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Research Article

Joint Analysis of the Commuting Departure Time and Travel Mode Choice: Role of the Built Environment

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This paper aims to conduct an empirical study to evaluate the influence of built environment features and socioeconomic factors on commuters' simultaneous choice of departure time and travel mode. Using Kunming, China, as the study region, the 2015 Regional Household Travel Survey and 2016 Point of Interest data are used in the analysis. The results show that, in addition to socioeconomic factors, built environment, such as the density of residential building, employment, and service facility are correlated with joint choice behavior. Moreover, there exist differences regarding the influence of built environment and socioeconomic factors on departure time and travel mode choice. The dissimilarity parameters show that commuters prefer to shift travel mode than departure time generally when travel condition alters. In order to examine the policy measures' potential performance, the paper conducts simulation tests based on the Monte Carlo method. The simulation results show that congestion pricing of car travel during peak hours can reduce the number of commuting trips, and reducing travel time of public transit would be a better strategy to attract more passengers during peak hours. Moreover, reasonable land use planning, such as building more bus stops around commuters' home location, would be a long term and fundamental approach to reduce mobile-source emissions and attract more public transit passengers.

1. Introduction

Transportation in China is developing at a fast pace, and with the collaborative operation of various travel modes, traffic efficiency has improved considerably. However, the transportation development has also resulted in various problems. For instance, traffic congestion remains at the urban traffic core problems, especially in large metropolitan areas in China. Typically, the worst times for traffic condition of the day are during the morning and evening peak time when people commute to and from work. Choices, such as departure time and travel mode, are crucial ingredients of a commuter's decision about trip-making. Therefore, understanding the factors that affect the joint choice of departure time and travel mode for commuting trips is an indispensable prerequisite in evaluating policy measures potential effectiveness. In this manner, reasonable policy measures that can help reduce trip-making during peak periods and encourage commuters to use public transit to alleviate traffic congestion problems can be formulated.

Previous research on the factors that influence the joint choice of departure time and travel mode has focused primarily on socioeconomic factors, such as household, individual, and travel-related characteristics [1–4]. Recently, several literatures proved that the built environment has a great impact on travel behavior of individuals [5–12]. In addition, the built environment is also widely regarded as an effective planning measure to increase the performance of public transit, decrease the usage of cars, and then reduce vehicle miles traveled (VMT) and emission. These factors work together to promote high-density, mixed-use, and compact urban development [7]. This kind of built environment capacitates individuals to engage in community-oriented social exchanges, which usually brings shorter travel distances and more dependence on the modes of public transit or walk and bicycle. Nevertheless, limited studies are undertaken to analyze the role of built environment features in affecting the departure time.

Although lots of existing studies analyzed the connections between travel behavior and land use in developed countries [7, 13–15], only a few explored the influence of built environment on the simultaneous choice of departure time and travel mode in developing countries [16]. The research findings of existing literature are not likely to be generalized into Chinese cities due to certain different characteristics from the developed countries. For example, in China, the rapid increase of cities is more associated with strong centralized planning and stages of land use and transport development. Thus, the literature offered limited clues on this issue for China. Consequently, studying the effect of built environment in large metropolitan areas in China is necessary to alleviate the unique traffic congestion problem in developing countries.

To make up for the abovementioned deficiencies, this paper aims to present an empirical research on the effect of built environment features and socioeconomic factors on commuters' joint choice on departure time and travel mode for commuting trips. This paper chooses Kunming metropolitan area in China as the study region and uses the 2015 Regional Household Travel Survey and 2016 Point of Interest (POI) data in the analysis. The main contributions of this paper are threefold: (i) the paper considers more influencing factors and evaluates the impact of built environment on commuters' joint choice on departure time and travel mode for commuting trips departed from home to workplace; (ii) based on the empirical results, the paper examines the potential effectiveness of some transportation demand management and land use planning measures using Monte Carlo simulation tests; and (iii) the study region of this paper is Kunming, China; hence, the results can likely be generalized to other cities in developing countries to meet their rapid increase and strong centralized planning [17].

The remaining of the paper is organized as follows. Section 2 provides a literature review of existing studies about the joint model of departure time and travel mode choices, and built environment features influencing travel behavior. Section 3 elucidates the modelling process of the paper based on the cross-nested logit (CNL). Section 4 describes the study areas and two parts of data. Section 5 presents the estimation results on built environment features and socioeconomic factors. Furthermore, the paper makes changes in travel-related attributes and bus stop density based on Monte Carlo simulation tests in this section to assess the performance of policy measures. Finally, Section 6 makes summary and conclusions.

2. Literature Review

2.1. Combined Choice of Travel Behavior. Over the last three decades, the theory of random utility maximization (RUM) and discrete choice model have been applied in most literatures that deal with choices on departure time and travel mode. The multinomial logit (MNL) model was often utilized in previous studies [18–20] because of its ease of estimation and simple mathematical structure. However, the MNL model imposes a restriction; namely, for each alternative, its random error terms distribution is identical and independent. This characteristic generates the independence of irrelevant alternatives (IIAs) property, which leads each alternative owning the same cross-elasticity [21]. Hence, the MNL model may be not suitable for simultaneous choice. To avoid these drawbacks, many scholars started using the nested logit (NL) model to study joint choice of travel behavior. The NL model divides the choice-set into different levels and mutually exclusive nests, thereby allowing alternatives of the same nest to have correlations [22]. Palma and Rochat [23] presented empirical studies of the mode choice for commuting trips in Geneva using the NL model. They described the joint nature of car ownership in the household and usage of a car for a commuting trip. Using a NL model with two levels, Hess and Polak [24] chose San Francisco Bay area as the study region to present the air travel choice behavior and considered passengers' simultaneous choice of an airline, a departure airport, and an access mode. The results showed that the NL model performed better compared to the MNL model. However, as for NL model, alternatives of different nests remain independent [25]. In other words, it cannot simultaneously capture the correlations of departure time and travel mode dimensions.

