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CO_2 emissions: can built environment change commuter's driving behavior? Joint analysis the spatial impacts of built environment on car ownership and travel mode choice

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Abstract:

Concerns over transportation energy consumption and transport emissions have prompted more studies into the impacts of the built environments on driving-related behavior, especially car ownership and travel mode choice. This study contributes to examine the impacts of the built environment on commuter's driving behavior at both spatial zone level and individual level. The aim of this study is threefold. First, a multilevel integrated multinomial logit (MNL) and structure equation model (SEM) approach was employed to jointly explore the impacts of the built environment on car ownership and travel mode choice. Second, the spatial context in which individuals make the travel decisions was accommodated, and spatial heterogeneities of car ownership and travel mode choice across traffic analysis zones (TAZs) were recognized. Third, the indirect effects of the built environment on travel mode choice through the mediating variable car ownership were calculated, in other words, the intermediary nature of car ownership was considered. Using the Washington metropolitan area as the study case, the built environment measures were calculated for each TAZ, and the commuting trips were drawn from the household travel survey in this area. To estimate the model parameters, the robust maximum likelihood (MLR) method was used. Meanwhile, a comparison among potentially different model structures was conducted. The model results suggest that the application of the multilevel integrated MNL and SEM approach obtains significant improvements over other models. The findings confirmed the important roles that the built environment played in car ownership and commuting mode choice. The significant spatial heterogeneities of car ownership and commuting mode choice were found. The study are expected to give transportation planners and policy makers a better understanding on how the built environment and individual level factors influence the driving-related behavior, and consequently develop more effective and targeted countermeasures to reduce the auto dependency, thereby reducing the vehicle energy consumption and emissions.

Keywords: car ownership, travel mode choice, built environment, spatial heterogeneity, mediating effect

1 Introduction

With the increases in car ownership and usage, transportation sector's shares of energy consumption and emissions are significant and increasing. Between 1970 and 2005 average annual vehicle miles travelled (VMT) per household increased by 50 percent (Bureau of Transportation Statistics, 2007[1]). The transportation sector accounts for approximately 33 percent of total CO_2 emissions from fossil fuel combustion, the largest share of any end-use economic sector (Liu and Shen, 2011[2]). In addition to the environmental damages, extensive transport emissions caused by the increased automobile usage also results in public health problems (Xue et al., 2015[3]). As to the CO_2 emissions, fuel consumption and emission reduction from the transportation sector can be achieved by coordinating the "three-leg stool": fuel types, vehicle fuel efficiency, and VMT (Ewing et al. 2008[4]).

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[2] Chao Liu, Qing Shen. An empirical analysis of the influence of urban form on household travel and energy consumption. Computers, Environment and Urban Systems. 2011, 35(5), 347-357.
[3] Xiongzhi Xue, Yan Ren, Shenghui Cui, Jianyi Lin, Wei Huang, Jian Zhou. Integrated analysis of GHGs and public health damage mitigation for developing urban road transportation strategies. Transportation Research Part D, 2015, 35, 84-103.
[4] Reid Ewing, Keith Bartholomew, Steve Winkelman, Jerry Walters, Don Chen. Growing Cooler: The Evidence on Urban

Adapting from the study conducted by Cervero and Murakami (2010[5]), the combination of the "three-leg stool" to reduce the transport CO_2 emissions can be described as follows:

$$transport\ emissions = \underbrace{\underbrace{\left(\frac{gallons}{mile}\right)}_{fuel\ consumtion} \times \underbrace{\left(\frac{carbon}{gallons}\right)}_{carbon\ content}}_{sustainable\ mobility} \times \underbrace{\underbrace{\left(\begin{matrix} vehicle\ miles \\ traveled \end{matrix}\right)}_{activity}}_{sustainable\ urbanism} \tag{1}$$

