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Cross-nested logit model for the joint choice of residential location, travel mode, and departure time

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A B S T R A C T

This paper aims to describe the joint choice of residential location, travel mode, and departure time. First, based on random utility maximization theory, the Cross-Nested Logit model and traditional NL models are formulated respectively. House price, travel time, travel cost, and factors depicting the individual socio-economic characteristics are defined as exogenous variables, and the model choice sets are the combination of residential location subset, departure time subset, and travel mode choice subset. Second, using Beijing traffic survey data of 2005, the model parameters are estimated, and the direct and cross elasticity are calculated to analyze the change of alternatives probability brought by factors variation. Estimation results show the Cross-Nested Logit model outperforms the three kinds of NL model. It is also found by estimation results that decision makers will change first their departure times, then their travel modes, and finally their residential locations, when exogenous variables alter. Moreover, elasticity analysis results suggest that, for long-distance commuting, it is difficult to decrease car travels even if additional charges are imposed on car users. The effect on choice probability by variations in travel time of other travel mode can be considered as negligible for alternatives within 5 km commuting distance, and this effect are greatest for alternatives between 10 and 20 km commuting distance. These findings have important implications for transport demand management and residence planning.

Introduction

There is a strong correlation between commuting travel behavior and residential neighborhood type. Brown (1986) suggested that travel behavior and residential location are not independent goods and, therefore, demand for either good needs to be modeled considering the other. Travel behavior and residential location have a profound and lasting impact on urban transport pattern, land use, and urban form change. As a consequence, the study of them has attracted considerable attention from researchers in several disciplines, including transportation (see Khattak & Rodriguez, 2005; Lerman, 1976; Vega & Reynolds-Feighan, 2009), geography (see Waddell, 1996), and urban economics (see Brown, 1986; Clark & Onaka, 1985; Kim, Pagliara, & Preston, 2005).

Travel behavior includes a series of choices, among which travel mode choice and departure time are so important that they usually influence the efficiency of the whole transportation system, especially during the peak period. As Hess, Daly, Rohr, and Hyman (2007) and Ozbay and Yanmaz-Tuzel (2007) indicated, a strong relation exits between mode choice and departure time choice, and people often make the two choices simultaneously.

Modeling the choices of residential location, travel mode, and departure time, will give us an insight into these three choice dimensions, and the interactions between them, and also be seen as a prerequisite to the process of urban planning, transportation planning and transportation demand management.

However, studies considering the three choice dimensions are rare, which partly due to the limits of the existing choice model.

Discrete choice modeling based on the random utility maximization (RUM) hypothesis is an effective tool to analyze the choice problem of residential location and travel behavior. Within the RUM-based models, the Multinomial logit (MNL) model (MacFadden, 1973) has been the most widely used structure due to its simple mathematical structure and ease of estimation (see Albert, 1993; Gabriel & Rosenthal, 1989; Guo & Bhat, 2001; Wafaa, 2005). However, MNL imposes the restriction that the distribution of the random error terms is independent and identical over alternatives. This restriction leads to the independence of irrelevant

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alternatives property which causes the cross-elasticities between all pairs of alternatives to be identical (Wen & Koppelman, 2001). This representation of choice behavior produces biased estimates and incorrect predictions in cases that violate these strict conditions.

The best known relaxation of the MNL model is the nested logit (NL) model (Williams, 1977), which divides the choice-set into hierarchical and mutually exclusive nests of alternatives, allowing correlation across alternatives sharing a nest. However, the NL model is not without its limitations. In analyzing the joint choice problem of residential location, travel mode, and departure time, three possible one-level nesting structures arise, either of which can only accommodate correlation along at most one of the three dimensions. For example, the first structure uses nesting by residential location, such that in the case of R residential locations, each elementary alternative (triplet of residential location, travel mode, and departure time) is assigned to exactly one residential location nest, hence acknowledging correlation in the unobserved utility terms for alternatives sharing the same residential location.

An important development in the field of discrete choice modeling was the introduction of the generalized extra value (GEV) class of models within the RUM framework (Ben-Akiva & Francois, 1983; McFadden, 1978). The GEV class of models allows flexible substitution patterns between different choice alternatives, while maintaining a simple closed-form structure for the choice probabilities. Several models have been developed within the GEV class, as recently discussed by Bekhor and Prashker (2008), Daly and Bierlaire (2006), Koppelman and Sethi (2008), and Sener, Pendyala, and Bhat (2011). Although the GEV class have been popularly applied in the filed of spatial choice, the use in the joint choice of residential location and travel behavior is very limited.

The current paper presents a new cross-nested model structure within the theoretical framework of GEV class to describe and quantify the joint choice behavior of residential location, travel mode, and departure time. The sample is mainly drawn from Beijing traffic survey of 2005. Different from the existing studies, the key feature of the cross-nested model proposed by this paper is that it accommodates correlation among all three dimensions of residential location, travel mode, and departure time.

The reminder of this paper is organized as follows. The next section reviews the main contributions to the choice of residential location, travel mode, and departure time, and the progress made on the discrete choice model. The third section presents a detailed formulation of the cross-nested model proposed in this paper. The fourth section describes the data set used for the model while the fifth section presents detailed model estimation results. The final section outlines the main conclusions and discusses briefly the policy implications of the analysis presented.

Existing research

There is a substantial and rich body of literature related to the choice of residential location and travel behavior. However, many studies have focused only on one dimension choice, on residential location (for example, Bhat & Guo, 2004; Gabriel & Rosenthal, 1989; MacFadden, 1978; Sener et al., 2011; Weisbrod, Lerman, & Ben-Akiva, 1980) or on travel behavior (for example, Albert, 1993; Bhat, 1998; De Jong, Daly, Pieters, Vellay, & Hofman, 2003; Wafaa, 2005).

The simultaneous choice of residential location and travel behavior (especially travel mode) is supported by early theoretical contributions that acknowledged the need for integrating both decisions in transport and land use models (Brown, 1986; Leroy & Sonstelie, 1983). Brown (1986) suggested that travel behavior and residential location are not independent goods and, therefore, demand for either good needs to be modeled considering the other. Desalvo and Huq (2005) suggested that high income individuals use faster modes and travel short distances to work and those commuting long-distances, use faster modes and experience lower marginal commuting costs. Vega and Reynolds-Feighan (2009) analyzed the simultaneous choice of residential location and travel-to-work mode and explored the effects of car travel variables on re-location and travel-to-work mode switching in the Dublin region.

As compared to mode choice, activity scheduling is often greatly simplified or ignored in urban travel models (TRB, 2007; Vovsha, Davidson, & Donnelly, 2005), though it represents an important component of travel behavior. Over the past several years, activity scheduling has received more attention, sine planning and policy questions have shifted toward congestion and demand management. It is essential to combine time choice model with residential location model to get more valuable and comprehensive findings guiding the work of urban planning and traffic management.

