Cross-Nested Joint Model of Travel Mode and Departure Time Choice for Urban Commuting Trips: Case Study in Maryland–Washington, DC Region

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Abstract: The aim of this paper is to contribute to describe the simultaneous choice of travel mode and departure time by making use of a cross-nested logit structure that allows for the joint representation of interalternative correlation along the both choice dimensions. Traditional multinomial logit model and nested logit model are formulated respectively. The analysis uses the revealed preference data collected from Maryland-Washington, DC, regional household travel survey during 2007–2008 for commuting trips, considering more work-related characteristics than previous studies. A comparison of the different model results shows that the presented cross-nested logit structure offers significant improvements over multinomial logit and nested logit models. The empirical results of the analysis reveal significant influences on commuter joint choice behavior of travel mode and departure time. Moreover, a Monte Carlo simulation for two groups of scenarios arising from transportation policies, congestion pricing, and improvements to transit service during peak period is undertaken respectively to examine the impact of a change in car travel cost and transit travel time on the travel mode and departure time switching. The simulation results show that US$5 increase in car travel cost during peak period has a similar effect on reducing drive alone in peak hours as 30% saving in transit travel time but only half of the latter policy in the transit ridership increase. **DOI: 10.1061/(ASCE)UP.1943-5444.0000238.** © *2014 American Society of Civil Engineers.*

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Introduction

Traffic congestion at the morning peak and evening peak are the most severe time of day. Due to the serious traffic congestion, transportation CO_2 emissions are increasing. In large metropolitan areas, such as Maryland-Washington region, the major freeways are highly occupied and congested with commuters. Although car-based commuting trips are partly reduced with the public transit service availability, it is still not enough. In this way it becomes important to model the commuter travel behavior of travel mode choice and departure time choice so that efficient solutions may be proposed to alleviate the congestion problems.

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Commuting travel mode choice and departure time choice both play an imperative role in travel demand analysis and transportation policy assessment. Previous studies have widely focused on the travel mode choice (Bhat 1997; De Palma and Rochat 2000) and to a lesser degree on departure time (Hendrickson and Plank 1984; Gadda et al. 2009; Chu 2009). As Bhat (1998a, b) indicated there is a strong relationship between travel mode and departure time, and individuals often make the two choices simultaneously. More researchers focus on the joint choice travel behavior (Tringides et al. 2004; Bajwa et al. 2008; Yang et al. 2013; Ding et al. 2014). Joint analysis of travel mode and departure time is helpful to understand the interactions between the two dimensions and necessary to assess the impact of the transport policies.

However, studies accommodating correlation along the both dimensions of travel mode and departure time are limited. In this paper, a joint model is presented of the both dimensions of travel mode and departure time using a new cross-nesting structure that allows for flexible representation of correlation along the both choice dimensions, avoiding constraints associated with a multilevel nesting structure. Furthermore, simulation is used to examine the impact of a change in travel cost and travel time arising from transport policies on the commuting travel mode and departure time switching.

Multinomial logit (MNL) model and nested logit (NL) model based on the random utility maximization have been most widely used (De Jong et al. 2003). However, MNL model cannot account for unobserved similarities which exist among choice alternatives because of the independence of irrelevant alternatives (IIAs) assumption. In the NL model a uniform amount of correlation within a nest of alternatives is allowed but alternatives not located in the same nest are uncorrelated (Hess et al. 2012). In the analysis of joint choice of travel mode and departure time, two appropriate structures for the NL model arise, as follows: (1) nesting by travel mode dimension, and (2) nesting by departure time dimension (Hess et al. 2007). However, the two structures based on NL model can only accommodate correlation along one of the two dimensions.

In the past few years, many discrete choice models were developed based on the generalized extreme value (GEV) theory proposed by McFadden (1978). The GEV models are able to capture the unobserved similarities among alternatives, thus relaxing the restriction of MNL and NL model. Several specific GEV models have been formulated, such as the studies done by Wen and Koppelman (2001) and Daly and Bierlaire (2006), and have been applied in the field of spatial analysis such as the residential location choice (Bhat and Guo 2004; Sener et al. 2011) and destination choice (Bekhor and Prashker 2008). Therefore, one of the motivations in this paper lies in presenting a cross-nested logit (CNL) model structure based on the GEV framework to analyze the joint choice behavior of commuting travel mode and departure time, and to capture the correlation among alternatives for the both dimensions of travel mode and departure time.

The remainder of this paper is organized as described next. The next section presents a brief overview of the existing literature on the studies of travel mode and departure time. The third section presents the model structures used in this paper. Data used for analysis is described in the next section. The fifth section presents the estimation results and empirical explanations for the model. The next section presents the direct and cross elasticities of the model and simulation results with different scenarios. The final section provides a summary and conclusions of this paper.

Literature Review

Multinomial logit models are widely used to analyze the travel mode choice and departure time choice in previous studies due to its simple mathematical structure and ease of estimation. Abkowitz (1981) and Small (1981) used a MNL model for the analysis of the commuter departure time decisions. Hendrickson and Plank (1984) examined the flexibility of departure time for the work trip based on a MNL model that combined travel mode and departure time using the data gathered in Pittsburgh. Departure time decisions were much more flexible than mode choices.

However, the MNL model imposes the restriction that the distribution of random error terms is independent and identical over alternatives, which leads to the independence from irrelevant alternatives property. The most widely known relaxation of the MNL model is the NL model, which can be derived from GEV model. Chin (1990) employed a MNL model and a NL model to analyze the choice of commuter trip departure time using household data collected in Singapore. The NL model was used to moderate certain violations of the independence of irrelevant alternatives property. Departure time choice was mainly influenced by journey time. The occupation and income affected commuter propensity for switching departure times.

Simultaneous choice caused an increasing concern in the travel behavior study. Bhat (1998b) used a MNL form for modeling travel mode choice at the higher level of the hierarchy and an ordered generalized extreme value (OGEV) form for modeling the departure time choice at the lower level. The proposed MNL-OGEV model was applied to data obtained from 1990 San Francisco Bay area household survey and performed better than the MNL and NL models. De Palma and Rochat (2000) investigated the joint nature of the decision of how many cars the household owns and the decision to use the car for the trip to work by means of a NL model.

Mixed logit is a highly flexible model that can approximate any random utility model (McFadden and Train 2000). It obviates the three limitations of standard logit by allowing for (1) random taste variation, (2) unrestricted substitution patterns, and (3) correlation in unobserved factors over time. Usually, the MNL and NL are used as the kernel for the mixed logit model. Therefore, a few studies have used the mixed logit based on the MNL and NL structures to capture the correlation between alternatives as well as variations among commuters. For example, Bhat (1998a) used a mixed MNL model to analyze the travel mode and departure time choice for home-based social-recreational trips using data drawn from the 1990 San Francisco Bay area household survey. The empirical results underscored the need to capture unobserved attributes along the both travel mode and departure time dimensions. De Jong et al. (2003) modeled departure time choice jointly with mode choice using a mixed MNL model with stated preference (SP) data for car and train travelers in the Netherlands. The results indicate that time of day choice in the Netherlands is sensitive to changes in peak travel time and cost. Börjesson (2008) applied a mixed logit model to test for correlation of scheduling sensitivity across real preference (RP) and SP choices within individuals.

In recent years the CNL model has received more attention in the literature. It allows alternatives to belong to more than one nest instead of each alternative being restricted to a single nest in NL model (Papola 2004; Bierlaire 2006). Therefore, CNL models have a more flexible correlation structure to account for various patterns of similarity and dissimilarity among alternatives.