Based on the further study of the MNL and NL model, some literatures presented the simultaneous equations model to solve the problem of combined choice of travel behavior. For the simultaneous choice of residential location, vehicle usage, and vehicle count by type, Eluru et al. [26] put forward a joint GEV-based logit regression model through a copula based framework. It promotes the joint equations systems estimation with error dependence structures. Eluru et al. [27] also integrated the multiple discrete continuous extreme value (MDCEV) model with the MNL model to analyze the combined choice of travel mode, activity type (generation), time use allocation (duration), time of day, and destination. Pinjari et al. [28] proposed an integrated simultaneous multidimensional model to study the choice of bicycle ownership, car ownership, travel mode, and residential location. The results show that the simultaneous equations model can connect the short term, medium term, and long term choices to get endogeneity and unobserved heterogeneity. Based on a simultaneous equation model system framework, Silva et al. [29] explored the correlation of land use patterns and travel behavior with multidimensional variables, like the number of trips, trip scheduling, car ownership, and home location. The result proves that the land use has great effect on travel behavior. Therefore, on some specific issues, simultaneous equations model may have better performance.

In recent years, several studies focused on simultaneous choice analysis using the CNL model. Allowing alternatives to belong to more than one nest [30, 31], the model is able to describe various similarities and dissimilarities among alternatives based on their more flexible correlation structure. Hess and Polak [32] presented a research on the integrated choice of airline, airport, and access mode with London area as an example. Their results showed that travelers would consider access time first for departure airport choices, while access cost, flight frequency, and flight time also have some influence. Using Dublin region as the study area, Vega and Reynold-Feighan [14] explored the joint choice of home location and travel mode for commuting trips. They also made simulation to explore the switching of travel mode and location. Hess et al. [25] proposed a model based on the individuals of California to explore the combined choices of fuel type and vehicle type. Their results showed that, in a multidimensional choice process, the CNL model performed better than the standard NL model. Yang et al. [3] applied the model to explain the combined choice of travel mode, departure time, and residential location using Beijing traffic survey data. Their results suggested that if travel conditions change, commuters will first make changes in departure time, then travel mode, and finally residential location. Ding et al. [4] presented the combined choice of travel mode and departure time selecting Maryland–Washington, DC, as the study area. Monte Carlo simulation demonstrated that increasing US$5 travel cost of car mode at the peak hours and saving 30% in public transit travel time can reduce the same percentage of driving alone on peak periods, while public transit ridership only increased in the latter condition. However, almost all previous researches analyzing the joint choice of departure time and travel mode focused primarily on socioeconomic factors using travel survey data.

2.2. Influence of Built Environment Features on Travel Behavior. Land use planning is widely regarded as a stable and long-term strategy, compared with other measures such as congestion pricing and gasoline tax [33]. Land use planning contributes to alleviating the influence of transportation on environment by determining the human activities' basic spatial settings. Therefore, various researches have focused on analyzing the connection of built environment and travel behavior at the time of the current study [34–36]. Based on New York Metropolitan Region dataset, Chen et al. [13] assessed the impact of density on travel mode choice decisions for commuting trips under the condition of controlling for confounding factors. Vos et al. [15] studied the role of residential dissonance in affecting travel mode choice, using Flanders, Belgium, as the study area. The results found that residential dissonance clearly affected people's ability to realize their preferred travel behavior. Hong et al. [7] reexamined the impact of built environment features on transportation in the area of Seattle metropolitan. Their results indicated that when travel attitude and spatial autocorrelation are controlled, land use features also have highly significant influence on VMT. Moreover, according to geographic scales and tour types, several of these impacts may change to different empirical outcomes. Kwoka et al. [37] compared the different effects of workplace near a light rail transit station and residence near a station on workers' travel behavior, using Denver, Colorado metropolitan, as a study area. They determined that, for commuters whose workplace is near a public transit station area, non-car modes have a higher level of mobility than a car mode with measures of personal trips and distances. Using residents in four Shanghai suburban neighborhoods as the study area, travel survey data is used in the analysis. Shen et al. [38] examined the role of urban expansion in rail transit-supported in affecting travel mode and car ownership. The research intensively suggested that urban expansion in rail transit-supported can generate significant positive results through transportation strategies and land use planning.

This brief review of past literature on built environment revealed that a large body of studies analyzing the relationship between built environment and travel behavior exists. However, they focus primarily on travel mode and selected developed countries as study areas [39]. In addition, to the best of the authors' knowledge, there are limited studies at present exploring the role of built environment features in affecting the departure time. Thus, research on the simultaneous choice of departure time and travel mode is also scarce [40]. However, departure time is also a significant component for an individual's decision regarding trip-making and determined by built environment around the work and residential areas [41, 42]. Consequently, analyzing the influence of built environment characteristics on the combined choice of departure time and travel mode is necessary.

In view of the existing research, two main limitations are outlined as follows. First, factors affecting the joint choice of departure time and travel mode for commuting trips in previous research are inadequate. Most of them have not considered the effect of built environment variables. Second, a few researches have investigated the role of built environment in affecting simultaneous travel behavior in developing counties. Thus, the literatures offer limited information for cities in China to put forward effective land use planning. Consequently, this paper aims to conduct an empirical study in Kunming, China, to investigate the influence of built environment features and socioeconomic factors on simultaneous choice of departure time and travel mode for commuting trips.

3. Methodology

3.1. Structure of the Joint Model. Based on the above research, this section builds a model with which to evaluate the impact of socioeconomic factors and built environment features on the simultaneous choice of departure time and travel mode for commuting trips. In contrast to MNL model and two types of NL model, Ding et al. [4] verified that CNL model has made greatest progress in capturing dissimilarity parameters of departure time and travel mode. Thus, when analyzing the relationship between departure time and travel mode, CNL model is a better choice compared with the MNL model and NL model. Following the conceptual framework introduced by a number of literatures [25] and taking the generalized extreme value (GEV) class theoretical framework as a core, this paper uses the cross-nested structure to build a model.