During the last three decades, most of the research presented in the literature dealing with the simultaneous choice of residential location and travel behavior has applied random utility maximization (RUM) theory and discrete choice modeling to empirically estimate joint probability choice models. McFadden's (1973) MNL model represents the most familiar and straightforward of these models. However, the MNL model suffers from the independence of irrelevant alternatives (IIA) property, which results in equivalent cross-elasticities across each pair of choice alternatives.

The nested logit model (Daly & Zachary, 1979; MacFadden, 1978; Williams, 1977) relaxes this assumption, allowing correlations to emerge across similar alternatives. However, choice alternatives in common nests still retain the IIA property (Lemp, Kockelman, & Damien, 2010).

In recent decades, the GEV class of models (MacFadden, 1978) has become a mainstay in travel behavior analysis of discrete choice behavior. The GEV models allow the random components of alternatives to be correlated, while maintaining the assumption that they are identically distributed (i.e., identical, non-independent, random components). In GEV models, the marginal distribution of the individual error terms is univariate extreme value, and different assumptions about the cumulative distribution of the vector of error terms lead to different model forms.

MNL model and NL model can be derived from GEV model. Other type of GEV models includes the paired combinatorial logit (PCL) model (Chu, 1989; Koppelman & Wen, 2003), which allocates each alternative in equal proportions to a nest with each other alternative and estimates a logsum (dissimilarity parameter) for each nest; the cress-nested logit (CNL) model, which allocates a fraction of each alternative to a set of nests with equal (Vovsha, 1997) or unequal logsum parameters (Papola, 2004; Vega & Reynolds-Feighan, 2009; Wen & Koppelman, 2001) across nests; the ordered generalized extreme value (OGEV) model (Small, 1987), which allocates alternatives to nests based on their proximity in an ordered set.

Model specification

In this section, based on the previous studies of Bierlaire (2006) and Hess and Polak (2006), a new cross-nested model structure within the theoretical framework of GEV class, was presented to investigate the joint choice of residential location, travel mode, and departure time. This model allows for a flexible correlation of the error terms and, thus can describe the correlation between the three choice dimensions of residential location, travel mode and departure time.

Model structure

The model choice set $\boldsymbol{C}$ is composed by three sub-sets, which are residential location sub-set $\boldsymbol{r}$, travel mode sub-set $\boldsymbol{md}$, and departure time sub-set $\boldsymbol{t}$. In contrast to some other studies of residential location and travel behavior, in this paper the location of employment is not part of the choice set. Job location is assumed to be exogenous. Travel time and the travel cost are computed as a function of the commuting distance, that is the distance between residential and employment location. The case study in this paper will mainly concern the main urban area of Beijing which is a classic example of a monocentric city. So we also assumed that all the jobs are located within a radius of 5 km from the CBD. Therefore, the residential location choice set is based on a series of concentric road-distance rings around CBD.

For each individual, the residential location sub-set $\boldsymbol{r}$ has 4 alternatives, i.e. 4 concentric road-distance rings around the CBD which radius are within 5 km, 5–10 km, 10–15 km, and over 15 km. The travel mode sub-set $\boldsymbol{md}$ consists of 3 modes of travel-to-work: bicycle, public transport, and private car. The departure time sub-set $\boldsymbol{t}$ has 3 alternatives: before AM peak (5:30–6:59), AM peak (7:00–8:29), and after AM peak (8:30–9:59). Therefore, the model choice set $\boldsymbol{C} = c_1,\ldots,c_I$ is defined as the joint choice set of $\boldsymbol{r} = 4$、$\boldsymbol{md} = 3$和$\boldsymbol{t} = 3$, which creates a set of I = 4*3*3 = 36 alternatives for each individual.

To compare the CNL model and other models, three different structures of NL model were estimated first. As mentioned above, NL model allows the correlation between alternatives sharing a nest, while alternatives in different nests remain independent. In the analysis of the joint choice of residential location, travel mode, and departure time, three possible one-level nesting structure arise. The first example uses nesting by residential location, such that in the case of 4 residential locations, each elementary alternative (triplet of residential location, travel mode, and departure time) is assigned to exactly one residential location nest. The structure is shown as Fig. 1, where $\mu_R (0 < \mu_R \le 1)$ is the dissimilarity parameter capturing the correlation between alternatives sharing the nest of residential location R. The correlation between alternatives sharing the same nest decreases as the dissimilarity parameter increases. As expected, the correlation between alternatives in the nest R is zero when $\mu_R = 1$. The NL model will collapse to MNL model, if all dissimilarity parameters are equal to 1.

The NL model shown as Fig. 1 can only accommodate correlation along one of three dimensions. The NL model can be extended to allow for multi-level nesting; this can be exploited to allow for correlation along multiple choice dimensions. The main problem with the use of multi-level nesting structures for the analysis of the three-dimensional choice process, as Hess and Polak (2006) indicated, is that this structure can only accommodate correlation along at most two of the three dimensions.

The deficiencies of NL model are one of the motivations for the efforts made in this paper to use cross-nesting structures. In CNL model, the allocation of alternatives to nests is fuzzy, with alternative i belonging to nest m with proportion α_{im} $(0 \le \alpha_{im} \le 1)$, where the allocation parameters for an alternative sum to 1 over nests, i.e. for alternative i, there is $\sum_m \alpha_{im} = 1$. The CNL model for the joint choice of residential location, travel mode, and departure time is shown in Fig. 2. Again, only a subset of the composite nests and of the elementary alternatives is shown, and the allocation parameters are not represented in this figure.

In this model, each elementary alternative belongs to exactly one residential location nest, one travel mode nest, and one departure time nest, and the model is able to jointly represent the correlations along the three dimensions.

Utility function

Under the RUM framework, a decision maker n facing a choice among I alternatives obtains a certain level of utility U_{jn} $(j = 1,2,\ldots I)$ from selecting alternative c_j ($c_j \in \mathbf{C}$). The decision maker will select alternative c_i if and only if the utility provided by alternative c_i is the largest utility, i. e. $U_{in} > U_{jn}$ $(\forall j \neq i)$.