Bajwa et al. (2008) applied the CNL and mixed NL models to estimate the combined choice of travel mode (car and rail) and departure time (arriving early, late, and on time with congestion) for the morning commuters using a SP data collected in Tokyo. The CNL structure used in their analysis cannot analyze correlations along the both dimensions of travel mode and departure time. Hess and Polak (2006) used a new CNL model structure that allowed for the joint representation of interalternative correlation along the three choice dimensions of (1) airport, (2) airline, and (3) access mode. In their model, the three choice dimensions were set in the same level, thus each alternative belongs to exactly (1) one airport nest, (2) one airline nest, and (3) one access-mode nest. The model is able to jointly represent the correlation along the three dimensions. The analysis used the data collected from the greater London area and the comparison of the different models showed that the new CNL model structure offered significant improvements over NL models. Hess et al. (2012) used similar CNL model structure to analyze the joint vehicle type choice and fuel type choice. Two separate vehicle type nests and three separate fuel type nest were put in the same level, with each alternative falling into one vehicle type nest and one fuel type nest. Therefore, correlations among those alternatives sharing the same vehicle type and between the vehicles sharing the same fuel type can be obtained. A SP data was used for their empirical analysis and the results verified that further gains can be made by using their proposed CNL model structure. The CNL model structure proposed by Hess et al. (2012) is allowed to capture the correlations along all the dimensions in the choice process, whereas this structure used in the field of joint choice of travel mode and departure time is limited. Vega and Feighan (2009) used a CNL model to analyze the simultaneous choice of residential location and travel-to-work mode under central and noncentral or suburban employment patterns for the greater Dublin area. The results showed that the CNL provided a more flexible correlation structure of the error terms than other closed-form discrete choice models such as the MNL and NL models.

Review of the past literature reveals that different model structures have been applied for the travel mode choice and departure time choice. However, the studies on the simultaneous choice of travel mode and departure time accommodating correlation along the both dimensions are limited. If there are K dimensions in the choice process, NL model structure that used in most previous studies can only be used to analyze correlations along at most $K-1$ of K dimensions by using a multilevel structure. The solution put forward by Hess and Polak (2006) and Hess et al. (2012) is to use a new CNL model structure through setting all K dimensions in the same level.

Therefore, the aim of this paper is to contribute to describe the simultaneous choice of travel mode and departure time by making use of the CNL structure that allows for the joint representation of inter-alternative correlation along the both choice dimensions. Traditional MNL and NL models are also formulated respectively, and a comprehensive study comparing the different model structures is carried out. Another contribution of this paper is that it considers more policy-oriented factors explicitly (such as whether the work schedule is flexible; whether employer provides free parking, subsidies for transit/vanpooling, and bike/pedestrian facilities or services for workers; and the job-housing location attributes), which can potentially affect commuting travel mode and departure time. Moreover, based on the estimated model a Monte Carlo simulation for two groups of scenarios arising from transport policies, congestion-pricing, and improvements to transit service during peak period is undertaken to examine the impact of a change in car travel cost and transit travel time on the travel mode and departure time switching.

Table 1. Alternatives for Joint Choice of Travel Mode and Departure Time

Alternative number	Mode of home-based work trip	Departure time for home-based work trip
1	Drive alone	Peak
2	Drive alone	Off-peak
3	Shared ride	Peak
4	Shared ride	Off-peak
5	Transit	Peak
6	Transit	Off-peak
7	Walk and bicycle	Peak
8	Walk and bicycle	Off-peak

Model Specification

This paper focuses on the joint choice behavior of travel mode and departure time for home-based work trips made by commuters. The travel mode choice subset consists of four modes, as follows: (1) drive alone, (2) shared ride, (3) transit, and (4) walk and bicycle. The departure time subset has two alternatives, as follows: (1) peak period, and (2) off-peak period. Therefore, the model choice set is defined as the joint choice set of travel mode and departure time, which creates a set of $N = 8$ alternatives for each decision-maker (Table 1).

Model Structure

The most widely used nesting approach is the NL model, which allows the correlation among alternatives sharing a nest, while alternatives in different nests remain independent. As an example, the appropriate structure for the two-level NL model using nesting by travel mode is shown (Fig. 1), with travel mode at the upper level and departure time at the lower level, where each nest has its own nesting parameter $\mu(0 < \mu \leq 1)$. The nesting parameter can be used to capture the correlation among alternatives sharing the nest of travel mode. It is also called dissimilarity parameter. The correlation among alternatives sharing the same nest increases as the dissimilarity parameter decreases. Fig. 2 shows another nesting structure indicating that alternatives are grouped together based on the departure time. The nesting parameter (Fig. 2) can be used to capture the correlation along the departure time dimension.

The both NL structures cannot be used to capture the correlations along the two dimensions of choice simultaneously. For example, the model structure (Fig. 2) cannot be used to capture

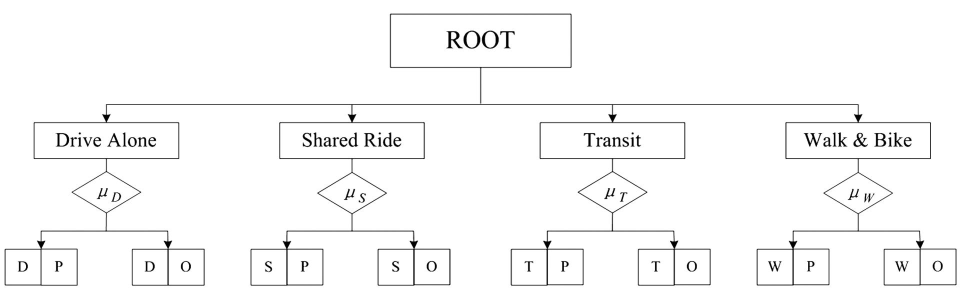

Fig. 1. Structure of two-level NL model, using nesting along travel mode dimension; μ_x is dissimilarity parameter; D, S, T, and W mean drive alone, shared ride, transit, and walk and bike, respectively; O and P mean off-peak and peak, respectively

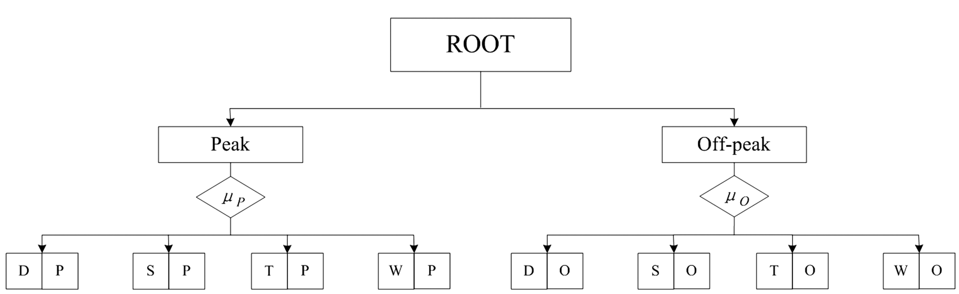

Fig. 2. Structure of two-level NL model using nesting along departure time dimension

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the correlation between the alternative using transit mode departing during peak period and the alternative using transit departing during off-peaking period. In general, this problem also applies in other multilevel nesting approaches. If there is a K-dimensional choice process it can only accommodate correlation along at most $K-1$ of K dimensions by using a multilevel nesting structure.

The deficiency of the NL structure model is one motivation for the efforts made in this paper to propose an improved structure for the joint choice model used by Hess and Polak (2006) and Hess et al. (2012). The improved structure for the joint choice model is specified by allowing each alternative to belong to two nests, (1) one by travel mode, and (2) another by departure time (Fig. 3).

