Dynamic Discrete Choice Model for Multiple Social Interactions

Masashi Kuwano, Junyi Zhang, and Akimasa Fujiwara

A dynamic discrete choice model for multiple social interactions was developed on the basis of retrospective panel data in the context of household vehicle-type choice. "Social interactions" refer to the influence of reference groups on household choice behavior. However, most studies in transportation have considered a household as a decision maker independent from the society to which it belongs. Social interactions have therefore not been well represented, especially if there were two or more types of reference groups, which may further vary over time. The model was built within the dynamic generalized extreme value framework, which included a set of dynamic elements, such as initial conditions, state dependence, and future expectation. This study defined three types of social interactions: diffusion rates of a vehicle type at the national level and at the neighborhood level and diffusion rate of households with the same income level. A survey was conducted in local Japanese cities in 2006. The survey focused on household vehicle ownership behavior over the 10 years from 1997 to 2006. Model estimation results confirmed that social interactions from reference groups of neighborhoods and households with the same income level were especially influential in decisions about household vehicle-type choice. On the contrary, social interaction from the whole society did not significantly influence the household choice. It was further found that effects of dynamic elements on the household choice were statistically significant.

It has long been recognized that various decisions in human society occur in the unit of a group (*1, 2*). According to McGrath and Kravitz, the concept of a group requires that two or more people be in dynamic interaction with one another (*3*). This concept implies that the people are mutually aware of one another and take one another into account and that the relationship has temporal continuity. Such interactions can be observed under two representative situations. One situation occurs when members in a group (size of the group is usually small) can be prespecified (e.g., household members joining in shared activities, carpooling users, a travel party with friends or colleagues, and buying centers in an organization). In the second situation, members in the group cannot be clearly specified. Such a group is called a reference group. The influence of reference group on decision maker's choice behavior is defined as social interaction in this study. This paper deals with the latter case in the context of household vehicle-type choice analysis.

The pioneering work about representing social interaction in decision-making analysis was conducted by Manski (*4*). Models with social interaction have been developed and applied to a wide range of contexts within both economics and social science. The role of social interactions in decision making has become an important area of research over the last decade. Manski argued that identification and inference of social interaction effects is not a trivial econometric task and further classified the social interaction into preference interaction, constraint interaction, and expectation interaction. These interactions can take various forms: endogenous interaction, contextual interaction, and correlated interaction. How to represent and measure these interactions is the main challenge in the research of social interaction. In the context of group decision making, there is also a large empirical literature that seeks to measure the influence of such social interaction in determining the performance of the individual member in the group. The goal of such analysis is to provide an explanation of group behavior that emerges from the interactions across individuals. Many of these studies are motivated by the observation that many individual decisions, such as academic achievement (*5*), teenage pregnancy (*6*), school dropout behavior (*6, 7*), student life (*8*), criminal behavior (*9*), and unemployment (*9, 10*), vary much more between social groups than within them. However, these studies also point out the difficulty of defining reference group in the most relevant and operational way. Concretely speaking, it has not been made clear whether such group refers to the whole society, the community in which the decision maker resides, or other groups of close friends. At the least, it appears realistic to assume that two or more reference groups exist. Social interactions observed in such cases are called multiple social interactions in this study. In particular, such reference groups may vary over time, making the representation of such social interactions more difficult. Little has been done with respect to such type of social interaction in literature.

The main purpose of this paper is first to empirically test and identify the existence of two or more reference groups and then to explore how to represent the influences of the reference groups (i.e., social interactions) over time in the context of household vehicle-type choice behavior by developing a dynamic discrete choice model. The vehicle-type choice is used as an example because of the ever-increasing importance of dealing with energy consumption and environmental emissions from vehicles. In most countries, energy consumption and pollutants from the transport sector have been increasing considerably in the past decade. Considering the growing concerns on global warming, this alarming rate of increase calls for measures of controlling car ownership level, enhancing energy efficiency, and reducing emissions in the entire transportation systems.

M. Kuwano, Infrastructure and Transportation Planning Laboratory, Graduate School of Engineering, Hiroshima University, 1-4-1 Kagamiyama, Higashi-Hiroshima 739-8527, Japan. Current affiliation: Transportation Engineering Laboratory, Department of Civil Engineering, Graduate School of Engineering, Kobe University, 1-1 Rokkodoi-Cho, Nada, Kobe 657-8501, Japan. J. Zhang and A. Fujiwara, Transportation Engineering Laboratory, Graduate School for International Development and Cooperation, Hiroshima University, 1-5-1 Kagamiyama, Higashi-Hiroshima 739-8529, Japan. Corresponding author: M. Kuwano, kuwano@port.kobe-u.ac.jp.