The model choice set C is composed by two sub-sets, namely, the travel mode sub-set $M = m$ and departure time sub-set $T = t$. Sub-set M has three alternatives, namely, car, public transit, and walk and bicycle, while sub-set T has two, namely, peak and off-peak periods. Therefore, model choice set $C = \{c_1, \ldots, c_k\}$ is defined as combined choice

Table 1: Alternatives of the developed CNL model.

Alternatives	Departure time	Travel mode
Alternative 1		Car
Alternative 2	Peak	Transit
Alternative 3		Walk and bicycle
Alternative 4		Car
Alternative 5	Off-peak	Transit
Alternative 6		Walk and bicycle

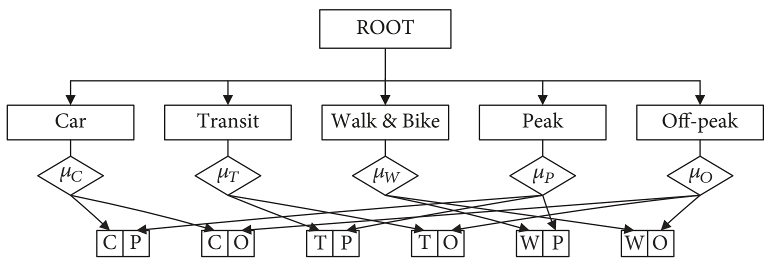


Figure 1: The developed CNL model structure; μ_i is a dissimilarity parameter; C, T, and W represent car, public transit, and walk and bicycle; P represents peak time and O represents off-peak time.

set of departure time $t = 2$ and travel mode $m = 3$. Thus, the developed model creates a set of $k = m * t = 2 * 3 = 6$ alternatives for each individual as shown in Table 1.

The developed model places departure time and travel mode in the same layer of consideration, thereby allowing each alternative to belong to exactly one departure time nest and one travel mode nest synchronously and express the correlations between the two choice dimensions jointly. The model structure is illustrated in Figure 1.

3.2. Utility Function. According to the utility maximization theory, for individual n, the utility function of alternative c_k ($c_k \in C$) is U_{kn}. If and only if $U_{kn} > U_{jn}$ (j $\in C, \forall j \neq k$), the commuter will choose alternative c_k. U_{kn} is a stochastic variable composed of a systematic item V_{kn} and random item ε_{kn}.

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

V_{kn} is a function for attributes, such as socioeconomic factors and built environment features, of alternatives and characteristics of individuals. Meanwhile, the random item ε_{kn} is used to describe all other influencing factors unobserved by researchers. The systematic utility function has various kinds of expression. The linear function is adopted in the paper, which is shown as follows:

$$V_{kn} = \sum_{l=1}^{L} \theta_l X_{knl} \tag{2}$$

where X_{knl} represents the attributes that influence commuters' combined choice of departure time and travel mode, while θ_ls need to be estimated with maximum likelihood estimation method to determine the extent of each attribute influencing the joint choice behavior.

3.3. Choice Probability. According to GEV theorem states [21, 43], the cross-nested logit model is a GEV model derived from the generator function G:

$$G(y) = \sum_m \left[\sum_k (\alpha_m y_k)^{1/\mu_m} \right]^{\mu_m} \tag{3}$$

where m means a nest; k means an alternative; α_m represents an allocation parameter; μ_m represents a dissimilarity parameter of a nest m; and y_k characterizes the value for each alternative. In addition, the choice probability P of the CNL model is derived by multiplying the conditional and marginal probabilities:

$$p(k) = \sum_m p(k \mid m)\, p(m) \tag{4}$$

An alternative k being chosen in nest m is defined as the conditional probability:

$$p(k \mid m) = \frac{\left(\alpha_{mk} e^{V_{kn}}\right)^{1/\mu_m}}{\sum_k \left(\alpha_{mk} e^{V_{kn}}\right)^{1/\mu_m}} \tag{5}$$

where α_{mk} is an allocation parameter. An allocation parameter means the proportion of an alternative k belonging to a nest m, $0 \leq \alpha_{mk} \leq 1$. Furthermore, for each alternative k, all of its allocation parameters summed to 1, that is, $\sum_m \alpha_{mk} = 1$. Based on the GEV structure, the CNL model can capture the portion of each alternative assigned to each nest. For example, if $\alpha_{mk} = 0$, this means that alternative k does not belong to nest m.

The marginal probability for nest m is shown:

$$p(m) = \frac{\left[\sum_k \left(\alpha_{mk} e^{V_{kn}}\right)^{1/\mu_m}\right]^{\mu_m}}{\sum_m \left[\sum_k \left(\alpha_{mk} e^{V_{kn}}\right)^{1/\mu_m}\right]^{\mu_m}} \tag{6}$$

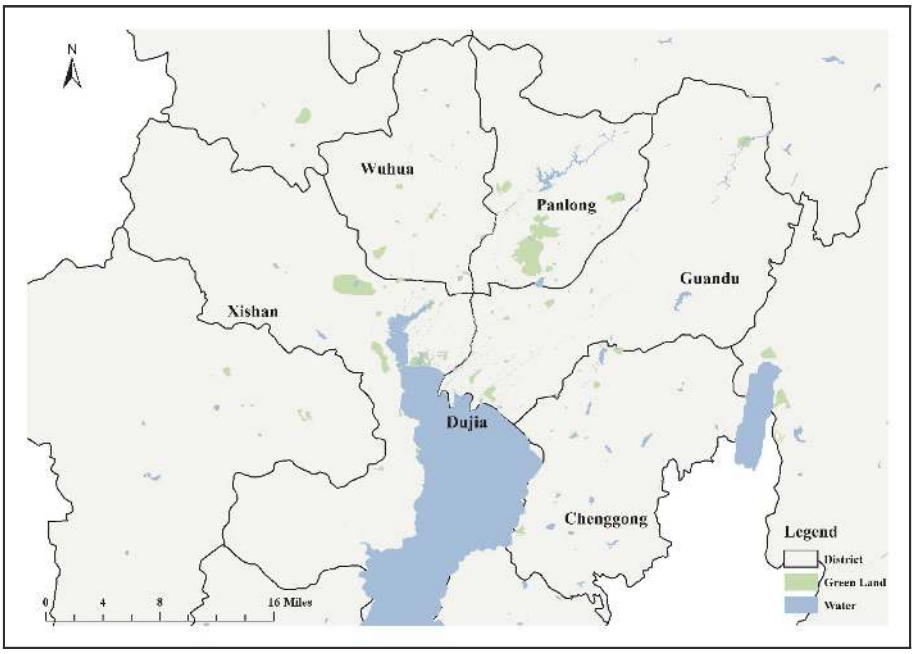


Figure 2: Six representative administrative districts of Kunming for the empirical work.