Cross-Nested Logit Model

There are two main advantages for application of the CNL model in this paper, as follows: (1) on the one hand, the CNL model structure provides a more flexible correlation structure of the error term than MNL and NL model structures that allows the potential correlation among alternatives to be captured; and (2) on the other hand, the CNL model structure has a closed-form expression derived for the calculation of the choice probability. The new model structure presented in this paper that allows for a more flexible correlation of the error terms can describe the correlation among the two choice dimensions of (1) travel mode, and (2) departure time.

According to the GEV theorem (McFadden 1978; Wen and Koppelman 2001; Bekhor and Prashker 2008), the CNL model choice probability that derived from the generator function G [Eq. (1)] is defined in terms of conditional and marginal probabilities P [Eq. (2)]

$$G(y) = \sum_m \left[\sum_k (\alpha_m y_k)^{1/\mu_m} \right]^{\mu_m} \tag{1}$$

$$P(k) = \sum_m P(k|m)P(m) \tag{2}$$

where k represents an alternative; m represents a nest; μ_m is a nest-specific coefficient; and α_m is a weight parameter. The conditional probability of an alternative k being chosen in nest m is

$$P(k|m) = \frac{(\alpha_{mk} e^{V_k})^{1/\mu_m}}{\sum_k (\alpha_{mk} e^{V_k})^{1/\mu_m}} \tag{3}$$

where α_{mk} is an allocation parameter that characterizes the portion of alternative k assigned to nest m, $0 \le \alpha_{mk} \le 1$. As such, the improved structure of the model is able to accommodate correlation along all the dimensions using the simultaneous pattern. In this paper, the allocation parameters $\alpha(0 \le \alpha_{mk} \le 1)$, governing the proportion by which an alternative belongs to each nest can also be obtained based on the GEV structure. A value zero indicates that the alternative does not belong to the nest at all. It is usually specified that the allocation parameters for a given alternative must sum to unity over all nests. In this paper, the nonzero allocation parameters for a given alternative were fixed to a value of 0.5, indicating that an alternative belongs by the same proportion to one travel mode nest and one departure time nest.

The marginal probability of a nest m being chosen is

$$P(m) = \frac{[\sum_k (\alpha_{mk} e^{V_k})^{1/\mu_m}]^{\mu_m}}{\sum_m [\sum_k (\alpha_{mk} e^{V_k})^{1/\mu_m}]^{\mu_m}} \tag{4}$$

Thus, the probability of a CNL alternative k being chosen is

$$\begin{aligned} P(k) &= \sum_m P(k|m)P(m) \\ &= \sum_m \left\{ \frac{(\alpha_{mk} e^{V_k})^{1/\mu_m}}{\sum_k (\alpha_{mk} e^{V_k})^{1/\mu_m}} \cdot \frac{[\sum_k (\alpha_{mk} e^{V_k})^{1/\mu_m}]^{\mu_m}}{\sum_m [\sum_k (\alpha_{mk} e^{V_k})^{1/\mu_m}]^{\mu_m}} \right\} \end{aligned} \tag{5}$$

where there are two key factors that the probability of choosing the alternative k depending on the following: (1) nesting coefficients μ_m, and (2) deterministic component of the utility function V_k. The parameters are estimated based on the maximum likelihood method.

Data and Sample Formation

The data used in this paper is drawn from the Maryland and Washington, DC, regional household travel survey (HTS), which was conducted by Baltimore Metropolitan Council (BMC) and Transportation Planning Board (TPB) at the Metropolitan Washington Council of Governments (MWCOG) during 2007–2008. Data for the survey was collected from randomly selected households and each household completed a travel diary that documented the activities of all household members on an assigned day. As with most household travel survey, detailed sociodemographic and trip information for each person were collected. Fig. 4 shows a map of the survey area.

In addition to the HTS, origin-destination travel time and cost matrices by different modes were obtained from Maryland statewide transportation model (MSTM). Travel time by auto includes in-vehicle time and terminal time. Travel time by transit includes walk and bicycle-access times, initial wait time, in-vehicle time, and transfer time. Travel cost by auto mainly includes operation cost and parking cost. Operating cost is computed as the monetary costs associated with fuel consumption, maintenance, insurance, registration, and tire. Auto parking cost is computed by a parking cost model for the attraction zone. For the shared ride mode the auto operating and parking cost are divided by the total passengers. The transit fare is computed from the transit network as the sum of the boarding fare and any transfer fares. For the walk and bicycle mode, it is assumed that a travel speed of 4.8 km/h (3 mi/h) for walking and 14.48 km/h (9 mi/h) for bicycling (Zhang 2004), and \$0.05/mi for the both modes.

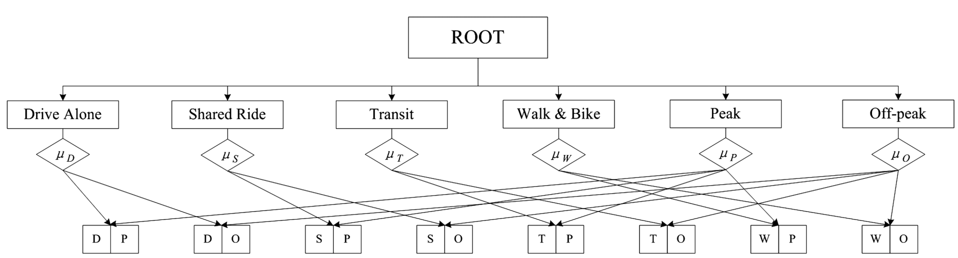

Fig. 3. Structure of CNL model for the joint choice of travel mode and departure time