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Because passenger cars have been producing a large percentage of total exhausted gases, this paper focuses on the analysis of household ownership behavior of passenger cars, especially the choice behavior of vehicle types, which here refers to engine displacement. Although it is known that environmental load from vehicles is a function of the number of vehicles, travel distance, travel speed, and environmental emission factors, this only paper deals with choice of the vehicle types, which are closely related to fuel efficiency of vehicles.

To date, many discrete choice models have been developed to describe different aspects of vehicle-type choice. As a result, various influential factors have been identified. Such discrete choice models include, for example, multinomial logit model (*11*), paired combinatorial logit model (*12*), mixed logit model (*13*), and dogit model (*12*). By contrast, it is expected that household vehicle-type choice could be significantly affected by the household's "previous car choice and use" and "future expectation of car use." Here, "future expectation" implies that the household might decide to own their cars anticipating the main purpose of car use, frequency, and ownership period after obtaining the cars. The existing literature about the analysis of vehicle-type choice behavior, however, has regarded the household as an independent decision-making unit from the society to which it belongs. In other words, the effects of social interactions, such as market trend, diffusion rate of compact cars, and neighborhoods' behavior in the past, at the present or in the future, are ignored. Such social interactions over time are called dynamic social interactions in this study.

This paper attempts to explore what kinds of reference groups are relevant and what types of specifications about the dynamic social interactions are more suitable in representing household vehicle-type choice over time. This is done by establishing a tractable dynamic discrete choice model, that is, the dynamic generalized extreme value (DGEV) model developed by Swait et al. (*14*). The DGEV model has various attractive features related to behavioral dynamics, such as state dependence, initial conditions, and future expectation. Dynamic social interactions were introduced as a part of the utility function of the DGEV model.

MODEL DEVELOPMENT

Kernel Structure of Dynamic Discrete Choice Model

Heckman presented a general structure of dynamic discrete choice model (*15*), of which the utility function is defined as follows:

$$u_{ijt} = \boldsymbol{\beta}\mathbf{x}_{ijt} + \sum_{k=1}^{\infty}\gamma_{t-k,t}d_{ij,t-k} + \sum_{k=1}^{\infty}\lambda_{k,t-k}\prod_{q=1}^{k}d_{ij,t-q} + \sum_{k} g_k u_{ijt-k} + \epsilon_{ijt} \tag{1}$$

where

u_{ijt} = utility of individual i for alternative j at time t,
d_{ijt} = choice result of alternative j that individual i chooses at time t (equal to 1 if the alternative j is chosen, 0 otherwise),
$\mathbf{x}_{ijt}$ = explanatory variable vector with parameter vector $\boldsymbol{\beta}$,
g_k = parameter describing influence of the kth-order lag-operator,
ϵ_{ijt} = error term of utility function, and
$\gamma_{t-k,t}$, $\lambda_{k,t-k}$ = time-varying parameters.

In Equation 1, the second term at the right side describes the effect of true state dependence, the third term explains cumulative effect, and the fourth term indicates the influence of behavioral inertia, respectively.

Heckman's dynamic model can include various models as special cases. Recently, in line with Heckman's modeling framework, Swait et al. developed a new dynamic model under the principle of random utility maximization by using the following generalized extreme value generation function (*14*):

$$G(y_{ijt}) = \sum_{j}\left\{\prod_{s=1}^{\infty}\gamma_{ijs}\,y_{ijt+s}\cdot\prod_{s=0}^{t}\alpha_{ijs}\,y_{ijt-s}\right\}^{\mu_t} \tag{2}$$

$$y_{ijt} = \exp(v_{ijt}) \tag{3}$$

where

G = generalized extreme value function,
v_{ijt} = deterministic term of utility function,
γ_{ijt} = discount parameter for past and future utilities,
μ_t = scale parameter at time t, and
α_{ijs} = influence of state dependence (habit persistence or variety seeking) at time s.

Assuming that future expectation can be expressed in Equation 4 results in Swait et al.'s DGEV model, as shown in Equations 5 and 6.

$$y_{ijt}^{\phi_{ijt}} = \prod_{s=1}^{\infty}\gamma_{ijs}\,y_{ijt+s} \tag{4}$$

$$p_{ijt} = \frac{\exp(\mu_t\tilde{V}_{ijt})}{\sum_{j'}\exp(\mu_t\tilde{V}_{ij't})} \tag{5}$$

$$\tilde{V}_{ijt} = (1+\phi_{ijt})v_{ijt} + \sum_{s=1}^{t}(v_{ijt-s} + \ln\alpha_{ijs}) \tag{6}$$

where $\tilde{V}_{ijt}$ is called metautility, which is different from the previously mentioned v_{ijt}, and ϕ_{ijt} is a nonnegative parameter introduced to capture the influence of future behavior (i.e., future expectation). Statistically significant ϕ_{ijt} means that future expectation influences the current behavior at time period t.