Therefore, in the CNL model, the probability for an individual selecting alternative k is shown as follows:

$$p(\mathrm{k}) = \sum_m p(k \mid m)\, p(m) = \sum_m \left\{ \frac{\left(\alpha_{mk} e^{V_{kn}}\right)^{1/\mu_m}}{\sum_k \left(\alpha_{mk} e^{V_{kn}}\right)^{1/\mu_m}} \cdot \frac{\left[\sum_k \left(\alpha_{mk} e^{V_{kn}}\right)^{1/\mu_m}\right]^{\mu_m}}{\sum_m \left[\sum_k \left(\alpha_{mk} e^{V_{kn}}\right)^{1/\mu_m}\right]^{\mu_m}} \right\} \tag{7}$$

Thus, the probability for an individual selecting alternative k depends on the following key factors: the dissimilarity parameter μ_m of nest m and systematic item V_{kn} of the utility function, whose coefficients need to be estimated using maximum likelihood estimation method.

4. Dataset

4.1. Study Areas. The study area is set in Kunming, an important tourist and commercial city in China with an area of 21,473 km^2. Six representative administrative districts of Kunming are selected, namely, Chenggong, Dujia, Guandu, Panlong, Wuhua, and Xishan, which constitute the main urban area for the empirical study, as shown in Figure 2. Kunming's total GDP in 2016 was 430.043 billion yuan. By the end of 2015, the permanent population reached 6.677 million, of which 4.677 million were urban residents, accounting for 70.05% of the region's total population. The city's retained motor vehicle count was 2.1507 million. Moreover, Kunming is one of the most important transportation hubs in western China with a road density of 4.4 km/km^2. With the increase in population and urban size and continuous improvement in mechanization, traffic pressure will become increasingly intense. Kunming's public transportation is still in its development stage. The traffic state of the CBD region is basically on the edge of paralysis during peak hours. Thus, improving the current traffic situation in Kunming is urgently needed. The results of the study can likely be generalized into cities in other developing countries.

4.2. Travel Data. The first dataset used in the study is obtained from the Kunming Regional Household Travel Survey, which was organized by Kunming Urban Transportation Research Institute in 2015 on the six representative administrative districts mentioned above. The dataset comprised data on 5,590 people in 2,020 households and 14,326 trips made. After selecting samples of commuting trips departed from home to workplace, we collected a total of 2,918 individuals, from 1,735 households.

Many socioeconomic factors have been proved affecting the choice of departure time and travel mode, such as household, individual, and travel-related attributes [36]. Although some factors, like household income, flexibility for job, and so forth, also have influence on travel behavior, they had not been fully investigated in the developing countries. Consequently, variables such as household size, car ownership, and bicycles ownership constitute the household attributes. Those of individual attributes are gender, age, and occupation. Travel-related attributes include travel cost and travel time. Table 2 presents descriptive statistics of socioeconomic factors selected for the developed model from Kunming Regional Household Travel Survey. Travel cost and travel time of a trip for different travel modes in Table 2 were estimated by the information of departure time, arrival time, travel distance, and total cost for each trip record in the Kunming Regional Household Travel Survey.

Table 2: Descriptive statistics of travel data.

Variables	Description [a]	Mean	St. Dev.
Household characteristics			
Household size	(1) Less than three persons	0.22	0.416
	(2) Equal to three persons	0.59	0.492
	(3) More than three persons	0.19	0.392
Cars Ownership	One or more	0.64	0.480
Bicycles Ownership	One or more	0.74	0.441
Individual characteristics			
Gender	Male	0.53	0.499
Age	(1) Equal to or less than 25 years old	0.10	0.303
	(2) Between 26 and 54 years old	0.86	0.347
	(3) Equal to or more than 55 years old	0.04	0.189
Occupation	Works in a government agency	0.07	0.258
Travel-related characteristics			
Travel cost	Total travel cost of a trip for different travel modes, in ¥		
Travel time	Total travel time of a trip for different travel modes, in min		

Note: N=2918. [a] An answer of yes is indicated by a value of 1.

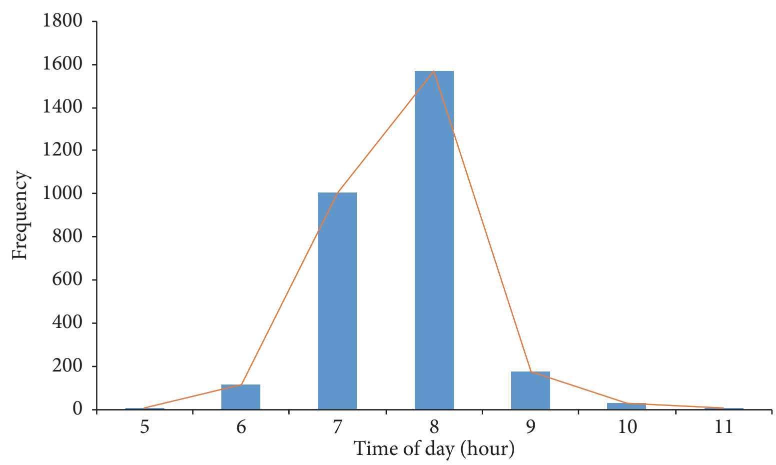


Figure 3: Time-of-day distribution of commuting trips.