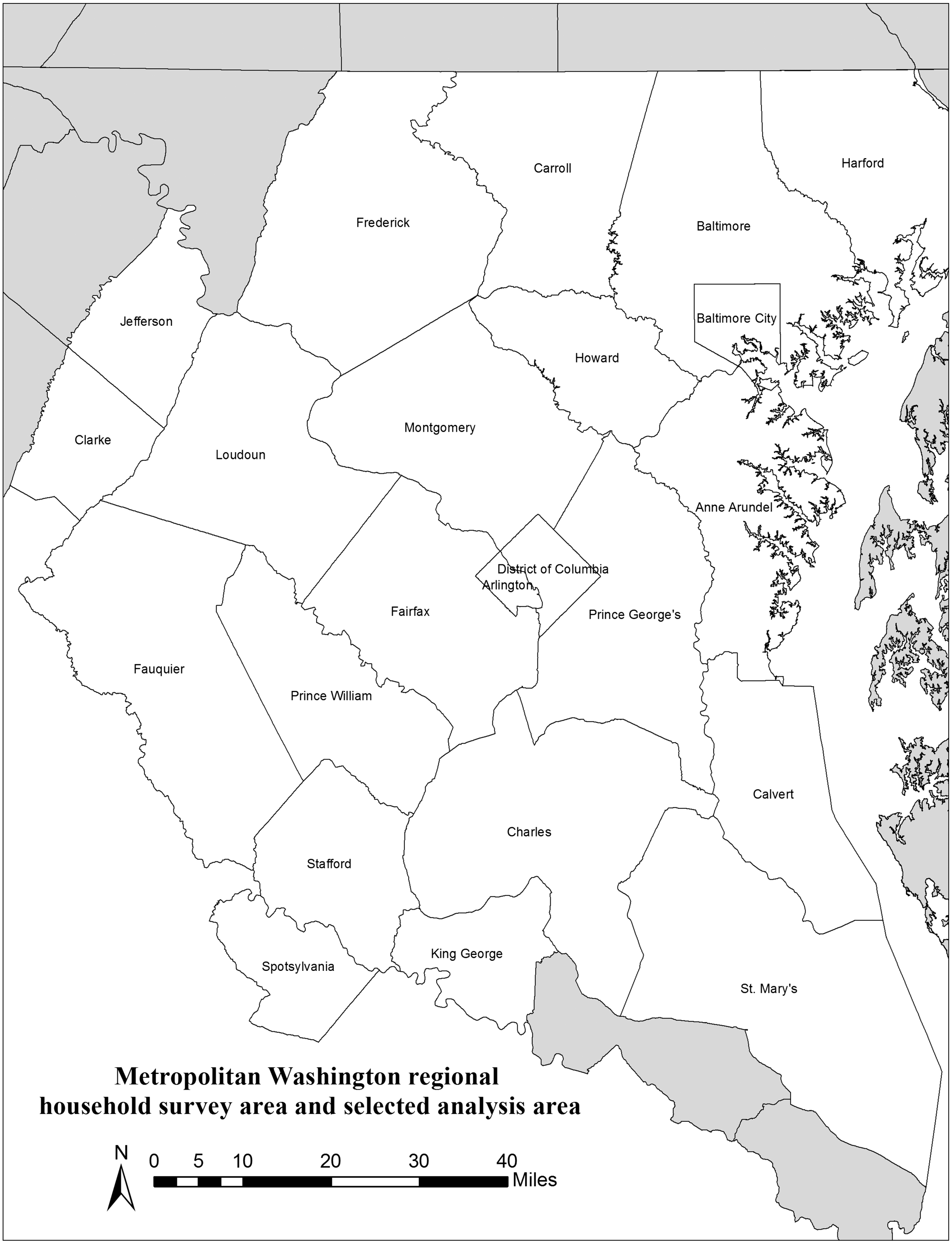

Fig. 4. Study areas in Maryland-Washington, DC, region [adapted from National (2012)]

Many factors have been identified that influence the decisions of travel mode and departure time (Cervero 2002; Vega and Feighan 2009; Ewing and Cervero 2010). There are four groups of variables used in this analysis, as follows: (1) household characteristics, (2) individual characteristics, (3) work-related characteristics, and (4) travel-related characteristics. The variables of household characteristics include household size, income, location, and the number of cars and bicycles available in the household. The variables of individual characteristics include gender, age, race, occupation, and the number of current jobs. Whether the work schedule is flexible, whether the employers provide free parking, subsidies for transit/vanpooling, bicycle/pedestrian facility, and the work location are potentially important variables influencing the choice of commuting travel mode and departure time (Abkowitz 1981; Chu 2009); thus these variables are used in analysis as work-related explanatory variables. Travel-related characteristics include travel time and travel cost computed from residential location and workplace for different travel modes. The variables used in analysis are shown (Table 2).

The time-of-day distribution of commuting trips is shown (Fig. 5). The distribution shows that most workers tend to make commuting trips during two peak periods, as follows: (1) 6 to 8 a.m. and 3 to 6 p.m. The peak time-periods are certain consistent with the classification presented by Bhat (1998b).

A descriptive analysis (Table 3) is conducted to get intuitive findings regarding to the association between household, individual, travel-related characteristics, and the preferences of commuting travel mode and departure time. Young individuals are more likely to use shared ride mode to work and depart during off-peak period to avoid traffic congestion than older individuals (Table 3). This may be seen as a character-related effect for young individuals intuitively. People who work in a government agency are more likely to use transit as commuting travel mode and depart during peak period. As expected, people with smaller household size, low household income, and low car ownership are more likely to use transit or walk and bicycle for commuting trips. People whose employer provides charged parking, subsidies for transit/vanpooling and bike/pedestrian facilities or services, and people who work in the central business district (CBD) are more likely to use transit for commuting trips. People who enjoy flexible work hours, low income people, low car ownership, without subsidies for transit or vanpooling, are more likely to depart during off-peak period to avoid traffic congestion.

Empirical Results

The findings of the proposed model are discussed in this section. The trust-region algorithm is used for the MNL model and the two kinds of NL model. Due to the nontrivial constraints on the allocation parameters, C of the feasible sequential quadratic programming (CFSQP) algorithm is used for the CNL model (Lawrence et al. 1997). All the models presented were estimated using *Biogeme* (Bierlaire 2002, 2003, 2006), including the MNL model, two kinds of NL model, and the CNL model. The probability of choosing each alternative can be estimated using the proposed model based on the given independent variables about each individual.

The detailed estimation results based on the CNL model are presented (Table 4). The results for the variables of household characteristics, individual characteristics, and work-related characteristics for Washington and Baltimore region suggest that these characteristics have important influences on the individuals' commuting travel mode and departure time choice decisions. In terms of the household characteristics, single persons are significantly more likely to drive alone to work, compared with the base alternative (drive alone in peak hours; Table 4). People in larger household are significantly more likely to choose shared ride and depart

Table 2. Descriptive Statistics of Sample Data for Home-Based Work Trips

Variable name	Variable description[a]	Mean	Standard deviation
Household characteristics			
Household size	Single person household	0.18	0.387
	Household size is equal to two persons	0.38	0.485
	Household size is equal to or more than three persons	0.44	0.496
Household income	Household income is less than US$30,000	0.04	0.206
	Household income is between US$30,000 and US$100,000	0.45	0.498
	Household income is equal to or more than US$100,000	0.50	0.500
Cars ownership	Household owns no car	0.04	0.191
	Household owns one car	0.26	0.438
	Household owns two or more cars	0.70	0.457
Bicycles	Household owns one or more bicycles available	0.57	0.495
Household location	Household locates in suburban area	0.29	0.454
Individual characteristics			
Gender	Male	0.52	0.499
Age	Person is less than 25 years old	0.06	0.240
	Person is between 25 and 54 years old	0.69	0.463
	Person is equal to or more than 55 years old	0.25	0.433
Race	African American	0.16	0.363
	Caucasian	0.74	0.440
Occupation	Person works in a government agency	0.36	0.480
Jobs	Person has more than one job	0.07	0.253
Work-related characteristics			
Flexibility for job	Person enjoys flexible work hours	0.54	0.499
Parking cost	Employer provides free parking	0.56	0.497
Subsidies for transit	Employer provides subsidies for transit/vanpooling	0.18	0.383
Bicycle facility	Employer provides bike/pedestrian facilities or services	0.11	0.317
Work location	Person works in the CBD	0.26	0.438
Travel-related characteristics			
Travel time	Continuous variable: total time of a trip for different travel mode, in units of minutes, provided by MSTM		
Travel cost	Continuous variable: total travel cost of a trip for different travel mode, in units of U.S. dollars, as a function of distance provided by MSTM		

Note: $N = 18{,}510$.
[a]An answer of yes is indicated by a value of 1.

