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Comparing travel mode and trip chain choices between holidays and weekdays

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ABSTRACT

Choices of travel mode and trip chain as well as their interplays have long drawn the interests of researchers. However, few studies have examined the differences in the travel behaviors between holidays and weekdays. This paper compares the choice of travel mode and trip chain between holidays and weekdays tours using travel survey data from Beijing, China. Nested Logit (NL) models with alternative nesting structures are estimated to analyze the decision process of travelers. Results show that there are at least three differences between commuting-based tours on weekdays and non-commuting tours on holidays. First, the decision structures in weekday and holiday tours are opposite. In weekday tours people prefer to decide on trip chain pattern prior to choosing travel mode, whereas in holiday tours travel mode is chosen first. Second, holiday tours show stronger dependency on cars than weekday tours. Third, travelers on holidays are more sensitive to changes in tour time than to the changes in tour cost, while commuters on weekdays are more sensitive to tour cost. Findings are helpful for improving travel activity modeling and designing differential transportation system management strategies for weekdays and holidays.

1. Introduction

Understanding people's travel behavior is essential for the planning and management of transportation systems. Among all travel behaviors, travel mode choice (such as bike, bus, car) and trip chain pattern (which refers to a sequence of trips that starts and ends at home within a day) are important decisions that impact the efficiency of the whole transportation systems, and thus have attracted considerable attentions from researchers in multiple disciplines including transportation engineering (Shiftan, 1998), geography (Albert, 1993), and urban economics (Anas, 2006). Previously, many studies have developed models to evaluate individuals' choice of travel mode or trip chain pattern, although in early days those two types of models were built separately without considering the connection between the two choices (Adler and Ben-Akiva, 1979; Albert, 1993; Shiftan, 1998; Wen and Koppelman, 2000; Anas, 2006; Yang et al., 2007).

In recent years, with the development of activity-based modeling techniques of which a key feature is the recognition of the interdependent nature of choice facets, several studies have evaluated the interplay between the choices of travel mode and trip chain. For example, Hensher and Reyes (2000) estimated a Nested Logit (NL) model to analyze the relationship between the choice of public transit and trip chain pattern. They found that complex trip chain pattern usually serves as

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a barrier to public transit use. Ye et al. (2007) used a recursive bivariate probit model to investigate the relationship between mode choice and complexity of trip chain. The study found that people decide on activity agenda and tour complexity first, and this decision drives their mode choices. Krygsman et al. (2007) studied the choice order of travel mode and activity pattern in work trips in the Netherlands, and found that in the majority of cases the activity decision is made before the mode decision. Islam and Habib (2012) investigated the hierarchical relationship between trip chain and mode choice using a six-week travel diary collected in Thurgau, Switzerland. They found that for work tours trip chain and mode choice decisions are made simultaneously and remain consistent across weeks. In the study by Li et al. (2013), a co-evolutionary binary logit model was developed to explore each individual's decision order between bicycle use and trip chain selection.

The aforementioned studies generally focused on understanding travelers' behaviors on ordinary weekdays. Until recently, few studies have examined the choices of travel mode and trip chain, as well as their interplays, during big national holidays. The differences in travel behaviors between holidays and weekdays have not been studied yet. One possible reason could be that most of attentions have been paid to commuting tours on weekdays with travel surveys conducted on weekdays. Few travel surveys were particularly for holidays. Even though some studies analyzed the non-commuting trips on weekdays or weekends, travel behaviors and decision mechanism are still very different from those on national holidays.

Another reason for the lack of relevant study could be that traffic problems on holidays have not gotten as much attention as they deserve. In recent years, holiday travel demands have increased tremendously, since shopping, sightseeing, dining, and gathering have become a common lifestyle in modern society (Liu and Sharma, 2006). For example, the Bureau of Transportation Statistics in the United States reported that the number of long-distance trips increases by 54% during Thanksgiving (Liu and Sharma, 2006). In Canada, substantial traffic growth was found during Canadian statutory holidays (Liu and Sharma, 2006). In China, it was reported that nearly 211 million people travelled as tourists during the 2013 Spring Festival as compared to 40 million in 1999 (Wang et al., 2015).

Due to the sudden increase in travel demand on holidays, severe traffic jams occurred on both freeways and local streets resulting in significantly increased travel delay and crash count (Cools et al., 2010; Anowar et al., 2013). Meanwhile, few policies or strategies have been developed particularly for mitigating traffic problems on holidays. Existing policies for weekdays do not work well for holidays, due to the lack of understanding on how travel decisions are made in holiday tours. Therefore, the objective of this study is to examine the difference in travel decisions between holidays and weekdays. In particular, the choices of travel mode and trip chain pattern are analyzed. To achieve the research objective, travel survey data on both holidays and weekdays were gathered. The findings can help better understand the travel decision mechanism both on holidays and weekdays, which will be essential for making differential transportation policies to effectively relieve traffic problems within urban areas.

The remainder of this paper is organized as follows. Section 2 introduces the travel survey data on weekdays and holidays. Section 3 presents the methodologies used for modeling. Section 4 discusses the results of model estimates. Section 5 outlines the main conclusions of the study and gives policy suggestions.

2. Data

2.1. Data source

Two data sources were used in this study to analyze travel behaviors on weekdays and holidays, which are the Beijing Comprehensive Travel Survey (BCTS) data in 2010 and the Beijing Holiday Travel Survey (BHTS) data in 2007. Both the surveys were administered by the Beijing Municipal Commission of Transport.

Weekday travel data are from the BCTS which contains information of 10,650 residents in 8900 households in Beijing, China. The investigation area covers main urban areas of Beijing (see Fig. 1). Questionnaires were distributed and collected by investigators managed by the local government. The survey data includes individual and household socio-economical characteristics, and information of all trips (i.e., start time/location, end time/location, trip purpose, travel mode, etc.) on one typical weekday.