U_{in} is a stochastic variable, modeled as the sum of a systematic component and a random component. The systematic component V_{in} is a function of the attributes of the alternatives and of the characteristics of the decision maker, while the random component ε_{in} captures all other factors unobserved by the researcher:

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

The systematic utility function has several expression forms, and linear function, the most widely used utility function structure, is adopted in this paper, shown as follows:

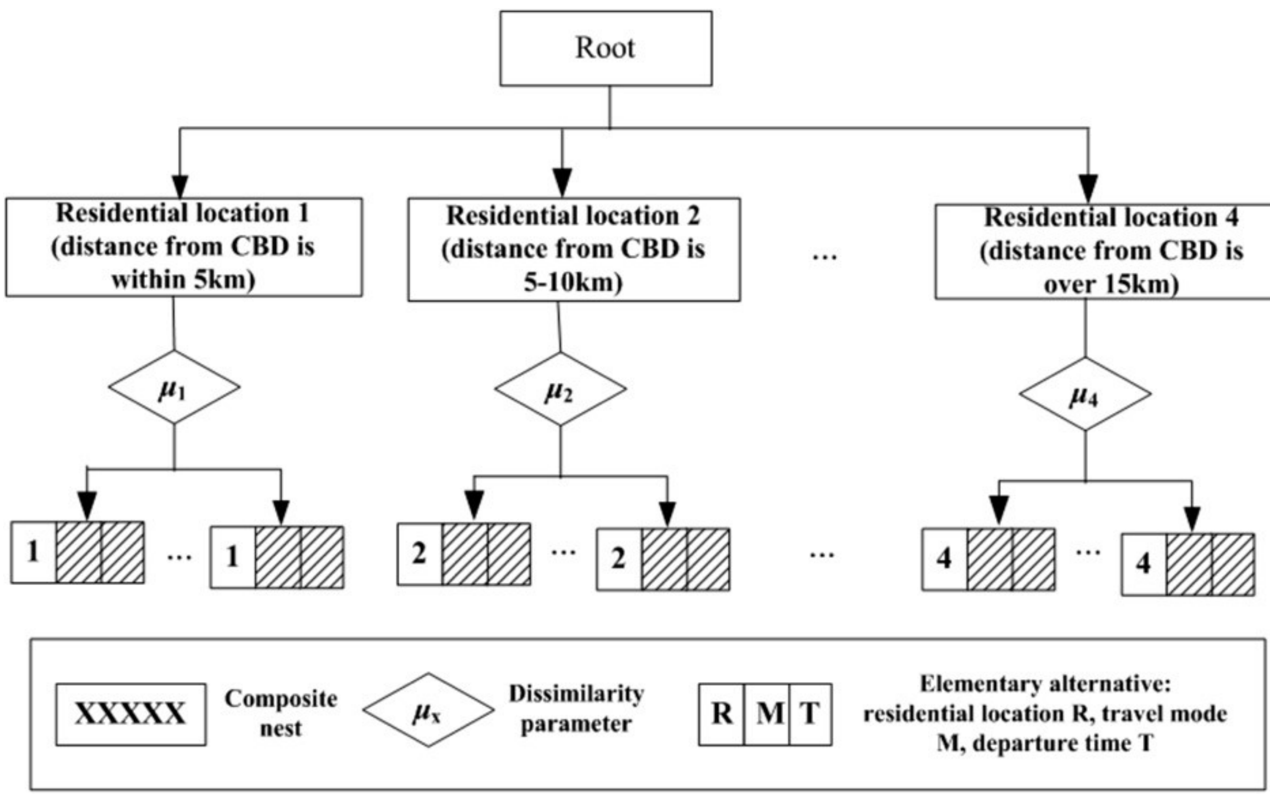

Fig. 1. Structure of NL model for the joint choice of residential location, travel mode, and departure time (using nesting by residential location).

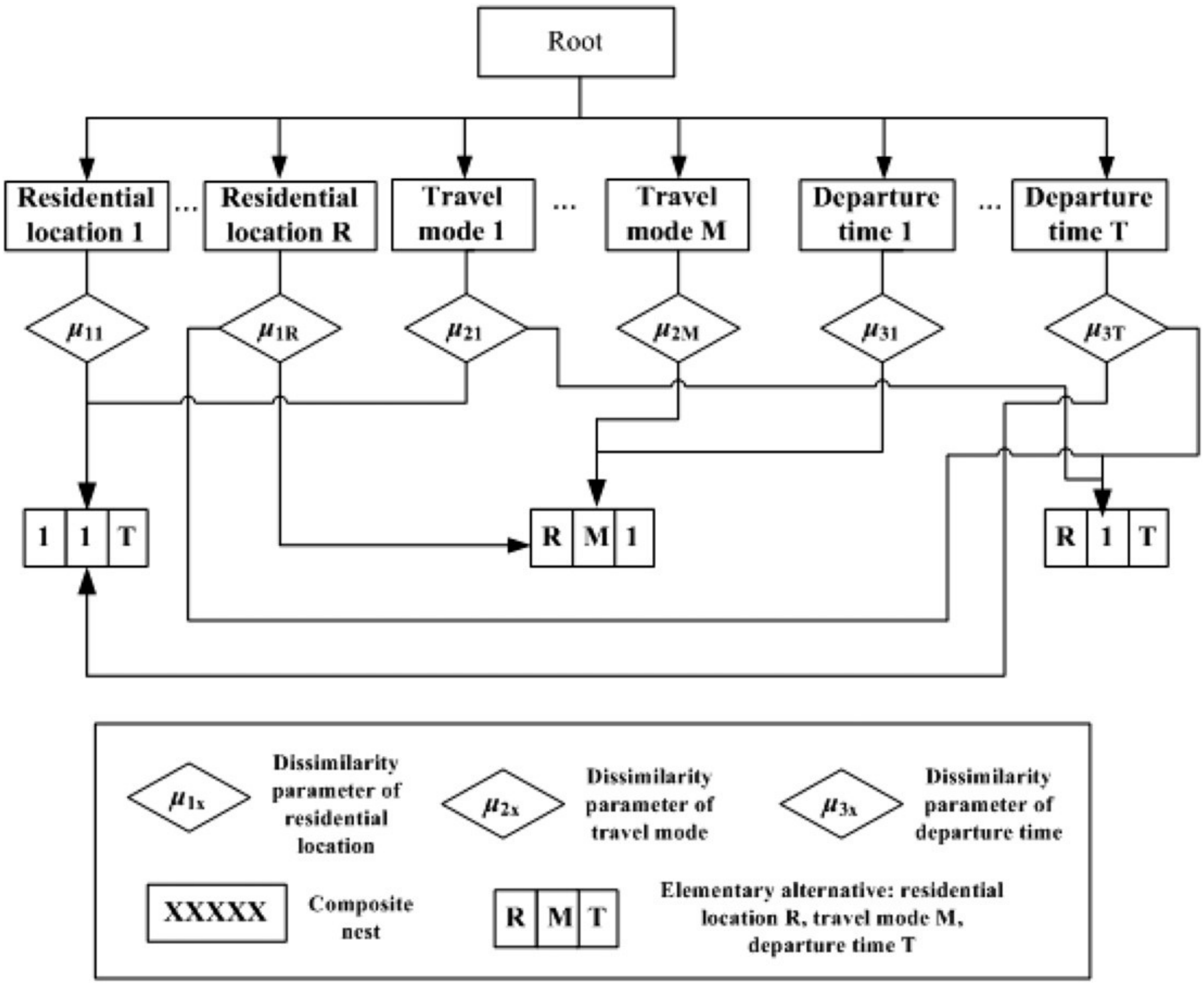

Fig. 2. Structure of CNL model for the joint choice of residential location, travel mode, and departure time.

$$V_{in} = \sum_{l=1}^{L} \theta_l X_{inl} \tag{2}$$

WhereX_{inl} is the lth variable of alternative c_i for the decision maker n, θ_l the unknown parameter to be estimated. (Note: For convenience, letter 'n' representing the decision maker is omitted in all expressions described below.)