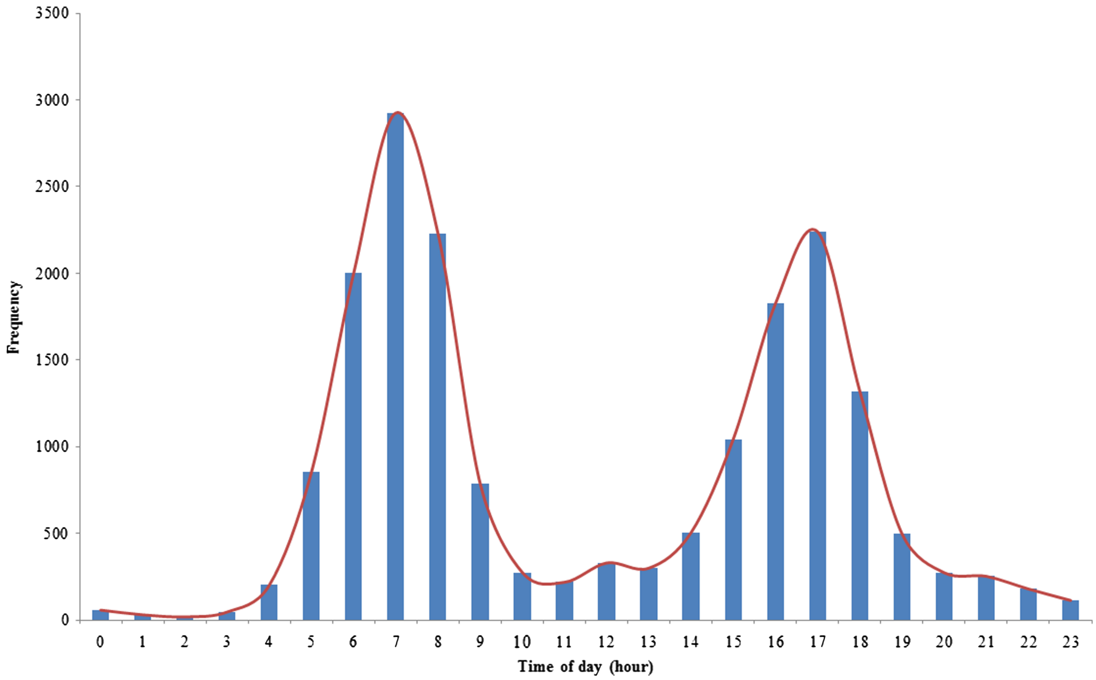

Fig. 5. Time-of-day distribution of home-based work trips

in the off-peak period. It may reflect the fact that commuters choosing the shared ride usually depart much earlier so that each passenger can arrive at the workplace on time. Low income groups are found to contribute positively to choose the shared ride in the off-peak period compared with the drive alone in peak hours. High income groups are significantly less likely to depart in the off-peak period to work; however, they may prefer the walk and bicycle to drive alone in peak hours, considering the commute distance. As expected, persons in low car ownership households show a positive propensity to use the shared ride, transit, and walk or bicycle to work. People with bicycle available are significantly more likely to choose the walk or bicycle and depart in peak period compared with the base alternative. People whose household locates in a suburban area are significantly more likely to depart in the off-peak period to work. This seems logical because suburban residents usually travel longer distances to work and hence need to depart earlier.

In terms of the individual characteristics, males are significantly more likely to drive alone in off-peak period and to use the transit, and walk or bicycle to work than women. However, males are significantly less likely to choose the shared ride to work. Young adults are significantly less likely to drive alone to work, which may be due to the fact that they have limited car availability thus contributing to greater propensity to use the share ride, transit, and walk or bicycle. The variable of race has negative coefficients, indicating that both African American and Caucasian people are more likely to drive alone to work, except that Caucasian people are significantly at above the 10% level more likely to choose the walk and bicycle to work in peak period. Compared with the base alternative, people who work in a government agency are significantly less likely to depart in off-peak period. However, they are significantly more likely to choose the walk and bicycle to work in peak period. As expected, people who have more than one job are significantly more likely to depart in off-peak period using the travel modes of drive alone, transit, and walk or bicycle.

In terms of the work-related characteristics, people who enjoy flexible work hours are significantly more likely to depart in the off-peak period using the travel modes of drive alone, transit, and walk or bicycle. People whose employers provide free parking show a significantly positive propensity to drive alone in the peak period to work. As expected, people whose employers provide subsidies for transit and vanpooling, and bike and pedestrian facilities or services, are significantly more likely to choose transit, and walk or bicycle to work in the peak period, compared with the base alternative. People who work in the CBD are significantly less likely to drive alone in peak period to work, presumably to avoid severe congestion prevailing in the downtown areas. People working in the CBD are significantly more likely to use transit, walk, and bicycle to work. This finding may be due to the fact that there are better transit services and better bike/pedestrian facilities or services in the downtown area relative to other areas.

The travel-related parameters, dissimilarity parameters, and data fit measures from the four models are presented (Table 5). In terms of the adjusted ρ^2, the CNL model outperforms the MNL model and the two NL models. As expected, the signs of the travel-related parameters are negative. The value of travel time savings is about US\$0.33/ min (about US\$20/h), which is quite similar to that have been reported in the studies done by Hess et al. (2008) and Bajwa et al. (2008). The CNL model offers the greatest improvement in dissimilarity parameters for travel mode and departure time when compared to the MNL, and two types of NL model.

In terms of the correlation among alternatives (Table 5), the number of the dissimilarity parameters from the proposed CNL model is more than from MNL and NL models, thus the CNL model is superior in capturing the correlation among alternatives. The dissimilarity parameter along the off-peak dimension is minimal, indicating that the alternatives in off-peak nest have high correlations. In other words, the dissimilarity parameters can capture the pattern of substitutability across alternatives (Wen and Koppelman 2001; Pels et al. 2009). Due to the high substitutability for the alternatives in off-peak nest, the decision-makers are more likely to shift their commuting travel mode than departure time when the situations change (such as due to transportation control measures). The dissimilarity parameter along the shared ride dimension is as its maximum, indicating there is low substitutability

Table 3. Choice Percentage by Independent Variables

Frequencies percentage (%)		Travel mode: Drive alone	Shared ride	Transit	Walk and bicycle	Departure time: Peak	Off-peak
Overall percentage		75.2	4.1	16.8	3.8	73.4	26.6
Household characteristics							
Household size	Size 1, single person	67.6	1.3	25.3	5.8	73.8	26.2
	Size 2, two persons	73.9	4.6	17.0	4.5	74.2	25.8
	Size 3, more than two persons	79.6	4.9	13.1	2.4	72.5	27.5
Household income	Income 1, <30,000	60.0	9.4	24.6	5.9	65.3	34.7
	Income 2, 30,000–100,000	75.3	4.4	16.4	3.9	71.7	28.3
	Income 3, >100,000	76.5	3.4	16.5	3.6	75.6	24.4
Cars ownership	Car 1, no car	1.7	7.6	70.2	20.5	68.7	31.3
	Car 2, one car	62.2	5.5	26.0	6.3	74.4	25.6
	Car 3, more than one car	84.0	3.4	10.5	2.0	73.2	26.8
Bicycles	No bicycles	72.7	4.4	19.3	3.6	71.8	28.2
	Available	77.1	3.9	14.9	4.0	74.5	25.5
Household location	Suburban	70.0	4.1	21.1	4.9	70.2	29.8
	Others	88.1	4.3	6.3	1.3	74.7	25.3
Individual characteristics							
Gender	Male	76.2	2.7	16.8	4.3	71.1	28.9
	Female	74.2	5.7	16.8	3.3	75.8	24.2
Age	Age 1, 16–24	65.9	11.6	17.0	5.5	66.8	33.2
	Age 2, 25–54	75.1	3.8	17.2	3.8	74.1	25.9
	Age 3, >55	77.8	3.1	15.6	3.4	72.8	27.2
Race	Race 1, African American	69.4	5.8	23.3	1.6	71.8	28.2
	Race 2, White	77.0	3.3	15.3	4.4	74.1	25.9
	Race 3, others	71.3	7.5	17.9	3.2	70.6	29.4
Occupation	Government	69.3	3.7	23.1	3.9	77.2	22.8
	Others	78.6	4.4	13.3	3.8	71.2	28.8
Jobs	One job	75.0	4.1	17.1	3.8	73.9	26.1
	More than one job	79.1	4.5	12.5	3.9	66.2	33.8
Work-related characteristics							
Flexibility for job	Yes	75.8	3.7	16.2	4.2	71.0	29.0
	No	74.5	4.6	17.5	3.4	76.1	23.9
Parking cost	Free	91.2	3.2	3.6	1.9	73.1	26.9
	Nonfree	55.0	5.3	33.4	6.3	73.7	26.3
Subsidies for transit	Yes	35.7	3.1	56.1	5.1	80.1	19.9
	No	83.8	4.4	8.3	3.6	71.9	28.1
Bicycle facility	Yes	69.7	3.7	20.2	6.4	74.1	25.9
	No	75.9	4.2	16.3	3.5	73.3	26.7
Work location	CBD	52.7	4.7	34.1	8.5	73.8	26.2
	Not CBD	83.1	3.9	10.7	2.2	73.2	26.8