Overall, the three "three-leg stool" to deal with the growth of vehicle energy consumption and emissions can be divided into two potential solutions: sustainable mobility and sustainable urbanism. Strategies such as introduction of low-carbon fuels and new technologies that increase fuel efficiency aims to improve the first two "legs of the stool" belong to the ways of sustainable mobility solutions. Another way to alleviate vehicle energy consumption and transport emission is through the sustainable urbanism such as re-planning our cities (i.e. built environment) so there is less need to drive. A growing body of literatures has focused on investigating the relationship between the built environment and travel behavior (Ewing and Cervero, 2001[6]; 2010[7]). Especially, the studies related to the causal effects of the built environment on driving behavior (e.g. car ownership, mode choice, and VMT) have obtained more attentions (Ding et al., 2014[8]; Nasri and Zhang, 2014[9]; Heres-Del-Valle and Niemeier, 2011[10]; Cervero and Murakami, 2010; Van Acker and Witlox, 2010[11]; Zegras, 2010[12]; Manaugh et al., 2010[13]; Bhat and Eluru, 2009[14]; Bhat and Guo, 2007[15]; Cao et al., 2007[16]). However, the debate on the influences of various built environment measures on travel behavior is far away from reaching the consensus due to the different empirical contexts, geographical scale, residential self-selection, and methodologies (Cao, 2015[17]; Antipova et al., 2011[18]; Mokhtarian and Cao, 2008[19]; Limtanakool et al., 2006[20]; Handy et al., 2005[21]).

Development and Climate Change. Urban Land Institute, Washington, D.C. 2008.

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[19]Patricia L. Mokhtarian, Xinyu Cao. Examining the impacts of residential self-selection on travel behavior: a focus on methodologies. Transportation Research Part B, 2008, 42(3), 204-228.

This aim of this study is to investigate the effects of the built environment on car ownership and travel mode choice simultaneously, by using a multilevel integrated MNL and SEM model that jointly accommodates the spatial context in which individuals make travel decisions and considers the intermediary of car ownership. Moreover, a comparison among potentially different model structures was conducted. Finally, the spatial heterogeneities of car ownership and travel mode choice across TAZs were recognized, and the direct, indirect and total effects of the built environment on car ownership and travel mode choice were obtained. Hence, this study makes efforts to answer the question: can the built environment change commuter's driving behavior?

The remainder of this paper is organized as follows. The next section presents a brief overview of the existing literatures. The third section presents the modeling approach used for the analysis. The following section presents the data sources and the built environment measurements. The model results are explained in fifth section. Finally, the highlights and future directions of this paper are concluded.

2 Literature review

As vehicle energy consumption and emissions increases in recent years, driving-related behavior especially car ownership and travel mode choice has received a great amount of attention in travel demand analysis because of its important roles played in transportation and land use planning (Ding et al., 2014, 2015[22]; Nielsen et al., 2013[23]; Van Acker and Witlox, 2010; Zegras, 2010; Potoglou and Kanaroglou, 2009[24]; Cao et al., 2007[25]; Zhang, 2004[26]; Cervero, 2002[27]; Bhat and Pulugurta, 1998[28]). According to the theoretical framework of hierarchical travel behavior given by Ben-Akiva and Atherton (1977[29]), car ownership should be considered as a medium-term decision, and it depends on the long-term decisions (e.g. residential choice). Car ownership, in turn, impacts the short-term decisions (e.g. travel mode choice). In other words, car ownership is a key mediating linkage between the built environment and travel mode choice. However, in the most existing transportation studies, car ownership is assumed to be exogenous factor to travel mode choice with ignoring its intermediary nature (Ding et al., 2014). To our knowledge, there are limited empirical studies that confirmed the intermediary nature of car ownership when exploring the built environment on travel mode choice behavior

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(Acker and Witllox, 2010; Cao et al., 2007; Scheiner and Holz-Rau, 2007[30]). Therefore, to be more consistent with the actual travel decision process, car ownership should be taken as a mediating rather than a given factor.

Most studies on the impacts of the built environment on travel behavior are often conducted at a certain aggregated spatial unit such as TAZ, census tract, or the zip code level, thereby spatial issues (i.g. spatial dependency, spatial heterogeneity, and spatial heteroscedasticity) occur among travelers living within the same zone because of the locational effects (Bhat and Zhao, 2002[31]; Bhat, 2000[32]). Generally speaking, ignoring the spatial context in which individuals make travel decisions can lead to inconsistent model results. To solve this problem, the multilevel modeling framework has been employed to the relationship analysis between built environment and travel behavior in recent years (Ding et al., 2014, 2014[33], 2015; Nasri and Zhang, 2014; Hong et al., 2014[34]; Hong and Goodchild, 2014[35]; Hong and Shen, 2013[36]; Antipova et al., 2011). The previous empirical researches show that there are significant spatial variations across TAZs for car ownership and travel mode choice, and the studies conducted by Ding et al. (2014a, 2014b, 2015) and Hong et al. (2014) indicated that ignoring the spatial heterogeneity of travel behavior across TAZs could result in erroneous conclusions. Although previous studies highlights the need to accommodate the spatial context in which individuals make the duration travel decisions, the recognition of spatial issues in travel modeling is not still sufficiently investigated, which might be relevant to the complicated estimation for the multilevel model.