Referring to the studies made by Hess et al. (2007) and Vega and Reynolds-Feighan (2009), the systematic utilities for each of the alternatives are a function of their travel and land use attributes, i.e. travel time TT, travel cost TC, housing price HP, and the socio-economic characteristics of the decision maker. Table 1 provides descriptions for the entire set of independent variables used in the modeling process.

Choice probability

One of the advantages of GEV models is they have closed-form expressions for the choice probabilities. As one member of the GEV class of models, the CNL model also has this property.

Let ε_i represent the random element of utility for elementary alternative c_i, and the distribution for each ε_i is a typeIextreme value (or Gumbel), thus the following function represents a cumulative extreme-value distribution

$$F(\varepsilon_1, \varepsilon_1, \cdots \varepsilon_I) = \exp\left\{ -\sum_m \left(\sum_{i \in N_m} \left(\alpha_{im} e^{-\varepsilon_i} \right)^{1/\mu_m} \right)^{\mu_m} \right\} \tag{3}$$

Table 1
Variables used in the residential location, travel mode, and departure time choice model.

Variable name		Description
Housing price		Continuous variable: average housing price in the traffic analysis zone (thousand RMB/m^2)
Travel time		Continuous variable: total time of a trip (min)
Total travel cost		Continuous variable: travel cost for car calculated by oil fees proportional to travel distance; travel cost for public transit calculated by ticket price
Age	Age1	Dummy variable indicating whether the individual is below 25 years old
	Age2 (Reference variable)	Dummy variable indicating whether the individual is between 26 and 55 years old
	Age3	Dummy variable indicating whether the individual is over 56 years old
Working time flexibility		Dummy variable indicating whether the individual's working time is flexible
Income	Income1 (Reference variable)	Dummy variable indicating whether the individual's monthly income is below 5000 RMB
	Income2	Dummy variable indicating whether the individual's monthly income is between 5001 and 10,000 RMB
	Income3	Dummy variable indicating whether the individual's monthly income is over 10,001 RMB
Car ownership		Dummy variable indicating whether the individual owns a car

Note: In calculating car travel cost, oil consumption is averaged to be 10 l per 100 km, and oil price 6.5 RMB per liter.

Based on the GEV theory (MacFadden, 1978; Wen & Koppelman, 2001), the probability of choosing the alternative c_i in the CNL model is as follows:

$$\begin{aligned} P_i &= \sum_m P_m \cdot P_{i|m} \\ &= \sum_m \left(\frac{\left(\sum_{i\in N_m} \left(\alpha_{im} e^{V_i}\right)^{1/\mu_m}\right)^{\mu_m}}{\sum_m \left(\sum_{i\in N_m} \left(\alpha_{im} e^{V_i}\right)^{1/\mu_m}\right)^{\mu_m}} \cdot \frac{\left(\alpha_{im} e^{V_i}\right)^{1/\mu_m}}{\sum_{i\in N_m} \left(e^{V_i}\right)^{1/\mu_m}} \right) \end{aligned} \tag{4}$$

In the above formulation, α_{im} is the allocation parameter that characterized the portion of alternative c_i assigned to nest m, with $0 \le \alpha_{im} \le 1$ for all i and m, and $\sum_m \alpha_{im} = 1$ for all i. N_m is the set of all alternatives included in nest m. $\mu_m (0 < \mu_m \le 1)$ is the logsum or dissimilarity parameter for nest m capturing the correlation between alternatives in nest m. The correlation between two alternatives in nest m increases as μ_m gets closer to zero, while decreases as μ_m approaches 1.

The unknown parameters in Eq. (4) include allocation parameter α_{im}, dissimilarity parameter μ_m, and the coefficients θ_l in the systematic utility function V_i. The parameter estimating approach is maximum likelihood method (Bierlaire, 2006).

Data and descriptive analysis

Data description

Beijing, the capital city of China, is selected for the case study for its leading roles in China's urban development, the representative of its socio-spatial structure and its deteriorating traffic condition. The area selected for this study covers 8 out of 18 administrative districts of Beijing, Dongcheng, Xicheng, Chongwen, Xuanwu, Haidian, Chaoyang, Fengtai, and Shijingshan, as are shown in Fig. 3, which constitute the main urban area of Beijing. These 8 central administrative districts are divided into 64 traffic analysis zones (TAZ) illustrated in Fig. 4.

The primary data used in this paper is a sample extracted from the 2005 Beijing Comprehensive Travel Survey (BCTS) carried by Beijing Transportation Research Center (BTRC). The survey data set includes detailed information about individual and household socio-demographic, travel mode to workplace, travel time, travel distance. The data used in this paper consisted of 10,650 individuals coming from 8900 households. All respondents are above 18 years old. Property prices data come from 2005 Real Estate Market Monthly Reports (REMMR)[1] of China key cities.

As mentioned above, all analyses are based on the assumption that all jobs are located within a radius of 5 km from the CBD. In this paper, Tiananmen Square, the center of Beijing city, is regarded as the location of CBD. Four concentric rings constitute the spatial choice set at road-distances defined at less than 5 km, 5–10 km, 10–15 km and more than 15 km from the central employment location. Fig. 5 shows the GIS network analysis carried out for central employment location in the main urban area of Beijing city.

Descriptive analysis

We conduct some descriptive analyses to generate intuitive findings regarding the association between socio-economic variables and one's preference of commuting distance, travel mode, and departure time.

Table 2 presents the socio-economic characteristics of the sample stratified by the types of residential location. As shown in the table, the socio-economic profiles of respondents from the four different types of residential location are quite different. Older individuals are found to be more likely to live closer to the CBD than younger individuals. This can be seen as an income-related effect given the existent declining rates in housing price as distance to the CBD increases. It is worthwhile to note that the percentage of high-income group in the areas within 5 km from the CBD is rather small. This result seems contrary to what standard economic theory would predict. One would expect that those who live near the CBD usually have higher incomes so that they can afford higher housing price there. However, this result is explained from a further analysis of the built environment of Beijing. In the city center of Beijing one usually finds traditional residential area, marked by low and crowded houses, narrow paths and poor living conditions. Most of those private housings were built before 1949, and was confiscated by the socialist government and distributed to individuals who now constitute the most important part of the 'original inhabitants'. Most of original inhabitants have generally low income and mobility. Such phenomenon can also be found in other major Chinese cities.