Note: $N = 18{,}510$. Group 2 is reference variable for the variables of household size, income, car ownership, and age. Group 3 is reference variable for the variables of race.

between peak and off-peak in the share ride nest. When the situations change the individuals will change their travel mode first for commuters by shared ride.

Elasticities and Simulation Tests

Direct and cross elasticities with respect to travel cost and travel time are represented (Table 6). Direct elasticities represent the variation in a decision-maker's choice probability due to a change in one of the attributes affecting that alternative. Cross elasticities are the variation in a decision-maker's choice probability due to a change in one of the attributes affecting another alternative. Wen and Koppelman (2001) represented the direct and cross elasticities for the CNL model [Eqs. (6) and (7)]. The cross elasticities are $-P_k\beta X_k$ if the alternative k and k' do not share any common nest

$$\text{Direct elasticity} = \frac{\sum_m P_m P_{k|m}[(1-P_k) + (\frac{1}{\mu^m}-1)(1-P_{k|m})]}{P_k}\beta X_k \quad (6)$$

$$\text{Cross elasticity} = -\left[P_k + \frac{\sum_m(\frac{1}{\mu^m}-1)P_m P_{k|m} P_{k'|m}}{P_{k'}}\right]\beta X_k \quad (7)$$

Direct elasticities (Table 6) show that the influence of the travel cost and travel time on the car and transit choice probabilities is different. The direct elasticities for transit are larger than that for car, indicating that commuters by transit are more sensitive to travel-related attributes change than commuters by car. Commuters are more sensitive to changes in travel time than that of travel cost for the commuters by shared ride, transit, and walk and bicycle. From the cross elasticities, changes in travel cost and travel time for commuters by drive alone during the peak period have the largest effects on probability choice of using transit during peak period.

The direct and cross elasticities are calculated for a randomly selected individual (Table 6), making it difficult to obtain the aggregate results for travel cost and travel time changes. However, aggregate results are extremely useful for the transportation demand management (TDM), transportation control measures (TCM), and intelligent transportation system. Therefore, another critical motivation in this study lies in obtaining the aggregate

Table 4. Estimation Results of the CNL Model

	Drive alone		Shared ride				Transit				Walk and bicycle			
	Off-peak		Peak		Off-peak		Peak		Off-peak		Peak		Off-peak	
Variables	Parameter	*t*-statistic	Parameter	*t*-statistic	Parameter	*t*-statistic	Parameter	*t*-statistic	Parameter	*t*-statistic	Parameter	*t*-statistic	Parameter	*t*-statistic
Household characteristics														
Size 1	−0.01	−0.19	−1.48	−7.82[a]	−2.38	−12.30[a]	−0.16	−8.02[a]	−0.14	−2.32[b]	−0.18	−5.62[a]	−0.15	−2.35[b]
Size 3	0.05	1.32	0.12	1.21	0.38	2.75[a]	−0.03	−2.29[b]	0.07	1.63	−0.03	−1.22	0.05	1.12
Income 1	0.16	1.96[b]	−0.01	−0.06	0.65	3.14[a]	0.04	1.41	0.12	1.35	0.01	0.25	0.12	1.31
Income 3	−0.17	−4.63[a]	−0.16	−1.60	−0.30	−1.89	0.01	1.12	−0.18	−4.47[a]	0.07	2.82[a]	−0.19	−4.35[a]
Car 1	−1.27	−2.30[b]	0.46	2.01[b]	1.43	6.33[a]	0.72	8.47[a]	1.02	7.83[a]	0.76	8.36[a]	0.98	7.49[a]
Car 3	0.05	1.03	−1.24	−11.13[a]	−0.89	−5.06[a]	−0.21	−10.36[a]	−0.17	−3.13[a]	−0.21	−7.04[a]	−0.10	−1.82
Bicycles	−0.12	−3.29[a]	−0.12	−1.27	−0.08	−0.57	−0.03	−2.35[b]	−0.12	−3.00[a]	0.06	2.55[b]	−0.08	−1.86
Household location	0.23	5.70[a]	0.19	1.71	0.17	1.01	−0.15	−7.70[a]	0.13	2.93[a]	−0.01	−0.18	0.15	2.93[a]
Individual characteristics														
Gender	0.25	7.17[a]	−0.84	−9.09[a]	−0.61	−4.70[a]	0.04	3.67[a]	0.30	7.95[a]	0.11	4.88[a]	0.37	8.93[a]
Age 1	0.25	3.49[a]	1.14	8.42[a]	1.34	7.69[a]	0.11	4.75[a]	0.28	3.64[a]	0.13	3.21[a]	0.31	3.97[a]
Age 3	0.10	2.57[b]	0.09	0.73	−0.04	−0.21	0.01	0.14	0.12	2.76[a]	0.01	0.38	0.09	2.01[b]
Race 1	−0.08	−1.27	−0.62	−4.23[a]	−0.11	−0.59	−0.01	−0.38	−0.07	−0.95	−0.13	−2.48[b]	−0.14	−1.83
Race 2	−0.20	−3.26[a]	−0.68	−5.49[a]	−0.70	−3.67[a]	−0.03	−1.87	−0.17	−2.91[a]	0.07	1.90	−0.12	−1.87
Occupation	−0.20	−5.24[a]	0.07	0.74	−0.23	−1.44	0.02	1.40	−0.16	−4.12[a]	0.08	3.30[a]	−0.15	−3.33[a]
Jobs	0.35	5.51[a]	0.11	0.64	0.10	0.41	−0.05	−2.19[b]	0.28	3.97[a]	−0.04	−0.90	0.26	3.57[a]
Work-related characteristics														
Flexibility for job	0.28	7.96[a]	−0.04	−0.41	0.13	0.95	−0.03	−2.93[a]	0.27	7.13[a]	−0.02	−1.02	0.25	6.02[a]
Parking cost	−0.11	−2.87[a]	−0.63	−6.67[a]	−0.31	−2.30[b]	−0.40	−12.62[a]	−0.42	−8.47[a]	−0.26	−8.91[a]	−0.31	−6.74[a]
Subsidies for transit	−0.30	−5.40[a]	−0.26	−1.93	−0.62	−2.50[b]	0.43	12.90[a]	0.03	0.53	0.22	6.99[a]	−0.06	−0.86
Bicycle facility	0.12	2.25[b]	0.34	2.45[b]	−0.37	−1.40	−0.01	−0.14	0.06	2.51[b]	0.11	3.66[a]	0.18	2.92[a]
Work location	0.09	2.09[b]	0.15	1.35	0.09	0.54	0.11	8.33[a]	0.24	5.26[a]	0.20	6.93[a]	0.24	4.96[a]

Note: Alternative 1 is the base alternative.
[a]Significance at the 99% level.
[b]Significance at the 95% level.