Using different travel outcome dimensions, spatial scales, modeling approach, and estimation techniques, a substantial body of studies has examined the impacts of the built environment on driving-related behavior, and yet little consensus has been reached (Ewing and Cervero, 2001; 2010). To our knowledge, there is no effort that has been made to accommodate the spatial context in which individuals make travel decisions and consider the intermediary of car ownership simultaneously in the existing literatures related to investigate the impacts of the built environment on travel behavior. To fill up this gap, the aim of this study is threefold. First, a multilevel integrated MNL and SEM model was employed to jointly explore the impacts of the built environment on car ownership and travel mode choice. Second, the spatial context in which individuals make the travel decisions was accommodated, and spatial heterogeneities of car ownership and travel mode choice across TAZs were recognized. Third, the indirect effects of the built environment on travel mode choice through the mediating variable car ownership were calculated, in other words, the intermediary nature of car ownership was considered. Meanwhile, a comparison among potentially different model structures was conducted. This study is expected to better provide additional insights into the impacts of the built environment on driving-related behavior.

3 Model specification

To examine the impacts of built environment factors on car ownership and travel mode choice, several

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30 Joachim Scheiner, Christian Holz-Rau. Travel mode choice: affected by objective or subjective determinants? Transportation, 2007, 34(4), 487-511.

31 Chandra Bhat, Huimin Zhao. The spatial analysis of activity stop generation. Transportation Research Part B, 2002, 36(6), 557-575.

32 Chandra R. Bhat. A multi-level cross-classified model for discrete response variables. Transportation Research Part B, 2000, 34(7), 567-582.

33 Chuan Ding, Yaowu Wang, Binglei Xie, Chao Liu. Understanding the role of built environment in reducing vehicle miles traveled accounting for spatial heterogeneity. Sustainability, 2014, 6(2), 589-601.

34 Jinhyun Hong, Qing Shen, Lei Zhang. How do built-environment factors affect travel behavior? A spatial analysis at different geographic scales. Transportation, 2014, 41(3), 419-440.

35 Jinhyun Hong, Anne Goodchild. Land use policies and transport emissions: modeling the impact of trip speed, vehicle characteristics and residential location. Transportation Research Part D, 2014, 26, 47-51.

36 Jinhyun Hong, Qing Shen. Residential density and transportation emissions: examining the connection by addressing spatial autocorrelation and self-selection. Transportation Research Part D, 2013, 22, 75-79.

modeling frameworks can be obtained based on prior empirical research. Generally, built environment factors are measured at traffic analysis zone (TAZ) scale due to land use data availability. In this study, car ownership is taken as a continuous variable (i.e. number of household vehicles available). The travel mode choice subset includes three modes: car, transit, and non-motorized mode (i.e. walk and bicycling).

3.1 Model structure

The most widely used model structure is the MNL framework, which takes car ownership as an exogenous variable in addition to the socio-demographic and built environment variables as shown in Figure 1. In this framework, there are no indirect effects of socio-demographic and built environment variables on travel mode choice because car ownership is not considered as a mediating variable. In the second model structure as shown in Figure 2, two endogenous variables are depicted: car ownership as a mediating variable and travel mode choice as a final outcome. Consequently, the integrated MNL and SEM model structure can be used to reveal the intermediary nature of car ownership in travel mode choice decision process. Meanwhile, by assuming a relationship from socio-demographic variables to the built environment, the second model structure partly accounts for the issue of residential self-selection. This model structure can not only capture the direct effects of socio-demographic and built environment variables on car ownership and travel mode choice, but also reveal the indirect of socio-demographic and built environment variables on travel mode choice through the mediating variable car ownership.