Table 3 presents modal split of different population groups. As shown in this table, modal splits of different population groups are different. As expected, older and younger people, people whose working time is inflexible, low-income workers, are found to be more likely to commute by public transit. Almost 70% of car owners travel by car, indicating private car becomes the main travel mode of car owners.

Table 4 presents departure times of different population groups. As expected, car owners, and people whose working time are inflexible, are more likely to depart before AM peak period to avoid traffic jams.

Modeling results

While the results of descriptive analyses have shown meaningful variations in residential location and travel behavior between different population groups in Beijing, one's possibility to choose each elementary alternative (combinations of residential location, travel mode, and departure time) remain unknown, giving the individual's socio-economic characteristics and other independent variables.

In this section, CNL model and three kinds of NL model are estimated using the freely available optimization package Biogeme (Bierlaire, 2003), and disaggregate direct and cross elasticities with respect to travel time and travel cost are calculated. Given the independent variables, we are able to calculate one's probability of choosing each elementary alternative by the models, and are able to analyze the change of alternatives choosing probability brought by some variables' variation through elasticities analysis.

Estimation results

According to Fig. 2, there are a total number of 10 nests (4 residential locations, 3 travel modes, and 3 departure times) and 36 elementary alternatives in the CNL model, which leads to 10 dissimilarity parameters and a total of 108 allocation parameters (36 along each dimension). Given the condition that the allocation parameters for each alternative sum to 1, a total of 72 need to be identified. This will lead to a very expensive estimation process, and can be seen to result in an over-parameterized model. Referring to previous studies (Hess, 2004; Hess & Polak, 2006; Papola, 2004), the decision was taken to constrain all non-zero allocation parameters to a value of 1/3.

[1] Details about the monthly reports can be found in http://219.142.101.174/mrwebnew/default.aspx.

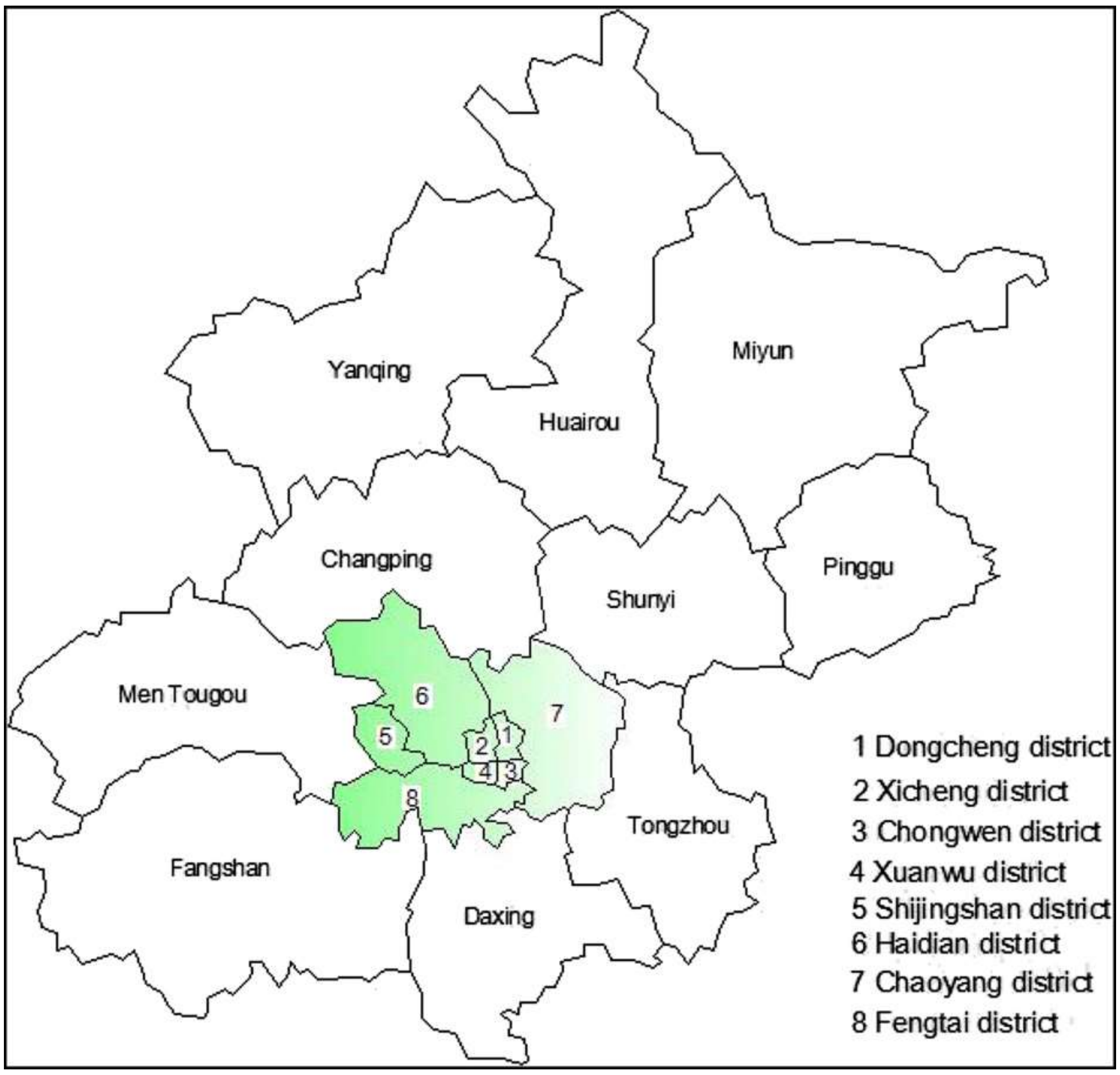

Fig. 3. All 18 administrative districts of Beijing (The colored section is the 8 central districts which is the study region of this paper).