Swait et al.'s DGEV model can be used to simultaneously represent the influences of initial condition, future expectation, state dependence, time-varying scale and taste parameters, and time-varying covariance structure. It has been argued that meta-utility shown in Equation 6 can be applied to any models of the generalized extreme value family.

Modeling Individual Choice with Social Interaction

Manski argued that attributes and behaviors of peer or social group affect individual behavior (*4*). These are collectedly called social interaction effects. Consider the problem of individual choice in the presence of social interactions in line with Manski's (*4*) modeling approach and assume the utility function u_{ijt} to be defined as follows:

$$u_{ijt} = \rho E(\tilde{d}_{njt}(i)|n\neq 1) + \gamma E(\tilde{x}_{ijt}(i)|n\neq 1) + \delta\tilde{x}_{ijt} + \eta z_{ijt} + \epsilon_{ij} \tag{7}$$

Here, $E(\tilde{d}_{ijt})$ indicates the average choice result of reference group for individual i choosing alternative j at time t. $E(d_{ijt})$ is used to determine the strength of endogenous social effects in explaining individual choice behavior, expressed by parameter ρ. The endogenous effects mean that the propensity of the individual to behave in some ways changes according to the behavior of the group. In addition, individual behavior might also change with response to the exogenous characteristics of reference group. This can be represented by using $E(\tilde{x}_{ijt}(i))$, a vector of individual characteristics of reference group. Such influence of reference group is called exogenous (contextual) social effects, expressed by parameter γ. Furthermore, parameter δ expresses the correlated effects, which indicate that an individual in the same group tends to behave similarly because he or she has similar individual characteristics or face similar institutional environments ($\tilde{x}_{ijt}$). Parameter η expresses the direct effects of attributes z_{ijt} of individual i choosing alternative j at time t on the utility u_{ijt}.

On the basis of Equation 7, each effect suggested by Manski (*4*) can be evaluated as follows:

- If $\rho \neq 0$, an endogenous effect exists,
- If $\gamma \neq 0$, an exogenous effect exists, and
- If $\delta \neq 0$, a correlated effect exists.

Manski further argued that identification is a core difficulty in testing the superiority of the proposed model structure over other competing behavioral models. Existing research usually builds up the decision-making models under the assumption that exogenous social effects and correlated effects are not present. Thus, methodologies have not been proposed that can successfully distinguish the endogenous effects from the exogenous effects and from the correlated effects.

Therefore, in this study, a simplified version of Equation 7, where exogenous social effect and correlated effect are ignored, was used. Then Equation 7 was rewritten as Equation 8.

$$u_{ijt} = \rho E\left(\tilde{d}_{njt}(i) \middle| n \neq i\right) = \eta z_{ijt} + \epsilon_{ijt} \tag{8}$$

As a consequence, Equation 8 is assumed to be partitioned into three components: the term of social interaction effect $\rho E(\tilde{d}_{njt}(i) | n \neq i)$, the observed individual-specific effect term ηz_{ijt}, and the error term ϵ_{jt}.

A simple and reasonable parametric representation for social interaction can be defined as follows:

$$E\left(\tilde{d}_{njt}(i) \middle| n \neq i\right) = \varpi_{ijt} = \frac{1}{N-1}\sum_{n} \tilde{d}_{njt}(i) \tag{9}$$

where $\tilde{d}_{njt}(i)$ is the choice result of alternative j of individual n in reference group of individual i at time t (equal to 1 if the alternative j is chosen, 0 otherwise). To shorten the expression, $E(\tilde{d}_{njt}(i) | n \neq i)$ is replaced by a new term ϖ_{ijt}. In this sense, Equation 9 denotes the expected proportion of the reference group choosing j.

It is known that individual behavior could be influenced by various reference groups such as the whole population, peer group, neighborhood or community, and homogenous group (*16*). To reflect the influences of various reference groups, Equation 8 was rewritten as follows:

$$u_{ijt} = \sum_{g} \rho_g \varpi_{ijt,g} + \eta z_{ijt} + \epsilon_{ijt} \tag{10}$$

where g denotes the group that the individual i might refer to in his or her decision-making process. With this equation, the multiple social interactions over time are explicitly represented.