Holiday travel data are extracted from the BHTS conducted on the May Day holiday. May Day is one of the biggest national holidays in China and it includes seven days since 1999.[1] To stimulate economic growth, policies and promotions were made by local governments and businesses to encourage more tourist and recreational activities during the May Day. The survey selected thirteen sites within the metropolitan area of Beijing (also see Fig. 1), including four famous scenic spots, four amusement parks, three shopping malls, and two large transportation hubs. Questionnaires were distributed at those locations. In total, 5690 respondents were randomly selected to do the interview.

2.2. Data processing

Survey data on both weekdays and holidays were processed to extract trip chain information. A commuting-based trip chain is defined if the trips in a day contain one or more commuting trip purposes regardless the existence of other purposes.

[1] The weeklong May Day holiday was shortened to three days by Chinese government after 2008.

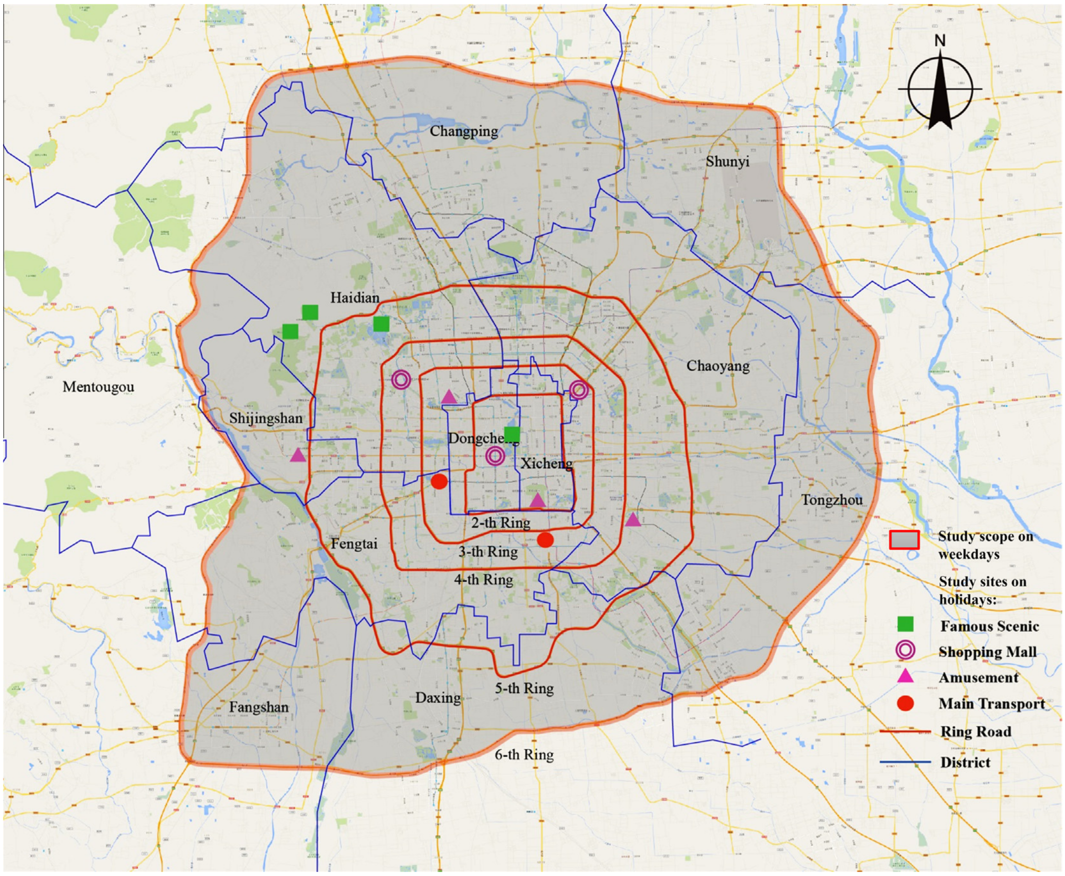


Fig. 1. Study scope/sites on weekdays and holidays.

According to the number of trip stops, a trip chain can be classified into single chain with one outside stop or complex chain with multiple outside stops.

Travel modes recorded in the survey include walk, bike, car, taxi, and public transit. Public transport system in the study area includes two modes: bus and rail transit. As the survey sites are all within the metropolitan area, they are covered by well-developed bus and rail transit networks. According to the survey data, about 48.4% and 35.6% travelers use bus for travel in weekdays and holidays, respectively. The rail transit has a smaller ridership, which is 12.3% in weekdays and 7.3% in holidays. In our study, taxi was classified as car in the data processing. Though differences exist between car and taxi, the two modes are very similar in occupying road space, causing traffic congestion, and worsening air pollution within city areas. They are also similar as they are both able to provide door-to-door travel services. Actually in recent years, private car owners may use phone-based Apps, such as Didi and Uber, to provide taxi services for travelers. By combining the two modes in the modeling, we can determine the decision process of travelers between automobile and public transit. Policies can be made to reduce both car and taxi uses to mitigate congestion and improve air quality in Beijing.

As one trip chain could involve more than one travel mode, a priority ordering scheme (Ye et al., 2007) was applied. Specifically, if car or public transit was used for any segment in the trip chain, the travel mode was assigned as the car or public transit. In only a few cases where both car and public transit are used, car was assigned as the travel mode in the trip chain. The sample size of non-motorized travel mode (i.e. walk plus bike) in holiday tours is relatively small (8.7% of all samples), probably because less people choose to walk or bike for recreational purposes on May Day in Beijing due to the long trip distance. In addition, traffic jams on urban roads are mainly caused by motorized travel modes. For those considerations, only motorized travel modes (i.e. car and public transit) were considered in our study for further analysis.

For weekdays, only commuting-based trip chains were selected. Chain types that have smaller sample size (less than 5% of all chains) were excluded from analysis. Samples with missing key information (such as travel mode and trip purpose) and with obvious errors (such as unreasonable travel time) were further excluded. Finally, 4840 valid samples with three major trip chain patterns were identified. The descriptions are given as follows, where 'H' denotes home, 'W' denotes a commuting activity location (work, school, etc.), and 'O' refers to a non-commuting activity (maintenance, recreational, etc.) location:

- *HWH:* There is one subsistence activity within a day. This type of chain contains only a simple commuting activity stop.
- *HWHWH:* There are two subsistence activities within a day. The chain contains commuting trips with a mid-trip that returns home. There are no non-commuting activity stops.
- *HW+OH:* There are two types of activities within a day. This trip chain is a combination of a simple commuting chain with at least one non-commuting activity stop.