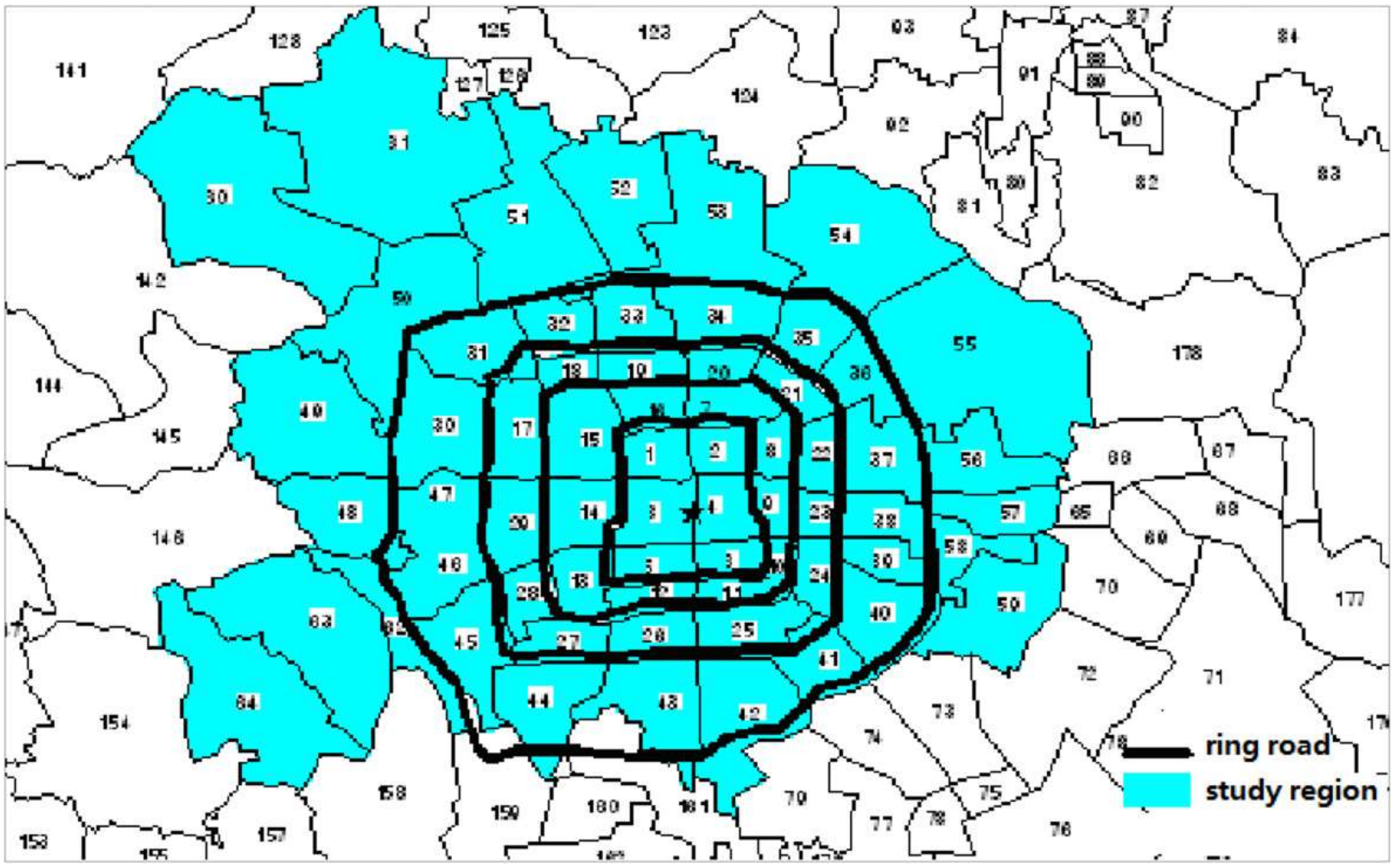

Fig. 4. Study region covering 64 TAZs.

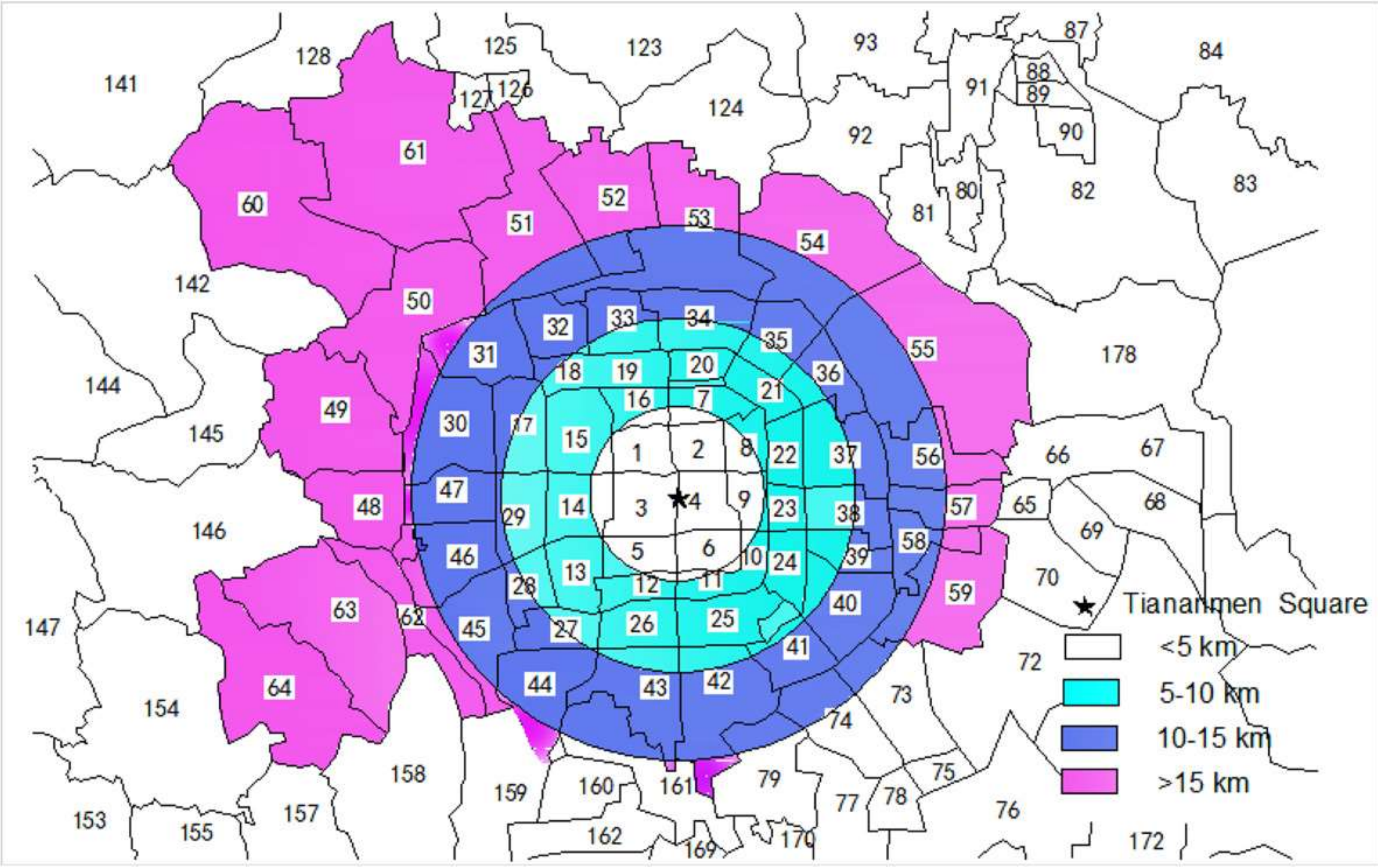

Fig. 5. Service areas computed for the monocentric city.

Three kinds of NL model estimation results and the CNL model estimation results are respectively reported in Tables 5 and 6.