Reflecting the influence of social interactions as shown in Equation 10, the dynamic discrete choice model for multiple social interactions can be specified in the following Equations 11 and 12, where LogL is the log likelihood function and d_{ijt} is a dummy variable to represent the choice result as defined in Equation 1.

$$\begin{aligned}\tilde{V}_{ijt} &= (1+\phi_{ijt}) v_{ijt} + \sum_{s=1}^{t} \left(v_{ijt-s} + \ln \alpha_{ijs}\right) \\ &= (1+\phi_{ijt}) \left(\sum_{g} \rho_g \varpi_{ijt,g} + \eta z_{ijt}\right) \\ &\quad + \sum_{s=1}^{t} \left(\sum_{g} \rho_g \varpi_{ijt-s,g} + \eta z_{ijt-s} + \ln \alpha_{ijs}\right)\end{aligned} \tag{11}$$

$$\text{LogL} = \sum_{i}\sum_{j}\sum_{t}\left\{ d_{ijt} \ln \frac{\exp\left(\mu_t \tilde{V}_{ijt}\right)}{\sum_{j'} \exp\left(\mu_t \tilde{V}_{ij't}\right)}\right\} \tag{12}$$

As mentioned previously, α_{ijs} expresses the influence of state dependence (habit persistence or variety seeking) at time s. Conversely, such influence of the behavior in the past on the present behavior might vary with the lapse of time after the behavior in the past occurred. To reflect the influence of the lapse of time, the parameter α_{ijs} is defined as a function of T, which is the length of time passed after the behavior in time t occurred. This is shown in the following equations:

$$\alpha_{ijs} = T\alpha_j \tag{13a}$$

$$\alpha_{ijs} = \ln(T)\alpha_j \tag{13b}$$

$$\alpha_{ijs} = (\alpha_j)^{T} \tag{13c}$$

$$\alpha_{ijs} = (\alpha_j)^{-T} \tag{13d}$$

Equation 13*a* assumes the influence of state dependence is in proportion to the length of the lapse time, and Equation 13*b* assumes that the lapse time shows positive influence with diminishing characteristic. Equation 13*c* argues that the influence becomes stronger as the time passes. Equation 13*d* argues the opposite influence. These equations will be selected on the basis of empirical analysis in this study. Moreover, α_j was designed to the following function of discount parameter γ_j as in Equation 2 to estimate easily:

$$\alpha_j = \left(1 + \exp(-\gamma_j)\right)^{-1} \tag{14}$$

ESTIMATION RESULTS AND DISCUSSION

Data

To examine the effectiveness of the proposed model (Equations 11 and 12) for the choice of vehicle type, a revealed preference data about household vehicle ownership behavior was used. The data were collected in October 2006 from the households living in Chugoku area (the largest city is Hiroshima city) in Japan. All the recruited households were asked to answer questions about household and individual attributes of currently and previously owned passenger cars over the 10 years from 1997 to 2006:

- Household attributes: number of household members, number of owned passenger cars, residential characteristics, and so forth;
- Individual attributes: age, gender, driving license, occupation, car use behavior, daily activity participation, and so forth; and
- Vehicle attributes: make, engine displacement, manufacture year, total travel distance of current and previous vehicles, and so forth.

As a result, questionnaires were collected from 500 households with cars. Results showed that 46.6% of households have two or more cars. For these households, choices of multiple cars might be interrelated with each other. Such behavioral phenomenon cannot be properly incorporated in the proposed model. This is also true for other existing relevant models. Because the main purpose of this study was to examine the influences of social interactions on household vehicle-type choice behavior, model improvement to reflect the complex choice mechanisms of multiple cars within a household was left for future research. Instead, the developed model was applied only to the case that the households choose the types of passenger vehicles when they renew them. As a result, the sample used for this case study was 225 households. Table 1 shows attributes of households and their vehicles.

To date, disaggregate choice models have been applied to describe the choice behavior of vehicle type, where household characteristics (e.g., household income, number of household members, and age of household head), characteristics of main users, and vehicle attributes (e.g., body price, operating cost, and number of seats) are usually used as explanatory variables (*17*). By contrast, existing research has also classified car type on the basis of various car attributes, for example, car size (*18*), car model type (*19*), fuel type (*17, 20*), and automaker (*20*). In Japan, such car type is usually classified on the basis of engine displacement. Such classification is well known for car users. Because different tax systems are applied to the cars with different engine displacements, the car users in Japan should be very sensitive to engine displacement when purchasing the vehicles. Therefore, this study defines the alternatives of passenger cars on the basis of engine displacement, considering that this category is directly related to evaluation of fuel consumption, emissions, and effects of car-related taxation. Exploring the choice behavior of passenger car types is important for both marketers and public policy makers, especially considering that more and more people are showing concerns about environmental issues.

For the purposes of estimating the choice models presented in this paper, the following three choice alternatives were adopted, with consideration to the influence of sample size on the model estimation:

Alternative 1 (small-sized vehicle). Passenger car with engine displacement ≤ 660 cm^3,

Alternative 2 (middle-sized vehicle). Passenger car with engine displacement > 660 cc and ≤ 2,000 cm^3, and

Alternative 3 (large-sized vehicle). Passenger car with engine displacement > 2,000 cm^3.