For holidays, following a similar data processing procedure, 1733 valid samples were obtained including three trip chain patterns as described below, where "T" denotes the location of tourist activities such as scenic spots, parks, and monuments, while "O" refers to the location of other activities such as shopping, dining, and watching movie.

- *HT(O)H:* Simple trip chain containing only one mid-stop for tourist or for another purpose.
- *HTT(OO)H:* Complex trip chain containing two or more tourist activities or two or more other activity purposes.
- *HT+OH:* Complex trip chain containing both tourist activities and other purposes with at least two mid-stops.

2.3. Descriptive analysis

Statistics of trip chain pattern and travel mode on weekdays and holidays are shown in Table 1 and 2. It is identified that several major differences exist between weekday and holiday tours. First, in weekday tours the dominant travel mode is public transit, while in holiday tours most people use car for travel. It suggests holiday tours have stronger dependency on car than weekday tours, with 57.1% of holiday tours involving car as compared to 39.2% in weekday tours. In addition, over half of trip chains on weekdays are simple ones while about two third of holiday tours contain multiple stops. The result is consistent with intuition as travelers on holidays are more likely to have multiple recreational activities.

Some common features are also found in weekday and holiday tours. For example, car is less used in simple trip chains while public transit is less used in complex trip chains, which are consistent with some previous studies (Hensher and Reyes, 2000; Wallace et al., 2000; Ye et al., 2007). The reason could be that because car provides more flexibility than public transit, car usually better accommodates the needs of trips with multiple travel purposes and stops.

Table 1
Statistics of trip chain and travel mode for weekday tours.

Travel mode	Trip chain pattern			Total
	HWH	HWHWH	HW+OH	
Frequency				
Car	679	484	734	1897
Public transit	1751	639	553	2943
Total	2430	1123	1287	4840
Column percent				
Car	27.9	43.1	57.0	39.2
Public transit	72.1	56.9	43.0	60.8
Total	100.0	100.0	100.0	100.0
Row percent				
Car	35.8	25.5	38.7	100.0
Public transit	59.5	21.7	18.8	100.0
Total	50.2	23.2	26.6	100.0

Table 2
Statistics of trip chain and travel mode for holiday tours.

Travel mode	Trip chain pattern			Total
	HT(O)H	HTT(OO)H	HT+OH	
Frequency				
Car	228	207	555	990
Public transit	262	197	284	743
Total	490	404	839	1733
Column percent				
Car	46.5	64.9	66.2	57.1
Public transit	53.5	35.1	33.8	42.9
Total	100.0	100.0	100.0	100.0
Row percent				
Car	23.0	20.9	56.1	100.0
Public transit	35.3	26.5	38.2	100.0
Total	28.3	23.3	48.4	100.0

Table 3
Description of explanatory variables.

Variables	Weekday tours	Holiday tours
	Sample (percent)	Sample (percent)
Social-economic characteristic		
Age group 1 (18–34)[a]	1534 (31.7%)	584 (33.7%)
Age group 2 (35–54)	2531 (52.3%)	539 (31.1%)
Age group 3 (⩾55)	775 (16.0%)	610 (35.2%)
Monthly income group 1 (⩽5000 RMB)	1036 (21.4%)	284 (16.4%)
Monthly income group 2 (5001–10000 RMB)[a]	3155 (65.2%)	901 (52.0%)
Monthly income group 3 (⩾10001 RMB)	649 (13.4%)	548 (31.6%)
Working time flexibility (1 = flexible)	1437 (29.7%)	/
Household size (in persons)	2.9 (0.9)[c]	2.8 (0.8)[c]
Number of worker (in persons)	1.9 (0.6)[c]	/
Tour-related attribute		
Tour time (in minutes)	66.9 (17.2)[c]	87.2 (20.5)[c]
Tour length (in kilometers)	28.5 (9.0)[c]	38.9 (15.3)[c]
Tour cost (in RMB)	24.8 (7.6)[c]	39.2 (9.7)[c]
Land use pattern		
Home location (1 = within center area[b])	581 (12.0%)	154 (8.9%)
Transit network density (1 = high[d])	2159 (44.6%)	541 (31.2%)

[a] Reference category in modeling.
[b] Center areas contain Dongcheng district and Xicheng district.
[c] Numbers represent the mean (standard deviation) for continuous variables.
[d] Public transit network density is equal or greater than 3.0 km/km^2.

Table 3 shows the statistical information of explanatory variables. Those variables include the social-economic characteristics, tour attributes, and land use patterns. The social-economic characteristics in our dataset are similar to those reported for Beijing in previous studies (Yang et al., 2013; Wang et al., 2015). In tour attributes, tour time was calculated directly from the survey data, and tour length was calculated as the distance between the geometric centers of origin and destination using the Geographic Information System tools. Tour cost in our study is calculated as the sum of cost spent in each trip. It is identified that the tour time, tour length, and tour cost on holidays are longer that those on weekdays.

3. Methodology

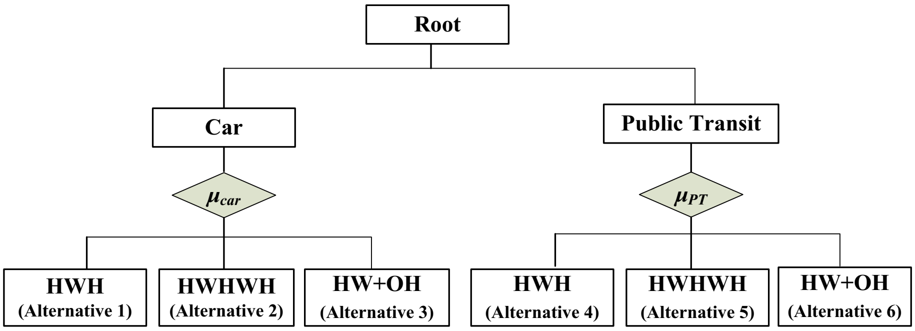
In this study, the decision structure of travel mode and trip chain choice was estimated by the NL model. The NL model is considered one of the most widely used methods which is simple and straightforward for specifying the decision order in the modeling framework (Hensher and Reyes, 2000; Hess et al., 2007; Ye et al., 2007). Based on the assumption of conditional choice mechanism, NL models representing different alternative tree structures can be formed. By comparing measures of goodness-of-fit between different models, the more plausible structure that fits the data best can be identified (Hess et al., 2007). Since the study did not aim to evaluate the decision order for each individual traveler, more advanced methods such as the Co-evolutionary Logit model was not considered. The NL mode used for our study purpose was briefly introduced in this section.