With the use of fixed allocation parameters, nested likelihood-ratio tests cannot be used. The models can however still be compared, using the adjusted ρ^2 statistic, which takes into account the cost of a model in terms of the number of parameters. From the values reported in Tables 5 and 6, it can be seen that the CNL model outperforms any of the NL models, which suggests that the combined analysis of the correlation structure along the three dimensions can offer great benefits.

Among the three kinds of NL models, the best-well fitting model is the one using nesting by residential location, while the performance of the model using nesting departure time is rather disappointing.

In terms of the actual estimation results, the CNL model and the NL models are relatively similar. As expected, coefficients for housing price, travel time, and travel cost have negative signs, and are statistically significant at levels of confidence well above the usual 95% limit. While aged below 25 has a negative impact on the systematic utility of a certain alternative, owning a car and monthly income of over 10,000 RMB have positive effects.

In terms of correlation, the CNL model has lower dissimilarity parameters (and hence high correlation) along all three dimensions of choice, compared with the NL models. Moreover, the significant levels of the dissimilarity parameters in the CNL model are also higher than in the all three NL models, indicating the superiority of the CNL model in depicting the correlation between the elementary alternatives.

From the values of dissimilarity parameters in the CNL model, it can be seen the dissimilarity parameters along the residential location dimension are the smallest, which means the alternatives in the nest of residential location have high correlations (i.e. high substitutability). When the utility variables alter, for example, travel time increasing, the individuals are willing to change their departure time and travel mode rather than their residential location. The dissimilarity parameters along the departure time dimension are the biggest, and have lower significant levels, showing that the alternative in the nest of departure time have low substitutability. When the utility variables alter, the individuals will change their departure time fist. To compare the values of dissimilarity parameters in the three NL model, a similar conclusion yields.

Table 2
Sample profiles stratified by the types of residential location

Frequencies (%)		Residential location (distance from the CBD)			
		Within 5 km	5–10 km	10–15 km	Over 15 km
Age	18–25	0.48	4.40	5.27	12.18
	26–55	79.50	79.09	90.12	85.26
	>56	20.03	16.50	4.61	2.56
Working time flexibility	Flexible	33.91	31.75	40.09	59.35
	Inflexible	66.09	68.25	59.91	40.65
Monthly income (RMB)	<5000	39.12	20.29	24.58	55.72
	5001–10,000	58.13	67.30	70.10	43.34
	>10,001	2.75	12.41	5.32	0.94
Car ownership		14.20	42.77	45.02	37.81

Table 3
Modal splits of different population groups.

Frequencies (%)		Travel mode		
		Bicycle	Public transit	Car
Age	18–25	38.04	44.71	17.25
	26–55	22.15	35.59	42.26
	>56	24.43	36.63	38.94
Working time flexibility	Flexible	30.57	29.29	40.14
	Inflexible	24.18	47.82	30.00
Monthly income (RMB)	<5000	37.27	51.95	10.78
	5001–10,000	28.12	37.53	34.35
	>10,001	19.71	29.87	50.42
Car ownership		10.71	20.52	68.77

Table 4
Departure times of different population groups.

Frequencies (%)		Travel mode		
		Before AM peak	AM peak	After AM peak
Age	18–25	35.74	42.59	21.67
	26–55	20.27	52.70	27.03
	>56	12.50	49.12	38.38
Working time flexibility	Flexible	15.37	36.85	47.78
	Inflexible	34.20	58.45	7.35
Monthly income (RMB)	<5000	25.19	49.02	25.80
	5001–10,000	14.61	60.28	25.11
	>10,001	31.36	51.35	30.08
Car ownership		39.61	40.81	19.57

Direct and cross elasticities analysis

Direct elasticities represent the variation in an individual's choice probability due to a 1% change in one of the attributes affecting that alternative; similarly, cross elasticities are the variation in the choice probability due to a 1% change in an attribute affecting another alternative. According to Wen and Kopplemen (2001), the disaggregate direct and cross elasticities with respect to the lth variable are formulated as follows.

$$\mathrm{DE}_l = \frac{\sum_m P_m P_{i|m}\left[(1-P_i) + (1/\mu_m - 1)\left(1 - P_{i|m}\right)\right]}{P_i}\theta_l X_{il} \tag{5}$$

$$\mathrm{CE}_l = -\left[P_i + \frac{\sum_m (1/\mu_m - 1) P_m P_{i|m} P_{j|m}}{P_j}\right]\theta_l X_{il} \tag{6}$$

In CNL model, given alternative i, the cross elasticity of the effect of alternative i on alternative j is influenced by the choice probability of alternative j, which means the change of variables of alternative i has different influence on different alternative j. It is quite different from that in MNL model. The cross elasticity expression of MNL model is $-P_i\theta_l X_{il}$, showing that the effects of alternative i on any alternative j are identical, determined by the IIA property.

The elasticities in the following respond to a change in a change in travel time and cost of the alternative travel mode within the same distance ring and departure period. For example, if alternative a corresponds to residential location at less than 5 km from the work place, traveling by car, departing at AM peak, the car travel time cross elasticity for alternative a shows the change in the choice probability of alternative a, due to a 1% change in travel time for public transport at that same distance to work and the same departure time. The direct and cross elasticities computing results are presented in Table 7.

Direct time elasticities for car travel increase the greater the distance to work, meaning that car travelers commuting long distance have high sensitivity to travel time. However, direct cost elasticities for car travel changed in the opposite direction, i.e. car commuters' sensitivity to travel cost decrease with the distance to work increase. Travel costs affect car and public transport probabilities in a different way, with larger elasticities for public transit than for car choice, which shows public transit travelers are more sensitive to travel cost than car users. In addition, with regard to the elasticities for each departure time period, the time and cost elasticities for AM peak is larger than for other periods.

Cross elasticities are so small for alternatives within 5 km commuting distance that their effect on choice probability can be considered as negligible. This implies that the effect of increasing car travel times within 5 km commuting distance has practically null effects on the probability choice of public transit and vice-versa. Cross time elasticities are largest for alternatives within 10–15 km commuting distance, which suggests that variations in car (public transit) travel times or costs are expected to have a relatively large effect on public transit (car) choice probabilities.

Table 5
Estimation results for the three kinds of NL model.