Large-sized cars are currently the majority of vehicle type (47%), and the shares of middle-sized and small-sized cars are 42% and 11%, respectively. As shown in Figure 1, the share of small-sized cars at the national level has been increasing over the past decades, and in 2005 small-sized cars accounted for 24% and middle-sized and large-sized cars were 47% and 29%, respectively. This is because multiple car ownership households are increasing, and these households own smaller cars as second or third vehicles. However, this study focused only on the single-car-ownership households, and consequently, compared with national share, the share of large-sized car is larger in sample.

TABLE 1 Household Attributes, Car Attributes, and Their Statistical Characteristics

Definition	Mean	Standard Deviation
Household Attributes		
Number of household members	2.89	1.06
Household income (10,000 yen)	747.72	280.50
Number of employed members	1.31	0.61
Number of license holders	1.84	0.51
Number of members over 65 years of age	0.05	0.26
Employed statement of main user	0.71	—[a]
Main purpose of car use (for commuting)	0.40	—[a]
Car Attributes		
Average car price of Alternative 1 (10,000 yen)	119.5	43.7
Average car price of Alternative 2 (10,000 yen)	167.7	60.1
Average car price of Alternative 3 (10,000 yen)	241.5	106.0
Average number of passenger seats of Alternative 1	3.92	0.41
Average number of passenger seats of Alternative 2	5.28	0.91
Average number of passenger seats of Alternative 3	6.43	1.55

NOTE: 10,000 yen = $85.96 in 2006 U.S dollars.
[a]Standard deviation cannot be calculated for dummy variables.

Specification of Utility Function

This case study used a panel data based on a retrospective survey. Different from normal panel data, which describe the behaviors of all the samples at the same time points, in this study, even though all the sampled households have the same number of time points (here,

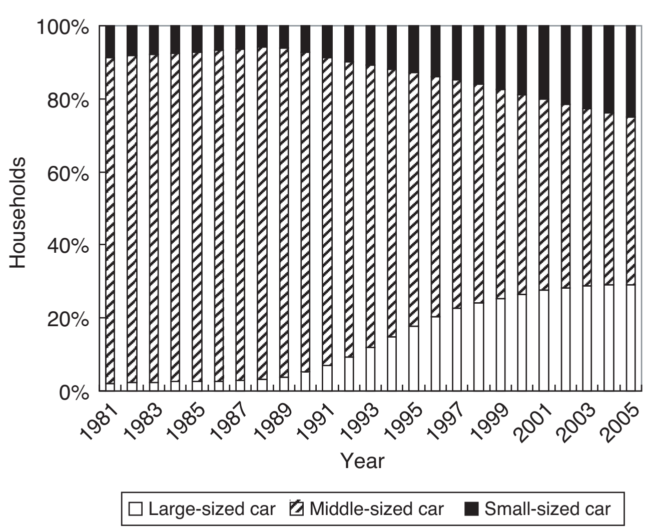

FIGURE 1 National diffusion ratio of vehicle type in Japan (*21*).

two time points), the time points used to describe household behavior are different across households and the interval between the two time points is not the same for all households. The metautilities ($\tilde{V}_{ijt}$) for the two time points are defined as follows:

$$\tilde{V}_{ij1} = \left(1 + \phi_{ij1}\right) v_{ij1} + v_{ij0} + \ln \alpha_{ij1} \tag{15}$$

$$\tilde{V}_{ij2} = \left(1 + \phi_{ij2}\right) v_{ij2} + \left(v_{ij0} + \ln \alpha_{ij1}\right) + \left(v_{ij1} + \ln \alpha_{ij2}\right) \tag{16}$$

$$v_{ij1} = \sum_{g} \rho_g \varpi_{ij1,g} + \sum_{k} \eta_k z_{ij1,k} \tag{17}$$

$$v_{ij2} = \sum_{g} \rho_g \varpi_{ij2,g} + \sum_{k} \eta_k z_{ij2,k} \tag{18}$$

where

ϕ_{ij1}, ϕ_{ij2} = parameters indicating influences of future expectation on choice of alternative j on Time Points 1 and 2,
v_{ij0} = influence of initial condition related to alternative j, and
$\varpi_{ij1,g}$, $\varpi_{ij2,g}$ = diffusion rates of alternative j at Time Points 1 and 2 of individual i's reference group g.

Explanatory Variable

In existing studies, zonal attributes (e.g., transit accessibility, land use mix) and vehicle attributes (e.g., vehicle price, acceleration, fuel type) are usually introduced as the explanatory variables. However, because of the limitation of the question items, this study considered only the household attributes $z_{ij1,k}$ and vehicle attributes $z_{ij2,k}$. The following variables were selected on the basis of preliminary analysis.