3.1. Model structure

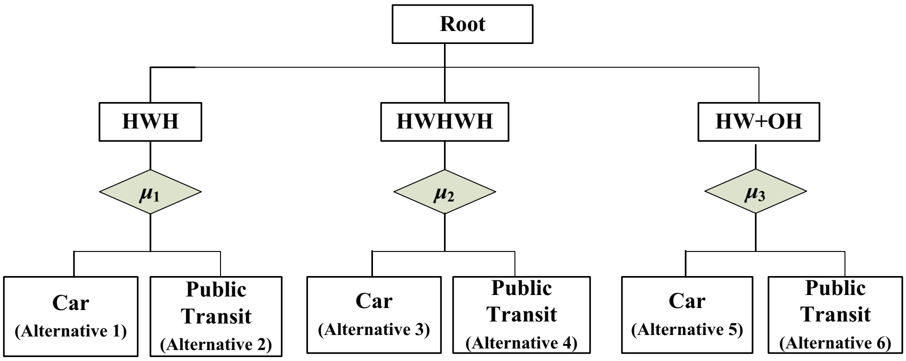
By defining different nesting structures in the NL model, the model performance and variable coefficients can be estimated to decide the prevailing decision structure. The model choice set $\boldsymbol{C}$ is composed of two subsets, one for travel mode represented by $\boldsymbol{t_m}$, and one for trip chain pattern represented by $\boldsymbol{t_c}$. There are two alternatives to be chosen in subset $\boldsymbol{t_m}$, i.e. car and public transit, while in subset $\boldsymbol{t_c}$, there are three alternatives for workday tours and three alternatives for holiday tours.

Two nesting structures for weekday tours are considered as illustrated in Fig. 2: (1) the tree structure with travel mode above trip chain pattern; and (2) the tree structure with trip chain pattern above travel mode. Two similar nesting structures for holiday tours are built, as shown in Fig. 3. One nests travel mode above trip chain pattern, and the other nests trip chain pattern above travel mode.

In the NL model, the nesting parameter μ ($0 < \mu \leqslant 1$) is called the dissimilarity parameter which captures the correlation between the alternatives sharing the same nest (Bierlaire, 2006). The correlations between alternatives in the nest m increase as μ_m gets closer to 0, and decrease as μ_m gets closer to 1. In the extreme case that $\mu_m = 1$, the NL model will collapse to the multinomial logit (MNL) model in which the alternatives are totally independent. In such case, the NL model structure is unstable and meaningless, and cannot represent any decision structures of travelers. On the contrary, if μ_m is close to zero,



(a) Travel mode above trip chain



(b) Trip chain above travel mode

Fig. 2. Two model structures for weekday tours.

the correlation between the alternatives in the nest m is high. In such case, the NL model is stable and statistically meaningful, and the nesting structure can well capture the decision structure in the data. Therefore, the dissimilarity parameter is often considered as a measure of goodness of fit in the NL models (refer to Bierlaire, 2006; Hess et al., 2007; Bekhor and Prashker, 2008 for more details).

In the models nesting travel mode above trip chain, the dissimilarity parameters are associated with the nests containing the composite alternatives that share the same mode. Taking μ_{car} in Fig. 2 for example, it represents the correlation degree between the chain alternatives sharing the nest of car for weekday tours. While in the models nesting trip chain pattern above travel mode, μ_1 is associated with the nests containing the mode alternatives that share the same trip chain HWH. The parameter μ_1' in Fig. 3 is the correlation between the mode alternatives sharing the nest of trip chain pattern HT(O)H.

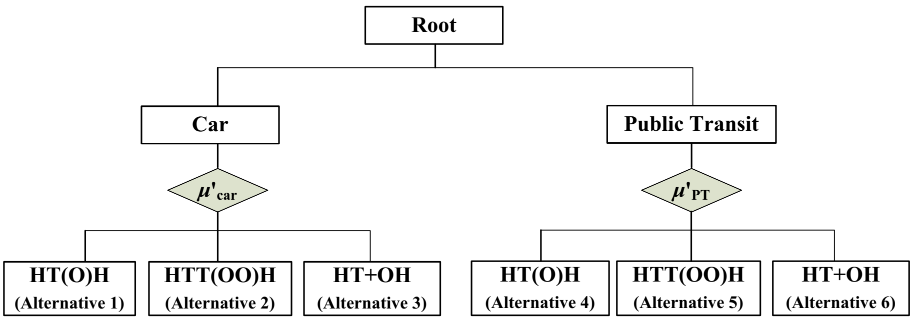
Except for the dissimilarity parameter, another goodness of fit measure, which is the adjusted ρ^2, is also considered to evaluate how well the nesting structure fits the empirical data (Bierlaire, 2006; Hess et al., 2007). In particular, a larger ρ^2 indicates a better model statistical performance. Another rule is that if the model structure is less preferred, the number of significant explanatory variables is less as compared to the preferred structure. Following such rules, the decision priority of travel mode choice and trip chain choice can be decided.