Model type	NL model using nesting by departure time		NL model using nesting by travel mode		NL model using nesting by residential location	
Variables	Parameter	*t*-Stat	Parameter	*t*-Stat	Parameter	*t*-Stat
Housing price	−1.102[a]	−11.1	−0.596[a]	−8.7	−0.475[a]	−7.9
Travel time	−0.0413[a]	−10.6	−0.0260[a]	−9.5	−0.0235[a]	−9.3
Travel cost	−0.0572[a]	−9.5	−0.0309[a]	−7.1	−0.0314[a]	−7.6
Working time flexibility	−0.0133[a]	−5.8	−0.0067[a]	−4.9	−0.0046[a]	−5.5
Age1	−0.0080[a]	−3.7	−0.104[a]	−3.7	−0.0093[a]	−3.2
Age3	−0.0035	−1.7	−0.0029	−1.7	−0.0066[a]	−2.5
Income2	0.0394[a]	2.8	0.0202	1.8	0.0157	1.4
Income3	0.0009[a]	2.5	0.0003	1.9	0.0002[a]	2.7
Car ownership	0.182[a]	9.1	0.125[a]	7.8	0.0738[a]	5.0
Dissimilarity parameter (μ)					Distance to work <5 km	
	Before AM peak		Bicycle		0.74	1.5
	0.79	1.0	0.88	1.0	Distance to work 5–10 km	
	AM peak		Public transit		0.66	1.9
	0.92	0.5	0.78	0.6	Distance to work 10–15 km	
	After AM peak		Car		0.59[a]	3.2
	0.89	0.4	0.65[a]	3.1	Distance to work > 15 km	
					0.51[a]	2.8
Adjusted ρ^2	0.2827		0.3235		0.3441	
Number of observations	10,650		10,650		10,650	

[a] Indicates a parameter is significantly different from 0 (or 1 in the case of the dissimilarity parameter) at the 95% confidence level.

Table 6
Estimation results for the CNL model.

Variables	Parameter	*t*-stat
Housing price	−0.332[a]	−14.5
Travel time	−0.0100[a]	−16.3
Travel cost	−0.0225[a]	−10.1
Working time flexibility	−0.0127[a]	−7.6
Age1	−0.0093[a]	−4.7
Age3	−0.0002	−1.5
Income2	0.0109	1.9
Income3	0.0011[a]	3.8
Car ownership	0.0945[a]	10.4
Adjusted ρ^2	0.3900	
Number of observations	10,650	
Dissimilarity parameter μ		
Before AM peak	0.67[b]	2.8
AM peak	0.83	1.5
After AM peak	0.76	1.9
Bicycle	0.70	1.2
Public transit	0.44[b]	4.6
Car	0.30[b]	4.8
Distance to work<5 km	0.11[b]	8.3
Distance to work 5–10 km	0.23[b]	5.4
Distance to work 10–15 km	0.16[b]	7.7
Distance to work>15 km	0.05[b]	11.4

[a] Indicates a parameter is significantly different from 0 at the 95% confidence level.
[b] indicates a parameter is significantly different from 1 at the 95% confidence level.

Summary and conclusions

The relationship between residential location and commuting pattern can be seen as the heart of activity-travel demand

Table 7
Direct and cross elasticities for a random individual.

Distance to work	Travel mode	Before AM peak				AM peak				After AM peak			
		Travel time elasticity		Travel cost elasticity		Travel time elasticity		Travel cost elasticity		Travel time elasticity		Travel cost elasticity	
		DE	CE	DE	CE	DE	CE	DE	CE	DE	CE	DE	CE
<5 km	Bicycle	−0.017	–	−0.077	–	−0.018	–	−0.096	–	−0.045	–	−0.080	–
	Public transit	−0.090	0.005	−0.052	0.000	−0.215	0.008	−0.085	0.001	−0.037	0.006	−0.062	0.000
	Car	−0.088	0.002	−0.039	0.002	−0.144	0.004	−0.051	0.002	−0.029	0.004	−0.018	0.001
5–10 km	Bicycle	−0.049	–	−0.182	–	−0.082	–	−0.259	–	−0.074	–	−0.197	–
	Public transit	−0.592	0.218	−0.094	0.025	−0.731	0.200	−0.261	0.094	−0.458	0.192	−0.124	0.089
	Car	−0.269	0.171	−0.030	0.098	−0.400	0.348	−0.055	0.136	−0.176	0.260	−0.018	0.062
10–20 km	Bicycle	−0.703	–	−0.283	–	−0.728	–	−0.803	–	−0.512	–	−0.522	–
	Public transit	−1.404	0.735	−0.247	0.142	−2.633	0.852	−0.294	0.360	−1.239	0.688	−0.179	0.249
	Car	−0.974	0.779	−0.022	0.270	−2.205	0.796	−0.032	0.298	−0.701	0.535	−0.009	0.170
>20 km	Bicycle	−1.825	0.360	−0.192	0.092	−2.954	0.156	−0.346	0.140	−1.552	0.159	−0.284	0.077
	Public transit	−0.998	0.428	−0.004	0.125	−1.373	0.461	−0.013	0.187	−0.960	0.237	−0.006	0.114

modeling. Activity-travel behavior is characterized by interactions in time and space and it is widely recognized that the incorporation of time-space interaction effects is critical to understanding, explaining, and modeling activity-travel demand under a wide range of land use, transport, technology, and policy scenarios.

This paper has discussed the combined choice of residential location, travel mode, and departure time, using a number of traditional and more advanced discrete choice models.

The analysis shows that, when accounting for correlation along just one dimension of choice (i.e. using NL model), the best performances is obtained by the model nesting by residential location. However, the simultaneous treatment of correlation along all three dimensions has clear benefits, and the CNL model outperforms all three NL structures, which is consistent with the findings reported by Hess and Polak (2006) for the analysis of airport-choice.

In terms of dissimilarity parameter μ_m depicting the correlation between alternatives in nest m, most parameters are statistically significant, with the few exceptions. It shows that correlations among the alternatives generally exit. Comparing the values of dissimilarity parameters for different nests, we can find that the parameter for the nest of departure time is the biggest, next is the parameter for the nest of travel mode, and that for the nest of residential location is the smallest. On the contrary, the order of significance level of the dissimilarity parameters for the three kinds of nests from high to low is: residential location, travel mode, and departure time. The estimation results suggest that, there is higher substitution between alternative residential locations than between alternative travel behaviors. Moreover, higher substitution exists between alternative departure time periods than between alternative travel modes, showing that travelers in Beijing city are more sensitive to transport levels of service in their choice of departure time than in their choice of travel mode. The results have profound implications for transport demand management policy. For example, to improve Beijing's deteriorating traffic condition, charging to car travels during some peak period may be more effective than the measures only focusing on public transit supply.

Direct elasticities analysis suggests that, for long-distance commuting, it is difficult to decrease car travels even if additional charges are imposed on car users. As expected, public transit users are more sensitive to travel cost than car users. Cross elasticities analysis shows that the effect of increasing car travel times within 5 km commuting distance has practically null effects on the probability choice of public transit and vice-versa. For 10–15 km distance commuters, variations in car (public transit) travel times or costs are expected to have a relatively large effect on public transit (car) choice probabilities.

In conclusion, the CNL model offers a rigorous approach in multi-dimension choice like the joint choice of residential location, travel time, and departure time modeling than standard logit model. Future research includes not only extending the model to other population segments, and testing the robustness of the finding in other empirical contexts, but also formulating more advanced model structures, allowing for continuous departure time information or more choice dimensions such as travel route.

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