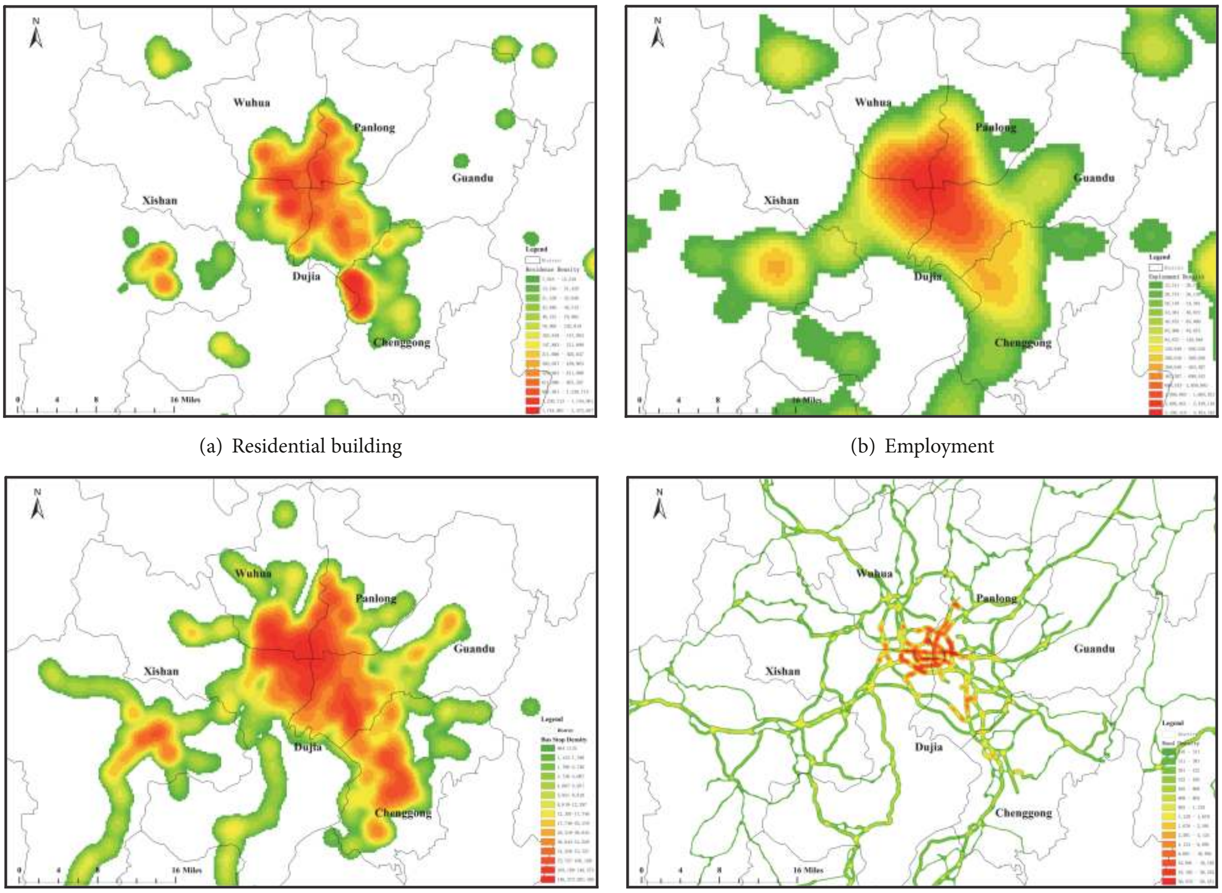
According to the dataset of Kunming Regional Household Travel Survey introduced in last paragraph, Figure 3 shows the distribution of time for commuting trips between 5:00 am and 12:00 pm. The distribution demonstrates that most workers depart to workplaces from home locations during 7:00 am–9:00 am, when the traffic congestion becomes severe. Therefore, the peak time is set as 7:00 am–9:00 am, and the off-peak time consists of two parts, 5:00 am–7:00 am and 9:00 am–12:00 pm.

4.3. Built Environment Characteristics. The second part of the dataset used in this paper is the Point of Interest (POI), which demonstrates the built environment features of Kunming in 2016. Building on POI data and using ArcGIS, the Point of Interest is classified into several categories: residential building, hotel, commerce, service facility, employment, attractions, bus stop, automobile road, parking lot, and external stations. Figure 4 shows four typical built environment thermodynamic charts of Kunming in 2016. Their maximum density is concentrated on one spot, which is the confluence of the six main urban areas (Figure 4(d)).

Some literatures have demonstrated that the densities of residential building, commerce, service facility, employment, bus stop, automobile road, and parking lot have certain influence on travel behavior [7, 33, 38]. Thus, in the model analysis, the paper selects these seven variables from the above-mentioned built environment characteristics and studies their effect on the joint choice of departure time and travel mode. The computational method is defined as follows. Because each commuter's origin is the home, the built environment variables are quantified for each commuter's home locations within a 500m buffer [38].

5. Case Study and Result Analysis

Based on the empirical results of the developed model, the effects of the above-mentioned built environment features and socioeconomic factors on commuters' simultaneous



(a) Residential building (b) Employment

(c) Bus stop (d) Automobiles road

Figure 4: Typical built environment thermodynamic charts of Kunming in 2016.

choice of departure time and travel mode for commuting trips are discussed. We also examine the potential effectiveness of certain policy measures. The CNL model uses C of the feasible sequential quadratic programming (CFSQP) algorithm, because of the characteristic of nontrivial constraints on the allocation parameters. The model presented is estimated and simulated using Biogeme [31, 44, 45]. The results of the estimation consist of the probability of choosing each alternative, systematic item V_{kn} of the utility function, and the results of the simulated choices following the changes.

5.1. Model Interpretation

5.1.1. Estimation Results of Built Environment Features. Based on the developed model, Table 3 presents detailed estimation results of built environment features. On the city level, because built environment features are relatively unmodifiable factors, they determine the basic spatial settings for human activities. Therefore, capturing the relationship between built environment of commuter's home locations and their choices of departure time and travel mode is very necessary to evaluate and prioritize land use planning strategies.