3.2. Utility function

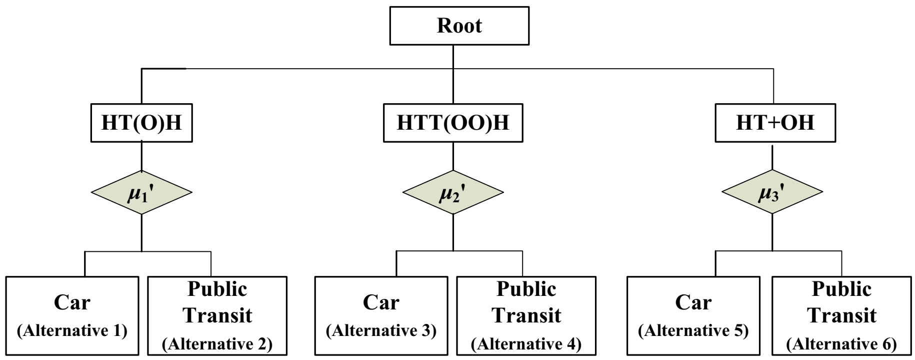
Under the random utility modeling framework, a decision maker n facing a choice among I alternatives obtains a certain level of utility U_{in} ($i = 1, 2, \ldots, I$) from selecting alternative c_i ($c_i \in \boldsymbol{C}$). In this study, the alternatives that a traveler needs to choose are the six outcomes of travel decisions; each alternative is a combination of a trip chain and a travel mode. 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. In this study, the systematic component V_{in} is a function of the explanatory variables associated with traveler n and alternative i, while the random component ε_{in} captures all other factors unobserved by the researcher:

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



(a) Travel mode above trip chain



(b) Trip chain above travel mode

Fig. 3. Two model structures for holiday tours.

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

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

where X_{inl} is the lth variable of alternative c_i for the traveler n, θ_l the unknown parameter to be estimated. Note that for convenience, letter n representing the traveler is omitted in all expressions described below. Referring to the studies by Vega and Reynolds-Feighan (2009) and Hess et al. (2007), the systematic utilities for each of the alternatives are a function of their travel (tour)-related attributes, land use attributes and the socio-economic characteristics of the traveler, as presented in Table 3.

3.3. Choice probability

Compared with other advanced Logit models such as Mixed Multinomial Logit model, one of the advantages of NL model is that it has closed-form expressions for the choice probabilities (Wen and Koppelman, 2001; Hess et al., 2007). Let ε_i represent the random element of utility for elementary alternative c_i, and the distribution for each ε_i is a type I extreme value (or Gumbel). Based on the GEV theory (MacFadden, 1978; Wen and Koppelman, 2001), the probability of choosing the alternative c_i in the NL model is as follows

$$P_{\mathrm{i}} = P_m \cdot P_{\mathrm{i|m}} = \frac{\left(\sum_{j\in N_m} (e^{V_j})^{1/\mu_m}\right)^{\mu_m}}{\sum_m \left(\sum_{j\in N_m} (e^{V_j})^{1/\mu_m}\right)^{\mu_m}} \cdot \frac{(e^{V_i})^{1/\mu_m}}{\sum_{j\in N_m} (e^{V_j})^{1/\mu_m}} \tag{3}$$

In the above formulation, P_i is the probability of choosing the alternative c_i. P_m is the probability of choosing the nest m. $P_{i|m}$ is the conditional probability of choosing the alternative c_i conditional on nest m being chosen. N_m is the set of all alternatives included in nest m. As presented above, μ_m $(0 < \mu_m \leqslant 1)$ is the 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, but decreases as μ_m gets closer to 1. The parameters in Eq. (3) including the dissimilarity parameter μ_m and the coefficients θ_l in the systematic utility function V_i are estimated using the maximum likelihood method (Bierlaire, 2006).

4. Modeling results

The NL models with different nesting structures were estimated using the freely available optimization package Biogeme (Bierlaire, 2003). The best decision structure between choices of travel mode and trip chain was determined on the basis of modeling results. The impacts of explanatory variables were estimated and the differences between holidays and weekdays were discussed.

4.1. Modeling results for holiday tours

Two NL models with different structures for holiday tours (see Fig. 3) were estimated. The modeling results are shown in Table 4. The model nesting travel mode above trip chain has smaller dissimilarity parameters (μ) with higher significance levels and a larger adjusted ρ^2 than the one nesting trip chain above travel mode. The later model has the dissimilarity parameter $\mu_1' = 1$, making this structure unacceptable. The results suggest that travelers on holidays in Beijing prefer to decide the travel mode prior to finalize the trip chain. The dissimilarity parameter μ_{car}' is smaller than μ_{PT}', meaning that the alternatives sharing the nest 'car' have higher substitutability than alternatives sharing the nest 'public transit'. It suggests holiday travelers in Beijing have a higher dependency on car than on public transit.

Coefficients of explanatory variables were estimated for holiday tours, as shown in Table 4. Those coefficients can be interpreted as follows (Vega and Reynolds-Feighan, 2009). For continuous variables such as tour-related attributes, negative coefficients were obtained. They suggest that as tour time, tour cost, and tour length increase, the utility of each alternative decreases and the alternative with the largest probability from Eq. (3) is the final choice. For discrete variables, the coefficients represent the impacts on the utility of alternatives with alternative 1 as the reference category. For example, age group 2 has a positive coefficient suggesting travelers aged between 35 and 54 is less likely to choose trip chain HT(O)H by car.

4.2. Modeling results for weekday tours

The modeling results of two NL models with different structures (see Fig. 2) are shown in Table 5. According to the dissimilarity parameters and the adjusted ρ^2, the better-fitting model is the one nesting trip chain above travel mode. The results suggest that travelers in weekday commuting tours in Beijing tend to decide the trip chain pattern first and make the selection on travel mode later. The findings are consistent with several previous studies which reported travel activity pattern was generally determined prior to the choice of trip mode in commuting-based trips (krygsman et al., 2007; Ye et al., 2007; Li et al., 2013). The coefficients of explanatory variables can be interpreted in a similar way as for holidays.

4.3. Comparing differences between holidays and weekdays

4.3.1. Decision structures

The preferred decision structure was compared between the weekday and holiday tours. The comparison suggests that the decision structure of travel mode and trip chain choices between weekdays and holidays is very different and even

Table 4
NL model estimates for holiday tours.

