational* attributes, while only about 25% (calculated by dividing 12.69 by 50.56) of them is explained in *commuting trips*. In other words, the introduced *situational* attributes could not explain 75% of intra-individual variations in *commuting trips*, indicating that other *situational* attributes may need to be explored.

6. Conclusions

With the aim of explaining the intra-individual variations by situational factors, this study developed a multi-level binary logit model and then applied the model to the bus choice of motorcycle owners in Hanoi city. In our analysis, we used the one-week travel diary data of 55 motorcycle owners who used buses to decompose the total variations of their bus choice into inter-individual variations and intra-individual variations. All variations were first treated as unobserved variations in order to determine what kinds of variations exist, and then we introduced three categories of explanatory variables (as observed variations) to provide reasons for the behavioral variations measured. Based on these results, we could evaluate what types and how many of the variations can be captured by introducing explanatory variables.

Our analysis has shown that the situational factors significantly improve the performance of the model in both travel purpose categories (i.e., commuting trips and non-mandatory trips) and the variation of motorcycle owners' bus choice behavior depends much on intra-individual variations which could partly be represented by situational attributes. Three attributes, including travel distance, accompany person(s) and complexity of tour, have strong impacts on the choice of buses. Other four attributes including departure time, week days, weather condition and traffic jam showed no significant impacts. In other words, the longer the travel distances the higher the probability of shifting the mode choice to use the bus from motorcycle owners. Moreover, without accompany person(s) and small numbers of stops during home to home tour also lead to a higher tendency to choose the bus.

Although this paper has shown some usefulness of exploring the variations properties of mode choice behavior, there still are some issues and topics to be discovered in future research. First, other situational attributes need to be further explored, since the introduced set in this study could not explain about 75% of intra-individual variations in commuting trips. Second, applying different setting in the variations structure, for example adding more variations such as spatial/temporal variations, would be an important for providing the behavioral variations information in greater detail. Finally, depending on the behavioral variations, how to simulate the policies for encouraging motorcycle owners' shifting to use public transportation modes would be a challenging task for future studies.

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