In the case of high residential building density around the commuter's home locations, they usually prefer to depart at peak time. The coefficient of commuting at peak hour by public transit is positive, indicating that higher density of residential building tends to rise the propensity to this choice. Maybe the reason is that public transport facilities are more perfect in places with high residential building density and convenient for travel. It is found that there is no strong correlation between commercial density and commuters' joint choice of departure time and travel mode. However, it is obvious that high density of commerce may encourage more commuters to depart during peak period by walk or bike. Commuters make this decision because a busy business district is usually a city's center. Hence, traffic jams are very common. However, these modes are restricted by traffic jams only to a low extent. In addition, when service facility density is high, commuters tend to depart at off-peak times to stagger traffic jams in busy business districts. As for high density of employment, commuters prefer to depart at peak hours, and public transit would be a favorite mode of transportation. In the case where a number of bus stops are established around home locations, the coefficient of taking cars is negative, indicating that more bus stops tend to lower the propensity to drive automobiles. And

Table 3: Estimation outcomes of the developed model.

Variables	Car		Transit				Walk and bicycle			
	Off-peak		Peak		Off-peak		Peak		Off-peak	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Constant terms	-1.290	-0.18	3.890	6.10[a]	3.570	4.94[a]	4.680	1.75[c]	3.500	7.23[a]
Household characteristics										
Size1	−0.230	−1.30	−0.435	−3.03[a]	−0.508	−3.30[a]	−0.192	−2.31[b]	−0.150	−1.12
Size3	−0.061	−0.37	−0.102	−0.72	0.065	0.58	0.007	0.10	0.059	0.44
Cars	−0.527	−0.07	−4.050	−7.02[a]	−4.190	−7.38[a]	−3.810	−6.37[a]	−3.930	−6.52[a]
Bicycles	0.288	1.78[c]	−0.627	−5.14[a]	−0.668	−4.98[a]	0.465	5.02[a]	0.367	2.58[a]
Individual characteristics										
Gender	−0.272	−1.91[c]	−1.270	−9.80[a]	−1.440	0.01	−0.573	−5.75[a]	−0.646	−5.13[a]
Age1	0.412	1.75[c]	0.942	5.32[a]	1.210	0.01	0.381	2.73[a]	0.418	2.15[b]
Age3	0.678	2.26[b]	0.705	2.38[b]	0.722	1.91[c]	0.378	2.51[b]	0.419	1.58
Occupation	−2.500	−2.84[a]	−0.262	−1.17	−3.470	−0.02	−0.120	−1.23	−1.600	−2.56[b]
Built environment variables										
Residential building density	−0.340	−4.53[a]	0.036	0.66	−0.052	−0.95	−0.045	−1.52	−0.269	−3.60[a]
Commercial density	0.001	0.01	−0.171	−1.63	−0.159	−1.29	0.083	1.46	0.034	0.37
Service facility density	0.305	1.90[c]	0.274	2.03[b]	0.394	3.05[a]	0.079	1.07	0.246	1.93[c]
Employment density	−0.156	−1.31	0.052	0.51	−0.100	−3.32[a]	−0.104	−1.75[c]	−0.137	−1.40
Bus stop density	−0.049	−0.59	0.032	0.47	0.007	0.09	0.025	0.72	0.027	0.44
Automobiles road density	0.003	0.04	−0.069	−1.20	−0.110	−1.87[c]	−0.056	−1.83[c]	−0.098	−1.70[c]
Parking lot density	0.047	0.65	0.025	0.39	0.041	0.57	0.028	0.85	0.032	0.52

Note: Alternative 1 is the base alternative; [a] Significant at the 99% level; [b] Significant at the 95% level; [c] Significant at the 90% level.

Table 4: Model parameters of the joint choice model.

Attributes	Travel cost	Travel time	μ_C	μ_T	μ_W	μ_P	μ_O	final LL	ρ^2	VTTS (CNY¥/h)
Coeff.	-0.179	-0.0622	0.17	0.23	0.38	0.22	0.12	-2918.815	0.422	20.85
t-stat	-8.33[a]	-10.89[a]	0.18	0.01	2.4[b]	7.19[a]	3.12[a]			

Note: [a] Significant at the 99% level. [b] Significant at the 95% level.

commuters prefer to depart at off-peak hours under such a circumstance. Moreover, commuters are more likely to depart at off-peak times by car where automobile road density is high; in other words, national, provincial, and county highways, expressways, and city express roads are plentiful. Consequently, increasing transportation supply, like building more automobile roads, may lead to an increase in car usage and be unable to ease congestion. In the same way, where parking lots around the commuter's home locations are ample, they prefer to leave at off-peak times by cars. Due to limitation of dataset, some factors may not be found to significantly influence the joint choice of departure time and travel mode, but discussing the relationship between these factor and the joint choice behavior is also necessary.

5.1.2. Estimation Results of Socioeconomic Factors. Table 3 also presents detailed estimation results of socioeconomic factors based on the developed model. Evidently, variables, such as household and individual attributes, of the Regional Household Travel Survey in Kunming have an important influence on commuters' combined choice of departure time and travel mode for commuting trips.

First, for household characteristics, commuters with a small number of family members are more likely to depart during peak hours by cars compared with the nuclear family. Meanwhile, when the number of family members is more than three, they will tend to choose public transit, walking, and bicycling as modes of travel and depart at off-peak times to avoid traffic jam. One of the reasons for this scenario is the old people and children in these families, such that arrangements have to be made before traveling to work. As expected, commuters who own cars would like to depart at peak times by cars. However, with the growth in ownership of motorbikes, electric bicycles, and bicycles, commuters prefer to travel by walk and bicycle compared with other travel modes. Walk and bicycle, as modes of travel, are less restricted by traffic jams and in which commuters tend to depart during peak time.

Second, for individual characteristics, compared with the females, male car owners prefer to drive during peak times and dislike public transit as a travel mode, which may be because driving a car is faster. Results show that young individuals are more likely to go to work by public transit than middle-aged people. Perhaps, young individuals have limited car availability and most of them, particularly those under the age of 25, do not have their own private cars. In addition, to get to work on time, they would rather depart early to avoid traffic congestion during peak times. With more leisurely work, older people prefer to depart after peak times by public transit, compared with middle-aged people. In contrast with other alternatives, civil servants working in government agencies are unlikely to depart during off-peak times, but these individuals prefer to depart during peak hours by cars.