Table 5. Travel-Related Parameters, Dissimilarity Parameters, and Data Fit Measures

Attributes/ data fit measures	Multinomial logit		Nested logit using nesting by travel mode		Nested logit using nesting by departure time		Cross-nested logit	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Travel cost	−0.0978	−22.23[a]	−0.0978	−22.23[a]	−0.0937	−19.82[a]	−0.0526	−14.24[a]
Travel time	−0.0323	−23.74[a]	−0.0323	−23.74[a]	−0.0311	−21.30[a]	−0.0180	−14.15[a]
μ_D	1.00	—	1.00	—	—	—	0.19	0.03
μ_S	1.00	—	1.00	—	—	—	1.00	—
μ_T	1.00	—	0.15	0.60	—	—	0.18	0.10
μ_W	1.00	—	1.00	—	—	—	0.16	4.28[a]
μ_P	1.00	—	—	—	1.00	—	0.15	13.70[a]
μ_O	1.00	—	—	—	0.88	16.22[a]	0.10	11.84[a]
VTTS (US$/min)	0.3303		0.3303		0.3319		0.3422	
Final LL	−19,308.127		−19,306.913		−19,305.824		−18,963.175	
Adjusted ρ^2	0.494		0.494		0.495		0.503	

Note: Alternative 1 is the reference category; LL = log-likelihood; and VTTS = value of travel time savings.
[a]Significance at the 99% level.

Table 6. Direct and Cross Elasticities for a Random Decision-Maker in Study Area

Travel mode	Direct elasticities				Cross elasticities[a]			
	Travel cost elasticities		Travel time elasticities		Travel cost elasticities		Travel time elasticities	
	Peak	Off-peak	Peak	Off-peak	Peak	Off-peak	Peak	Off-peak
Drive alone	−0.0906	−0.2019	−0.0847	−0.1886	—	0.3761	—	0.3532
Shared ride	−0.1282	−0.1298	−0.2392	−0.2423	0.3758	0.3758	0.3551	0.3511
Transit	−0.6134	−0.5546	−2.9297	−2.6489	1.6760	0.3758	1.5656	0.3511
Walk and bicycle	−0.0217	−0.0812	−1.9582	−2.3293	0.3811	0.3758	0.3560	0.3511

[a]Alternative 1 is the reference alternative when calculating the cross elasticities.

results when travel-related attributes change arising from transport policies, using the empirical results to examine the impact of changes in travel cost and travel time on commuting travel mode and departure time switching. The measure on travel-related attributes which yields changes in commuters' travel decisions can be identified based on the aggregate results.

Most transportation congestion management actions attempt to encourage a change in travel mode choice away form drive alone, or to reduce trip-making during the peak period by directly or indirectly impacting the level-of-service variables (Bhat 1997; Saleh and Farrell 2005; Bhat and Sardesai 2006; Mishra et al. 2014). For example, congestion-pricing relies on the use of monetary disincentive for use of the car mode. Improvements to transit service may involve more frequent service and more extensive route coverage (thereby decreasing transit out-of-vehicle travel time by reducing wait time and walking time), or introduction of additional express services (thereby reducing in-vehicle travel time). In this paper two different groups of scenarios are simulated for the commuting travel mode and departure time decisions, as follows: (1) one group of simulations is carried out assuming that there is an increase in car travel cost during peak period due to the congestion price, and (2) another group of simulations is done assuming that there is a decrease in transit travel time in peak period due to the improved transit service frequency (and schedule reliability).

The sample enumeration method is used to calculate the joint choice probabilities for each commuter based on the estimated parameters presented (Tables 4 and 5). This method is extremely useful for producing aggregate shares for all alternatives. To produce the analysis of the impact of a change in travel-related attributes, the simulated choices following the change can be obtained based on Monte Carlo simulation (K. A. Small, et al., "Uncovering the distribution of motorists' preferences for travel time and reliability: Implications for road pricing," Working Paper, University of California, Irvine, California). The correct predicted probabilities for all alternatives are calculated based on the simulated choice. Predicted shares approximately equal to the actual shares (Table 7). Therefore, the CNL model can be used to accurately represent the choice shares in the study area.

Simulated results for US$1, US$2.5, and US$5 increase in car travel cost during the peak period and for 10, 20, and 30% saving transit travel time are presented (Table 8). As expected, the simulated results show that the choice probability of drive alone during the peak period decrease with the car travel cost increase and transit travel time decrease. However, the changes in car travel cost and

Table 7. Comparisons between Actual Shares and Predicted Shares Using Sample Enumeration

Actual/predicted shares	Drive alone		Shared ride		Transit		Walk and bicycle	
	Peak (%)	Off-peak (%)	Peak (%)	Off-peak (%)	Peak (%)	Off-peak (%)	Peak (%)	Off-peak (%)
Actual shares	54.25	20.99	2.90	1.24	13.57	3.23	2.65	1.19
Predicted shares	54.42	20.49	2.95	1.26	13.71	3.32	2.86	0.97

Note: $N = 18{,}510$.

Table 8. Predicted Shares Based on Different Scenarios

Scenario group	Drive alone Peak (%)	Drive alone Off-peak (%)	Shared ride Peak (%)	Shared ride Off-peak (%)	Transit Peak (%)	Transit Off-peak (%)	Walk and bicycle Peak (%)	Walk and bicycle Off-peak (%)
Base scenario	54.42	20.49	2.95	1.26	13.71	3.32	2.86	0.97
Scenario1, increasing car travel cost during the peak period								
US$1	51.87	21.08	2.75	1.35	15.34	3.44	3.18	0.98
US$2.5	47.39	22.36	2.78	1.15	18.21	3.31	3.73	1.06
US$5	39.36	24.06	2.70	1.50	23.33	3.27	4.64	1.14
Scenario2, decreasing transit travel time during the peak period								
Savings 10%	49.48	20.67	2.91	1.29	18.82	3.06	2.90	0.90
Savings 20%	44.10	20.14	2.57	1.23	25.53	2.76	2.82	0.86
Savings 30%	38.83	19.43	2.55	1.13	31.80	2.65	2.78	0.83

transit travel time affect the choice of the drive alone mode during peak period in different ways.

The effects of travel cost and travel time on the joint choice of travel mode and departure time based on two groups of scenarios are shown (Fig. 6). The vertical axis shows percentage changes in the joint choice shares. Researchers can learn that shift occurs mainly between drive alone during peak hours and transit during peak hours. A little amount shift from drive alone during peak to drive alone during off-peak and walk and bike during peak. A US$5 charge and 30% saving in transit travel time have a similar effect on reducing drive alone in peak hours. However, the share increase of transit use during peak period arising from US$5 charge is far below that arising from 30% saving in transit travel time. It is due to the fact that transit time saving during peak hours attracts more people from drive alone to transit. High driving cost during peak period drags people to change travel mode and departure time together. The simulated results inform us that researchers had better improve the transit services if researchers aim at encouraging the commuters to use transit during peak period and researchers should increase the car travel cost if we aim at reducing traffic congestion during peak period.