1. Vehicle attributes:
   –Composite variable of vehicle price and household income: defined as a composite variable because household income strongly influences the evaluation of vehicle price and
   –Composite variable of number of passenger seats (i.e., seating capacity, which is the legally permitted number of passengers within a car) and number of household members: defined as a composite variable to avoid the multicollinearity issue because number of household members might influence the evaluation of seating capacity and
2. Household attributes:
   –Number of employed members,
   –Number of license holders,
   –Number of members older than 65 years,
   –Employed statement of main user defined by a binary variable (1: yes, 0: no), and
   –Main purpose of car use defined by a binary variable in regard to commute (1: used mainly for commuting, 0: otherwise).

Social Interaction

Marketing research tradition suggests that the key diffusion mechanisms are the imitative behavior of other people. This propensity relies mainly on external information sources (e.g., mass media) and behavior of other individuals. Social interactions may arise directly through communication links or indirectly through an expectation formation process, depending on the distribution of other people in the social space of the individual. This social space was defined in this study as an immediate spatial locality (i.e., a neighborhood or a small spatial unit) and a wider space (i.e., around nation). By contrast, individual behavior is influenced by not only the general trend but also the behavior of homogenous group. The homogenous groups mean, for example, that people have similar household characteristics, similar purpose of car use, and so on. In the case of vehicle-type choice, it is not necessarily the case that young peoples' trends do not influence elderly people. In this sense, it is important to categorize the household by the homogenous groups.

To categorize the household by the homogenous groups, this study made use of χ^2 test with data expected to obtain according to a specific hypothesis. The χ^2 test is commonly used to compare observed data. If the test statistic is smaller than a critical value under certain significance level and the null hypothesis is accepted, then it can be interpreted that the difference is not observed by the attribute in the car type choice. By contract, in case the test statistic is significant and the hypothesis is rejected, preference of car type is significantly different across household by the attribute of interest.

The sampled households were classified on the basis of household characteristics (i.e., income level, number of household members, number of license holders, number of employed members, residential area, and life stage), main user characteristics (i.e., gender, age, status of employment), and car use attributes (i.e., main purpose of car use, type of car purchase, car use frequency). The results of the χ^2 tests are shown in Table 2.

As a result, the attributes of (*a*) income level, (*b*) number of license holders, (*c*) number of employed members, (*d*) type of car purchase, and (*e*) gender of main user were rejected, which meant household car type choice was significantly different by these attributes. However, these attributes were also highly linearly related. In this study, for simplifying the discussion on the analysis of multiple social interactions, only one attribute from these five attributes was used in the model to avoid the multicollinearity issue.

State Dependence (Habit Persistence)

This study argues that influence of state dependence (or habit persistence) may change with the time passed after the target behavior in the past was observed. To clarify such dynamic influence, four types of specifications shown in Equations 13*a* through 13*d* were empirically examined. As a result, it was found that Equation 13*c*, that is, $\alpha_{ijs} = (\alpha_j)^T$, results in the highest model accuracy. This finding implies that habit persistence becomes stronger with the lapse of time.

Model Performance

On the basis of the previous explanatory variables, the dynamic model was estimated, and the results are shown in Table 3. For the model accuracy, the adjusted McFadden's rho-squared is 0.448, suggesting that the developed model is good enough to represent household ownership behavior in this study:

Goodness-of-Fit Measure	*Value*
Initial log likelihood	–247.188
Converged log likelihood	–130.734
McFadden's rho-squared	0.471
Number of parameters	19
Adjusted McFadden's rho-squared	0.448

TABLE 2 Results of χ^2 Tests

Segment Criterion	Target Segments	χ^2
Income level	High income Middle income Low income	Rejected
Number of household members	Fewer than two members Two to four members Four members and more	Accepted
Number of license holders	One holder Two holders Three holders or more	Rejected
Number of employed members	One employed member Two employed members Three or more employed members	Rejected
Residential area	Hiroshima, Okayama Tottori, Shimane Yamaguchi	Accepted
Life Stage 1[a] (presence of elderly members)	Household with elderly members over 65 years of age Household without elderly members over 65 years of age	Accepted
Life Stage 2[a] (presence of preschool children)	Household with children under 6 years of age Household without children under 6 years of age	Accepted
Car use frequency	6–7 days/week 3–5 days/week 0–2 days/week	Accepted
Main purpose of car use	For commuting For other purposes	Accepted
Type of car purchase	New car Used car	Rejected
Gender of main users	Female Male	Rejected

NOTE: Null hypothesis: there is no difference across target segments.
[a]The elderly (65 years of age or older) and preschool children (6 years of age or under) are two special groups, which usually have limited access to public transportation systems. As a result, households with these two groups might have much stronger preference for vehicle ownership.