5.1.3. The Correlation between Departure Time and Travel Mode. Table 4 shows the travel-related parameters, dissimilarity parameters, final log-likelihood, adjusted ρ^2, and value of travel time savings (VTTS) for the joint choice model. The signs for travel cost and travel time are negative, which means that commuters may abandon their original alternatives if the travel cost and time increased. Based on travel-related parameters, the VTTS of commuting trip for Kunming, China, is calculated to be 20.85 CNY¥/h (0.3475 CNY¥/min). According to dissimilarity parameters, it can be seen that the value of off-peak μ_O is minimal, which means that alternatives in the nest of off-peak μ_O have high correlations and substitutability. Therefore, when travel conditions alter due to policy constraints, commuters, who depart during off-peak time originally, are willing to change their travel mode rather than departure time. Moreover, the μ_W value of walk and bicycle is maximum, meaning low correlations spread along the nest of walk and bicycle. It can also prove that commuters are more likely to change their travel mode rather than departure time, when their original travel mode is walk and bicycle.

5.2. Monte Carlo Simulation Tests. Simulation tests are conducted to examine the potential performance of some transportation demand management and land use planning measures aimed at easing traffic jams and reducing mobile-source emission. It has been proved that some transportation demand management measures are effective at abroad [4]. For example, charging for car travel during peak hours can inhibit the use of cars and equilibrium time distribution of traffic flow. Furthermore, improving public transit services, increasing public transit accessibility and speed, and reducing the waiting time can also attract more individuals to choose public transit as travel mode. Land use planning is widely regarded as a fundamental and long-term strategy, compared with other policy measures such as congestion pricing and gasoline tax. Land use planning also contributes to alleviating the influence of transportation on environment by determining the human activities' basic spatial settings [7]. However, the stages of land use and transport development in China differ from those of developed countries because of the rapid increase of cities with strong centralized planning. Consequently, this section aims to assess the potential performance of these measures in Kunming, China, which can also be used as reference for other cities in the developing countries.

Table 5: The comparison of actual and predicted shares.

Shares	Car		Transit		Walk and bicycle	
	Peak (%)	Off-peak (%)	Peak (%)	Off-peak (%)	Peak (%)	Off-peak (%)
Actual shares	23.68	3.53	16.93	1.92	47.67	6.27
Predicted shares	23.94	3.27	17.08	1.88	47.54	6.29

Note: N=2,918.

Table 6: Predicted shares in different conditions.

Scenario group	Car		Transit		Walk and bicycle	
	Peak (%)	Off-peak (%)	Peak (%)	Off-peak (%)	Peak (%)	Off-peak (%)
Base scenario	23.94	3.27	17.08	1.88	47.54	6.29
Scenario1: increasing travel cost of car travel at peak hour						
CNY¥1	20.32	3.52	17.65	2.04	49.99	6.49
CNY¥2.5	15.53	3.97	18.68	2.01	53.26	6.55
CNY¥5	9.59	4.58	19.55	2.16	57.41	6.72
Scenario2: decreasing travel time of public transit at peak hour						
10% savings	22.30	3.10	21.14	0.99	46.34	6.13
20% savings	20.66	2.83	24.72	0.71	45.21	5.87
30% savings	19.01	2.59	28.27	0.48	43.86	5.80
Scenario3: increasing bus stop density around commuters' home location						
10% increase	19.49	1.24	19.84	1.00	50.56	7.88
20% increase	19.20	1.15	20.04	0.93	50.81	7.86
30% increase	18.80	1.08	20.22	0.94	51.00	7.97

The estimated outcomes shown in Tables 3 and 4 are necessary to get the aggregate shares for each alternative. And, the simultaneous choice probabilities of each commuter are calculated by a sample enumeration [14]. This paper proposed three scenarios for commuters' decisions. The first scenario assumes that travelling by car has a higher travel cost at peak times. The second one simulates that travelling by public transit has a less travel time at peak hours. The third one assumes that bus stop density around commuters' home location is increased because of land use planning. Based on the Monte Carlo simulation tests, simulated choices following the changes are obtained. And then, through the simulated choice above, predicted probabilities for choosing each alternative can be calculated. Table 5 shows that the predicted values are very close to the actual values, which proves that the developed model can be used to represent the choice probabilities for Kunming, China, accurately.

Table 6 shows the results of simulating charges of CNY¥1, CNY¥2.5, and CNY¥5 for car mode at the morning peak, saving 10%, 20%, and 30% travel time for public transit, and increasing bus stop density around the commuters' home location by 10%, 20%, and 30%, respectively. Apparently, under the abovementioned scenarios, the probability of the usage for car mode at peak time decreases and that of public transit travel during peak time increases. However, these three conditions impact each alternative through different ways.

Based on three groups of scenarios, this paper compares the predicted probabilities with the original probabilities of all alternatives in order to analyze the role of travel cost, travel time, and bus stop density in affecting the combined choice of departure time and travel mode. As shown in Figure 5, the horizontal axis presents six alternatives of the developed model. Meanwhile, the vertical axis presents the percentage changes in choosing each alternative. It can be concluded that the changes occur mainly at peak hours. In case of scenario one, with the increase in congestion pricing, a few of the commuters who drive during peak time originally have changed to public transit at off-peak times or walk and bicycle at off-peak times. A moderate number of the above-mentioned commuters have changed their original alternative to driving during off-peak times or travel by public transit during peak times. Additionally, most of them have shifted to walk and bicycle during peak times. It is probably because the original proportion of travelling by walk and bicycle is inherently very large in Kunming. As for scenario two, the amount of usage of public transit has been vastly improved, especially during peak times. A few are those commuters who depart during off-peak times using the types of travel modes, while most of them travel by cars during peak time or travel by walk and bicycle during peak time originally. In scenario three, the amount of usage of public transit during peak time has improved considerably with the increase in bus stop density increases similar to that in scenario two. Moreover, these commuters all drive cars originally, and most depart during peak times; thus the amount of usage of cars in scenario three decreases dramatically.