Variable	Model 1: trip chain - > mode		Model 2: mode - > trip chain	
	Parameter	t-stat	Parameter	t-stat
Age group 2	3.051	2.790	−0.087	−16.042
Age group 3	−0.002	−1.655	6.190	7.856
Monthly income group 3	4.142	6.750	−0.032	−9.894
Car ownership in household	1.610	1.954	−0.034	−9.046
Household size	3.137	3.580	−0.030	−1.670
Tour time	−0.063	−13.826	−0.085	−16.280
Tour length	/*	/	−0.009	−2.244
Tour cost	−0.005	−4.204	−0.012	−8.319
Home location	−0.004	−1.856	1.273	1.748
Transit network density	−0.009	−1.871	3.315	4.802
Dissimilarity parameter (μ)	μ_1' = 1.000	0.274	$\mu_{car}1'$ = 0.333	5.524
	μ_2' = 0.940	1.006	$\mu_{PT}1'$ = 0.507	3.189
	μ_3' = 0.708	2.531		
Adjusted ρ^2	0.097		0.283	

* Coefficient is not significant at a 90% confidence level.

Table 5
NL model estimates for weekday tours.

Variable	Model 1: trip chain - > mode		Model 2: mode - > trip chain	
	Parameter	*t*-stat	Parameter	*t*-stat
Age group 2	4.183	5.400	/[*]	/
Age group 3	−0.002	−1.889	1.504	1.652
Monthly income group 3	5.782	7.118	−0.037	−9.716
Car ownership in household	3.360	3.741	/	/
Household size	3.304	3.600	−0.025	−8.270
Number of workers	1.867	2.137	/	/
Tour time	−0.038	−10.262	−0.025	−8.439
Tour length	−0.009	−2.917	/	/
Tour cost	−0.055	−13.144	−0.042	−12.809
Home location	−0.008	1.232	1.547	1.881
Transit network density	−0.092	−11.871	3.562	4.090
Dissimilarity parameter (μ)	$\mu_1 = 0.769$	1.902	$\mu_{car} = 1.06$	0.833
	$\mu_2 = 0.494^a$	4.275	$\mu_{PT} = 0.92$	1.035
	$\mu_3 = 0.402^a$	4.405		
Adjusted ρ^2	0.304		0.156	

[*] Coefficient is not significant at a 90% confidence level.

opposite. In weekday commuting-based tours, people usually decide trip chain first and then choose travel mode. The reason would be that in commuting tours, time schedule, travel destination, and trip length are fixed or mandatory, and they cannot be changed freely by commuters' personal preference or subjectivity (Li et al., 2013). Thus, travelers need to make travel plans based on commuting trips and then choose appropriate travel modes to fit the plans.

While in holiday non-commuting tours, travelers prefer to determine travel mode prior to decide on travel activities. The reason would be that in holiday tours, travel schedules such as time, destination, and duration can be changed freely by travelers. Thus, travelers first tend to choose their preferred travel mode and then plan their travel activities in the day. The difference in the decision structure can help better understand how complex travel decisions are made on weekdays and holidays, and develop differential policies or strategies for transportation system managements.

4.3.2. Impacts of factors through elasticity analysis

Elasticity analysis was a comment method in NL models to quantify the impacts of key factors on travel choices (Wen and Koppelman, 2001). Direct elasticity represents the variation of an individual's choice probability due to a 1% change in one of the attributes affecting that alternative. The disaggregated direct elasticity with respect to the lth variable is formulated by:

$$DE_{il} = \frac{\sum_m P_m P_{i|m}[(1 - P_i) + (1/\mu_m - 1)(1 - P_{i|m}))]}{P_i}\theta_l X_{il} \quad (4)$$

where DE_{il} is the direct elasticity of the probability of alternative i with respect to the lth variable.

Two important variables related to the travel choices were selected to do the elasticity analysis, which are tour time and tour cost. The results for weekday and holiday tours are given in Table 6. The coefficient corresponding to a trip chain and a travel mode indicates how the probability of the choice alternative changes (in percentage) if the predicting variable is increased by 1%. For example, as shown in Table 6, the elasticity of tour time on car use in HWH chain is −0.767, meaning that when travel time is increased by 1%, the probability of car use in HWH chain will decrease by 0.767%.

By comparing the elasticity coefficients in Table 6, some differences between weekdays and holidays were found. In weekday tours, the decreases in car and public transit use due to one percent increase in travel cost are much larger than the decreases caused by one percent increase in travel time. While in holiday tours opposite results were found: the

Table 6
Direct elasticity for weekday and holiday tours.

Trip chain pattern	Tour time elasticity		Tour cost elasticity	
	Car (%)	Public transit (%)	Car (%)	Public transit (%)
Weekday				
HWH	−0.767	−0.017	−2.256	−0.084
HWHWH	−0.116	−0.492	−1.333	−0.900
HW+OH	−0.020	−0.701	−0.074	−1.921
Holiday				
HT(O)H	−0.201	−0.098	−0.169	−0.09
HTT(OO)H	−0.056	−0.041	−0.033	−0.028
HT+OH	−0.095	−0.198	−0.077	−0.114

Table 7
Switching of choices due to increase in car use cost for weekday tours.

Before change		After change					
		HWH		HWHWH		HW+OH	
		Car (%)	Public transit (%)	Car (%)	Public transit (%)	Car (%)	Public transit (%)
10% increase in car use cost							
HWH	Car (%)	76.5	23.5	0	0	0	0
	Public transit (%)	0	100	0	0	0	0
HWHWH	Car (%)	0	0	81.6	18.4	0	0
	Public transit (%)	0	0	0	100.0	0	0
HW+OH	Car (%)	0	0	0	0	88.8	11.2
	Public transit (%)	0	0	0	0	0	100.0
30% increase in car use cost							
HWH	Car (%)	39.7	58.0	0	0	0	0.3
	Public transit (%)	0	100.0	0	0	0	0
HWHWH	Car (%)	3.1	0	63.2	33.7	0	0
	Public transit (%)	0.1	0.5	0	99.4	0	0
HW+OH	Car (%)	3.1	0.8	0	0	66.3	29.8
	Public transit (%)	0	0	0	0	0	100.0
50% increase in car use cost							
HWH	Car (%)	22.0	78.0	0	0	0	0.3
	Public transit (%)	0	100.0	0	0	0	0
HWHWH	Car (%)	11.3	0	40.5	48.2	0	0
	Public transit (%)	0	0	0	100.0	0	0
HW+OH	Car (%)	9.5	0	0	0	41.4	49.1
	Public transit (%)	0	0	0	0	0	100.0

decreases in car and public transit use due to the increase in travel cost are smaller than those due to the increase in travel time. The results of elasticity analysis suggest that commuters in weekday tours are relatively more sensitive to the changes in tour cost than tour time. Travelers in holiday tours are more sensitive to travel time than travel cost.