TABLE 3 Estimation Results

Explanatory Variable	Parameter Estimates	t-Score
Household and vehicle attributes		
Car price/household income (S, M, L)[a]	–0.670	–1.210
Number of passenger seats/number of household members (S, M, L)[a]	0.853**	6.807
Number of employed members (M, L)[a]	–0.616**	–2.233
Number of license holders (M, L)[a]	1.052**	4.310
Number of members over 65 years of age (M, L)[a]	0.829*	1.648
Employed statement of main user (M, L)[a]	0.224	0.616
Main purpose of car use (M, L)[a]	–0.298	–1.043
Social interactions		
Diffusion rate at national level (S, M, L)[a]	–2.464	–1.125
Diffusion rate at neighborhood level (S, M, L)[a]	2.022*	1.753
Diffusion rate of homogeneous group by income (S, M, L)[a]	1.143*	1.654
Initial conditions (utility v_{ij0} in Equations 15 and 16)		
Small-sized car	0.332	0.205
Middle-sized car	–2.203**	–2.792
Large-sized car	–2.115	—
Decay (discount) factors[b] of state dependence (α_j in Equation 14)		
Small-sized car	–0.356**	–2.501
Middle-sized car	–0.297**	–2.545
Large-sized car	–0.286	—
Future expectation[c] (ϕ_{ij1} in Equations 15 and 16)		
Small-sized car	–10.08**	–5.942
Middle-sized car	–9.296**	–3.998
Large-sized car	–10.419**	–8.672

NOTE: Sample size = 225 households; — = not applicable.
[a]Letters in parentheses indicate the alternatives associated with this variable: S = 660 cm^3 or less; M = 661–2,000 cm^3; L = 2,001 cm^3 or more.
[b]$\alpha_j = (1 + \exp(-\gamma_j))^{-1}$, where γ is value shown.
[c]Expectation weights defined as $(1 + \phi)$, $\phi = \exp(\gamma)$, where γ is value shown.
*Significant at the 10% level, **significant at the 1% level.

Influence of Household and Vehicle Attributes

Concerning the influence of household and vehicles attributes, the composite variable "number of passenger seats per number of household members" has a positive value and is statistically significant. This means that people prefer to own larger cars depending on household size. For household attributes, the households with more driver's license holders and elderly member(s) tend to choose cars with large seating capacity. However, the parameter "number of employed members" has a statistically significant and negative value. This finding implies that as the number of employed household members becomes larger, the households prefer to have small-sized cars more than other cars. The reasons are not simple. More employed members would likely increase the likelihood of car ownership, and such increased car ownership might be further constrained depending on the level of household income. Small-sized cars usually involve cheaper maintenance costs.

Households consisting of more employed members are found in an adult stage in the life cycle. In the adult stage, children have already been independent from the family, and employed members are restricted against regular commuting by public transport in Japan. As a result of decline of carpooling with family members, they would like to own compact cars.

Social Interaction Effects

The model introduced three types of social interactions, that is, national-based social interaction (wider social space), neighborhood-based social interaction (locality), and homogenous group-based social interaction. As mentioned previously, households can be significantly classified on the basis of income level, number of license holders, and type of car purchase. Only the income level was used, which leads to the highest model accuracy to avoid the multicollinearity issue. Concerning the estimation results of parameters, diffusion ratios of neighborhood and homogenous groups have a positive significant parameter. This result shows that household car type choice has positive multiplier effects within locality and homogenous group. In particular, the result indicates that vehicle-type choice is more sensitive to changes in behavior of the locality than that of homogenous group. National diffusion ratio, conversely, has no significant effect on household vehicle-type choice.

Dynamic Features

Equation 16 shows that the total household utility consists of five partial utilities: future expectation, current utility, previous utility, initial condition, and state dependence. The average values of these terms were calculated, as shown in Figure 2. The largest portion of the total utility is the current utility, followed by the previous utility. The future expectations have weights of 0.0004, 0.0009, and 0.0003, for Alternatives 1, 2, and 3, respectively. These parameters are significant, but the effects of expectations occupy a small portion of the total utility.

The significant parameters of the initial utilities indicate that the middle-sized car alternative has the lowest overall sample average initial condition. All decay factor parameters in the model are highly significant. Because of identification restriction, the factor