Comparing the three policy measures, the CNY¥5 charge for car travel can decrease car-driving by 14.35% and increase public transit passengers during peak time by 2.48%. Meanwhile, 30% public transit travel time savings can decrease car-driving by 4.92% and increase public transit passengers

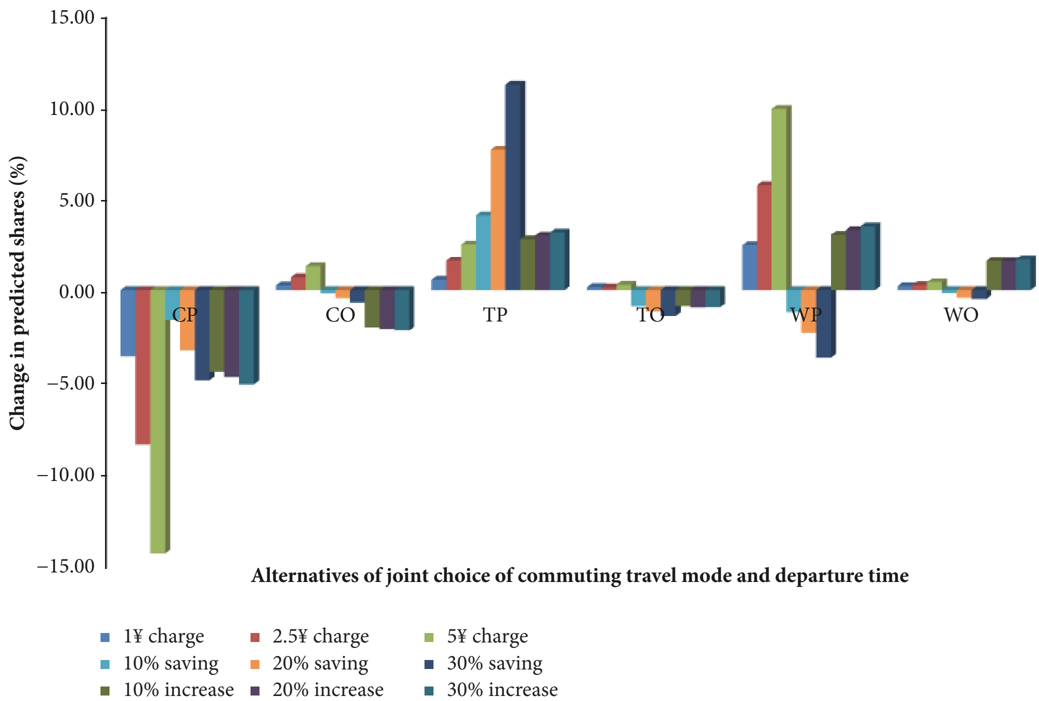


Figure 5: Percentage changes for choosing each alternative in different scenarios; C, T, and W represent car, public transit, and walk and bicycle; P and O represent peak time and off-peak time.

during peak times by 11.19%. Lastly, an increase in bus stop density by 30% can decrease car-driving by 5.13% and increase public transit passengers during peak time by 3.14%. The table also calculates when the car travel cost during peak times is increased by CNY¥5; the total amount of commuting trips during peak time will decrease by 2.1%. In contrast, when the travel time of public transit during peak time decreases by 30%, the total amount of commuting trips during peak time will increase by 2.58%. Furthermore, an increase in bus stop density around commuters' home location by 30% increases the total amount of commuting trips during peak time by 1.46%. Consequently, if the purpose of traffic policy measures is to reduce the amount of commuting trips during peak time, then congestion pricing of car travel during peak time is a good way. In contrast, if the purpose is to encourage commuters to take public transit during peak time, then improving the service level of public transit would be a better measure. Moreover, reasonable land use planning, such as building more bus stops around commuters' home location, would be a long term and fundamental approach to reduce mobile-source emissions and attract more public transit passengers.

6. Conclusions and Future Work

The primary objective of the paper is to conduct an empirical study to explore the impact of built environment features and socioeconomic variables on commuters' combined choice of departure time and travel mode for commuting trips. For study area, we choose the Kunming metropolitan region in China and use the 2015 Regional Household Travel Survey and 2016 POI data in the analysis.

In this paper, not only the correlation between socioeconomic factors and commuters' joint choice behavior, but also the relationship between built environment features and departure time is analyzed. Socioeconomic factors consist of household, individual, and travel-related attributes, while built environment features consist of residential building density, commercial density, service facility density, employment density, bus stop density, automobiles road density, and parking lot density. Moreover, the influence of these factors on departure time and travel mode is distinct. Commuters prefer to shift travel mode than departure time generally when travel conditions alter. This empirical finding is a prerequisite to assessing the potential performance of policy measures, and the results can likely be generalized into other cities in China or those of other developing countries.

The results of the Monte Carlo simulation show that if transportation demand management measures aim to reduce the amount of commuting trips during peak time, then congestion pricing of car travel during peak time is a good way of imposing payment. On the contrary, if the purpose is to encourage commuters to take public transit during peak time, then improving the service level of public transit would be a better measure. Moreover, reasonable land use planning, such as building more bus stops around commuters' home location, would be a long term and fundamental approach to reduce mobile-source emissions and attract more public transit passengers. In addition, the built environment determines the human activities' basic spatial settings, and it is also widely regarded as a planning measure to increase the performance of public transit, decrease usage of automobiles, and subsequently reduce VMT and emission. These factors work together to promote high-density, mixed-use and compact urban development.

Potential directions for future research include three aspects as follows. First, using an advanced model structure, for instance, the Network GEV model is another method with which to analyze joint choice behavior. Second, more influential factors, like travel attitudes, should be considered in further research. Third, comparing different land using planning strategies could enable us to obtain a comprehensive understanding of the correlation between built environment and the simultaneous choice of departure time and travel mode.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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