4.3.3. Switching of choices through simulation tests

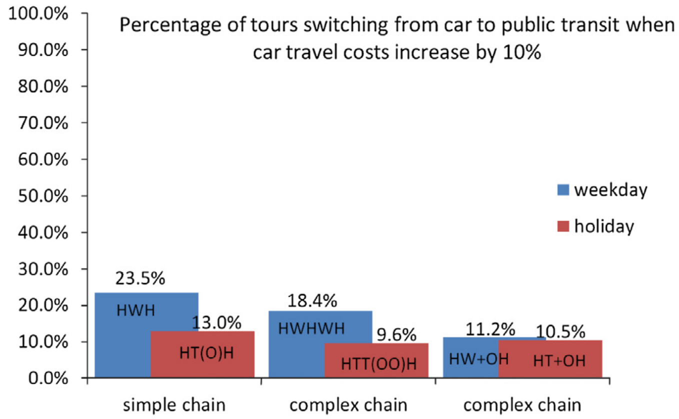
Another advantage of the modeling framework proposed in this study lies in its potential to simulate the switching effects of choices due to changes in explanatory variables. In this section, an example was given to analyze how travel choice changes due to the increase in car use cost. Sample enumeration is used as the aggregate forecasting technique and Monte Carlo simulation test is conducted to produce the choice probability of all alternatives (Vega and Reynolds-Feighan, 2009). In the simulation tests, car use cost was increased by 10%, 30% and 50% and the effects on the choices of travel mode and trip chain pattern were evaluated. Results for weekdays and holidays are shown in Tables 7 and 8. Each cell in the table

Table 8
Switching of choices due to increase in car use cost for holiday tours.

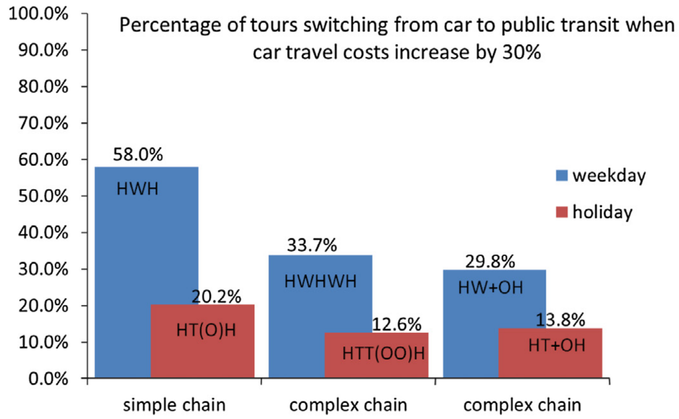
Before change		After change					
		HT(O)H		HTT(OO)H		HT+OH	
		Car (%)	Public transit (%)	Car (%)	Public transit (%)	Car (%)	Public transit (%)
10% increase in car use cost							
HT(O)H	Car (%)	64.2	13	10.7	0	12.1	0
	Public transit (%)	0	91.9	0	2.3	0	5.8
HTT(OO)H	Car (%)	29.5	0	50.3	9.6	10.6	0
	Public transit (%)	0	7.7	0	90.7	0	1.6
HT+OH	Car (%)	33.2	0	7.1	0	47.2	10.5
	Public transit (%)	0	6.1	0	0	0	93.9
30% increase in car use cost							
HT(O)H	Car (%)	58.1	20.2	4.8	0	16.9	0
	Public transit (%)	0	95.3	0	0	0	4.7
HTT(OO)H	Car (%)	38.0	0	32.9	12.6	16.5	0
	Public transit (%)	0	0.7	0	99.3	0	0
HT+OH	Car (%)	31.1	0	20.6	0	34.5	13.8
	Public transit (%)	0	5.9	0	0	0	94.1
50% increase in car use cost							
HT(O)H	Car (%)	47.7	43.2	1.1	0	8.0	0
	Public transit (%)	0	100.0	0	0	0	0
HTT(OO)H	Car (%)	42.0	0	21.6	18.0	18.4	0
	Public transit (%)	0	0	0	100.0	0	0
HT+OH	Car (%)	33.4	13.5	20.6	0	22.9	30.2
	Public transit (%)	0	0	0	0	0	100.0

represents the percentage of travelers move to that choice alternative after the increase in car use cost. The diagonal values in the table represent the percentage of travelers that remain at their original alternatives (diagonal values are 100% before car use cost increases).

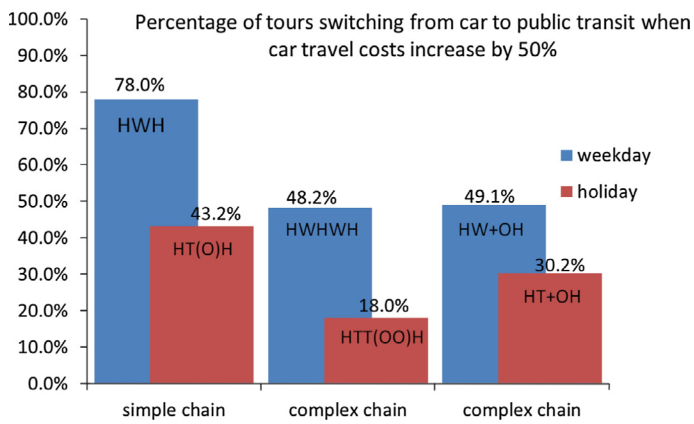
Table 7 shows that for weekday tours, the increase in car use cost mainly impacts on the change of travel mode rather than on the change of trip chain. For example, as car use cost increases by 10%, 11.2–23.5% of car users change to use public transit in the three trip chains but no trip chain changes were predicted. A small proportion of change of trip chain was