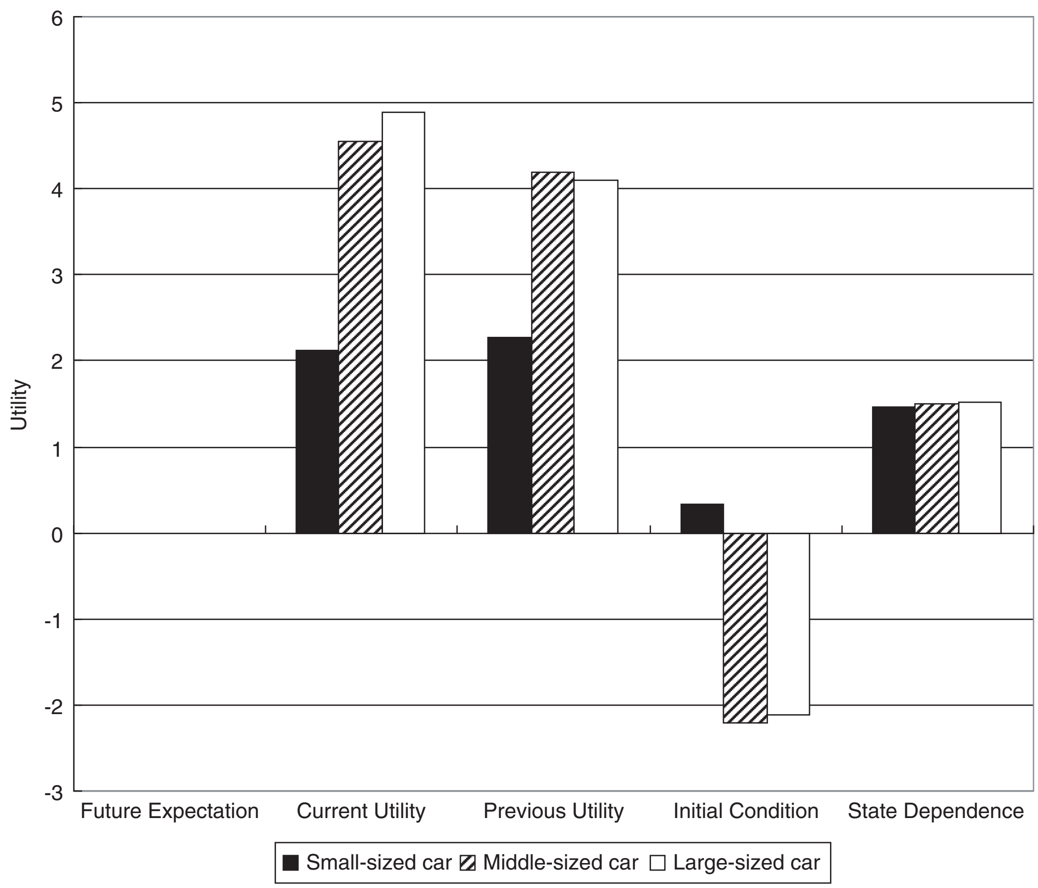

FIGURE 2 Average values of household utilities.

for one alternative must be held constant. In this model, the decay factor of large-class car was established by the optimization process, and then it held constant to permit identification of remaining parameters. The parameters imply decay factors of approximately 0.4 ($= (1 + \exp(-\gamma))^{-1}$) for all three alternatives. This means that after approximately 1 year, the impact ($\alpha_{ijs} = (\alpha_j)^1$) of a utility is reduced by approximately 6% of its original value.

CONCLUSIONS

Exploring the roles of social interactions in travel behavior analysis has its own academic and practical implications. Incorporating social interactions into travel behavior models agrees with the fact that an individual's travel behavior is usually affected by other people. A more convincible way to represent social interactions in travel behavior models could contribute to not only a better understanding of travel behavior but also a more proper evaluation about the effects of policy variables on travel behavior. Influential social interactions also suggest that a better communication strategy could encourage travelers to change their behaviors toward a better state. However, existing studies have not satisfactorily modeled social interactions. In particular, little has been done with respect to the modeling of multiple social interactions, which indicate that there are two or more types of reference groups that might influence travel behavior. Little has been done with regard to the influences of such social interactions over time, either. To fill in this gap, this study proposed a dynamic discrete choice model for multiple social interactions based on the DGEV modeling framework, which covers several dynamic elements, including initial conditions, state dependence (habit persistence), and future expectation. Three types of variables were used to represent the social interactions: diffusion rate of a corresponding car at national level, diffusion rate at neighborhood level, and diffusion rate of homogeneous group by income. A questionnaire survey was conducted in 2006 for the purpose of this study. In the survey, respondent households were asked to not only report the information about current car ownership behavior but also recall the ownership behavior over the 10 years from 1997 to 2006. In this sense, this study adopted retrospective panel data. With this panel data, first, the effectiveness of the model was examined from model performance and applicability to analysis of household vehicle-type choice behavior. Next, it was empirically confirmed that social interactions caused by reference groups of neighborhoods and households with the same income level are especially influential to decisions about household vehicle-type choice. On the contrary, social interaction from the whole society does not significantly influence the household choice. It was further found that dynamic elements have nonnegligible effects on the household choice.

There are some limitations in this study. Because this study introduced the diffusion rates of other households as a part of explanatory variables, it was difficult to apply the model directly for the purpose of future prediction and policy evaluation. Reflecting the influences of social interactions, it was necessary to explore the equilibrium process between microscopic household behavior and macroscopic social phenomenon. In addition, taste heterogeneity and serial correlation were not included in the dynamic model, either. Further modeling efforts should be made from these perspectives.

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