As estimated results (Table 4), the work-related variables also play important role in the decision of travel mode and departure time choice. Therefore, employer-based measures are likely to be useful tools in transportation system management, particularly if the measures are more than the simple subsidies for transit users. For example, the policy of allowing flexible work hours and higher single-occupancy vehicle (SOV) parking cost would reduce the peak demand on auto. In addition, conversion of some existing parking area to bicycle and pedestrian facility area to improve

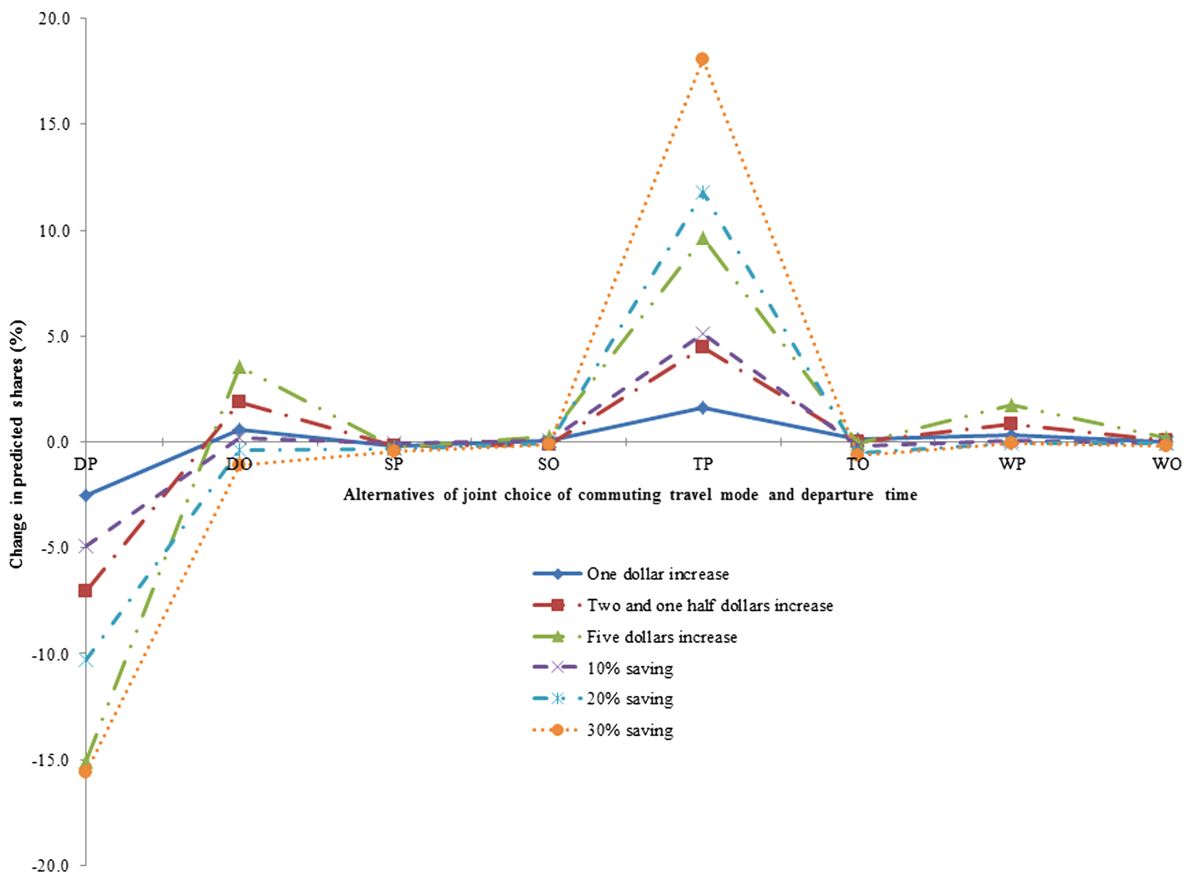

Fig. 6. Changes in predicted shares based on different scenarios; D, S, T, and W mean drive alone, shared ride, transit, and walk and bike, respectively; O and P off-peak and peak, respectively

the environment for nonmotorized trips is likely to stimulate the walking and bicycling trips, especially for the commuters whose residential locations are not far away from their workplace.

The importance of transferability of choice models is gaining popularity as the ability to transfer models from one region to another can help in significant cost and time savings for regions that cannot afford to invest in extensive data-collection and model-development procedures. However, choice models typically involve significant data ranging from socioeconomic, demographic, choice variables, and revealed and stated preference attributes. Literature suggests that simply transferring a model is not a preferable option because no model is sufficiently specified (Galbraith and Hensher 1982), which also means the transferred model will have limitations on reflecting the travel behavior of users. As a result, assessing model transferability only on the basis of the set of model parameters being equal in the two areas is unlikely to be met and additional econometric assessments should be made (Koppelman and Wilmot 1982; Badoe and Miller 1995). Empirical assessment of model transferability requires data and/or information from at least two different spatial regions.

Conclusion

This paper contributes to describe the simultaneous choice of travel mode and departure time by making use of a cross-nested logit structure that allow for the joint representation of interalternative correlation along the both choice dimensions. Moreover, a Monte Carlo simulation for two groups of scenarios arising from transportation policies, congestion-pricing, and improvements to transit service during peak period is undertaken respectively to examine the impact of a change in car travel cost and transit travel time on the travel mode and departure time switching. To conduct a comparative study between the proposed model and traditional model, this paper presents an analysis of the joint choice behavior using three different types of GEV structures, as follows: (1) MNL model, (2) two NL model types, and (3) CNL model.

A combination of data sources collected in the Maryland-Washington region was used to estimate the joint choice models for commuting trips. In terms of model performance, the CNL significantly outperforms other models. Meanwhile, the CNL model provides great benefits in capturing the correlation along all the dimensions. Therefore, the CNL model is seen as a valuable tool in analysis of the joint choice of travel mode and departure time. Similar to most previous studies, the analysis shows that household characteristics, individual characteristics, work-related characteristics, and travel-related characteristics play important roles in the joint choice of commuting travel mode and departure time. Comparing the values of dissimilarity parameters of different nests, the mean value of dissimilarity parameter for commuting travel mode is higher than departure time, indicating that in general the commuters are more likely to shift their commuting travel mode than their departure time.

Analysis of direct and cross elasticities suggests that commuters by transit are more sensitive to the travel-related attributes change than commuters by car. Commuters are more sensitive to the changes in travel time than that of travel cost except for the commuters by drive alone. Changes in travel cost and travel time for the commuters by drive alone during the peak period have the greatest effects on the probability choice of using transit during peak period. Two groups of simulations are conducted for increasing car travel cost and decreasing transit travel time during peak period to measure the aggregate choice shares, using the sample enumeration method. Significant choice switching effects are found and the simulated results suggest that transport policies aimed at increasing transit ridership during the peak period by improving transit services have better effects than increasing car travel cost. Similarly, reducing traffic congestion during peak period by increasing car travel cost resulted in better transportation performance than improving transit services. If the two policies are integrated the traffic problems can be alleviated more effectively.

Charging for the use of the road has been seen by researchers as a solution to traffic problems in the city. There are more potential applications of the framework presented in this paper, such as the impact study of a hypothetical road user charging scheme, and the effect analysis of parking charges, transit subsidies, and flexible work hours on a traveler's behavior. Further studies can be identified, which not only includes the applications of the framework based on the CNL model but also includes the use of advanced model structures, allowing jointly for cross-nesting and random taste heterogeneity to examine commuter travel behavior.

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