(a) 10% increase in car travel costs



(b) 30% increase in car travel costs



(c) 50% increase in car travel costs

Fig. 4. Switching of travel mode due to increase in car use cost.

observed as car use cost increases by 30% and 50%. Table 8 shows that for holiday tours, the increase in car use cost mainly impacts on the change of trip chain pattern rather than travel mode. For example, in HTT(OO)H trips 29.5% and 10.6% of car users switch to HTH and HT+OH chains, while only 9.6% of car users switch to use public transit when car use cost increases by 10%. Similar results are found for the scenarios with 30% and 50% increase in car use. Furthermore, travelers in complex trip chains are likely to switch to simple trip chain as shown in Table 8, probably because car users would like to simplify their travel plans to reduce travel delays during holidays.

Fig. 4 was created through simulation tests to show how travel mode switches due to the increase in car use cost. It is quite obvious that for either weekdays or holidays, the proportion of travelers switching from car to public transit is higher in the simple trip chain (HWH or HT(O)H) than that in the complex trip chains. The result suggests that complex trip chains are more dependent on private car than simple trip chains on both weekdays and holidays, probably because car meets the needs of multi-purpose travel activities. Another observation from Fig. 4 is the percentage of mode switching from car to public transit for holiday tour are much less than that for weekday tour, showing that holiday tours have stronger dependency on cars than weekday tours.

5. Conclusions and discussion

This study examined the differences in the choice of travel mode and trip chain and their interplay between weekdays and holidays. Based on travel survey data collected on both weekdays and holidays in Beijing, China, the NL models with different nesting structures were estimated. The preferred decision structures in weekday and holiday tours were decided. The impacts of variables on travel mode and trip chain choices were estimated through elasticity analysis. The switching of travel mode and trip chain due to changes in tour cost was predicted through simulation tests. The differences between weekdays and holidays were discussed.

The results showed that there are at least three differences between weekdays and holidays. First, the decision structure in weekday and holiday tours is opposite. In weekday tours, people prefer to determine trip chain prior to deciding on travel mode; while in holiday tours travel mode choice is made first. Second, holiday tours show stronger dependency on cars than weekday tours. Third, travelers on holiday are more sensitive to changes in tour time than tour cost, while commuters on weekdays are more sensitive to tour cost. Last but not least, an increase in car use cost mainly results in the switching in travel mode for weekday tours. But for holiday tours an increase in car use cost mainly results in the switching in trip chain pattern.

Findings of this study suggest the great importance of designing differential traffic policies and management strategies for weekdays and holidays. For weekday commuting-based tours, activity agenda (i.e. trip chain pattern) decision precedes mode choice decision, which brings a great challenge to public transit service providers to attract riders. The complexity of trip chaining serves as an impediment to public transport usage as it generally more burdensome to undertake multi-stop tours using public transit where travelers are constrained by routes, schedules, and access/egress issues. Then, public transit service providers not only have to improve service amenities, but also have to cater to a multi-stop oriented complex activity agenda, for example, providing more flexible circulator and paratransit-type services that may involve the use of smaller buses and vans than conventional vehicles.

For holiday tours, since travelers prefer to adjust their travel plan rather than travel mode, strategies aiming at balancing the spatial-temporal distribution of travel demand, such as guiding travelers how to plan their trips or activities, may be helpful for releasing severe traffic congestions on holidays. In addition, as this study shows, travelers in holiday tours are more sensitive to changes in tour time than tour cost, which is opposite to travelers in weekday tours. Thus, cost-based traffic management strategies such as toll lane and congestion pricing which are expected working well on weekdays are much likely to be ineffective on holidays.

Some earlier studies reported that trip chain length influences the mode choice decision of individuals. In those studies, chain length is considered as an explanatory variable and mode choice is the dependent variable. In our study, the trip chains are considered as a dependent variable together with the travel mode choices. The NL model predicts how people choose trip chains with different complexities and length as well as travel modes. Thus, the trip chain length is not considered as a predicting factor in mode choice. Recently, researchers have used advanced modeling techniques, such as co-evolutionary logit model, to capture the interdependency between dependent variables. By using such a model, the impact of trip chain on mode choice decision can be captured more directly. This will be considered in our future research.

This study is an initial step of examining differences in travel behaviors between holidays and weekdays. Future research efforts may aim to determine whether our findings hold for other holidays in other cities. In addition, the results of this study may not be applicable for normal weekends, as travel demands, trip purposes, and travel decisions could be very different. The comparison analysis of travel behaviors and decisions between holidays and normal weekends could be considered in our future research. In addition, the modeling framework can be extended to consider more travel mode choices, such as subway, taxi, bicycle and walk. Another consideration that merits further investigation is the reformulation of the modeling framework when intra-household decision interactions are taken into account, since travel decisions of individual household members are not made in isolation.

Up-to-date is an important factor in behavioral studies. In our study, we compared travel survey data obtained in 2007 and 2010, and our preliminary analysis showed that the mode share patterns are similar between the two years. According to the Beijing Transport Annual Reports, the share of public transit slightly increased from 34.5% in 2007 to 38.9% in 2010, but the mode share of car was quite stable (from 32.6% in 2007 to 34.0% in 2010). Even though significant efforts have been made by the government to promote public transit and reduce car use in Beijing, the mode share for public transit was 45.0% and that for car was 33.0% in 2015, which is close to the number in 2010. Thus, the findings from this study can still provide useful information for understanding current travel behaviors and supporting today's policy making. It is also worth noting that comprehensive travel survey is carried out every five years in Beijing. The latest survey was conducted in 2015 but until now the data is not available. New holiday travel survey has not been conducted. It will be valuable to validate our modeling results and compare the travel behaviors when newer survey data become available. The authors see this as an important future research effort.

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