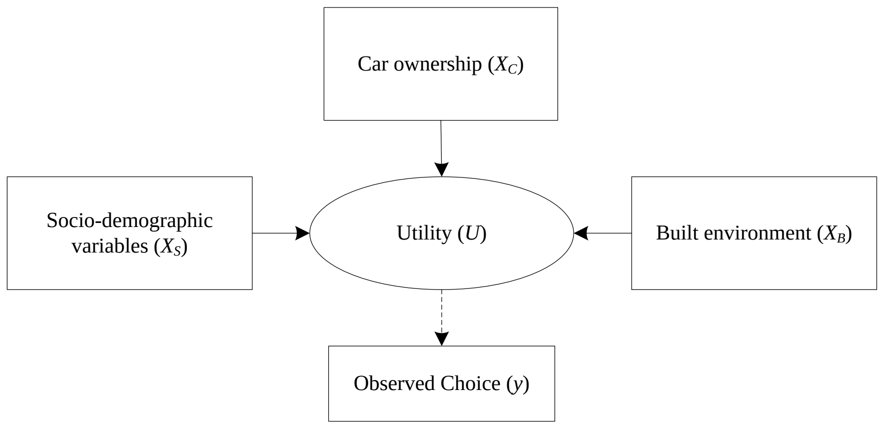

Figure 1 Traditional framework describing the relationship between built environment and travel mode choice behavior

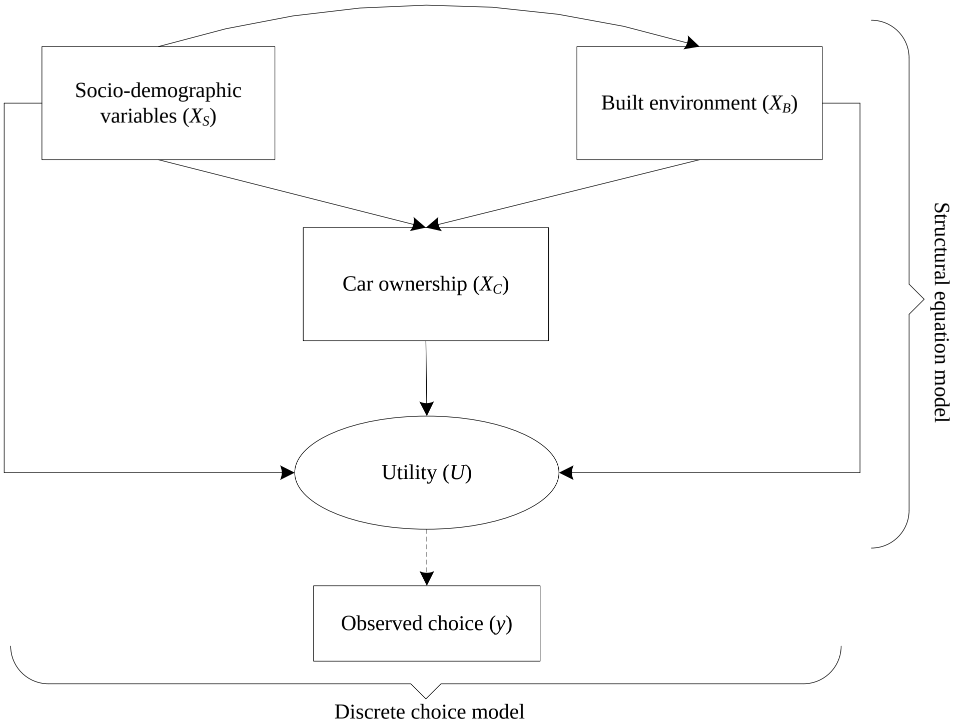

Figure 2 Framework of the integrated model of car ownership and travel mode choice

The both aforementioned model structures cannot be used to accommodate the spatial context in which individuals make travel decisions, especially modeling car ownership and travel mode choice simultaneously. The deficiency of traditional model structures is one motivation for the efforts made in this study. Considering the advantages of multilevel modeling approach in accounting for the hierarchical structure of the data, this study tries to incorporate the multilevel framework into the integrated MNL and SEM model, as shown in Figure 3. Such a model structure assumes the effects of individual level variables are fixed across TAZs and that TAZs vary as a function of built environment variables measured at TAZ level. For the multilevel integrated MNL and SEM model, varying intercepts are estimated by using both individual and group information. By specifying individuals nested within TAZs, the proposed model structure can separate the effects of built environment variables on car ownership and travel mode choice from individual associated attributes. Detailed model formulations of car ownership component and travel mode choice component are described as follows.

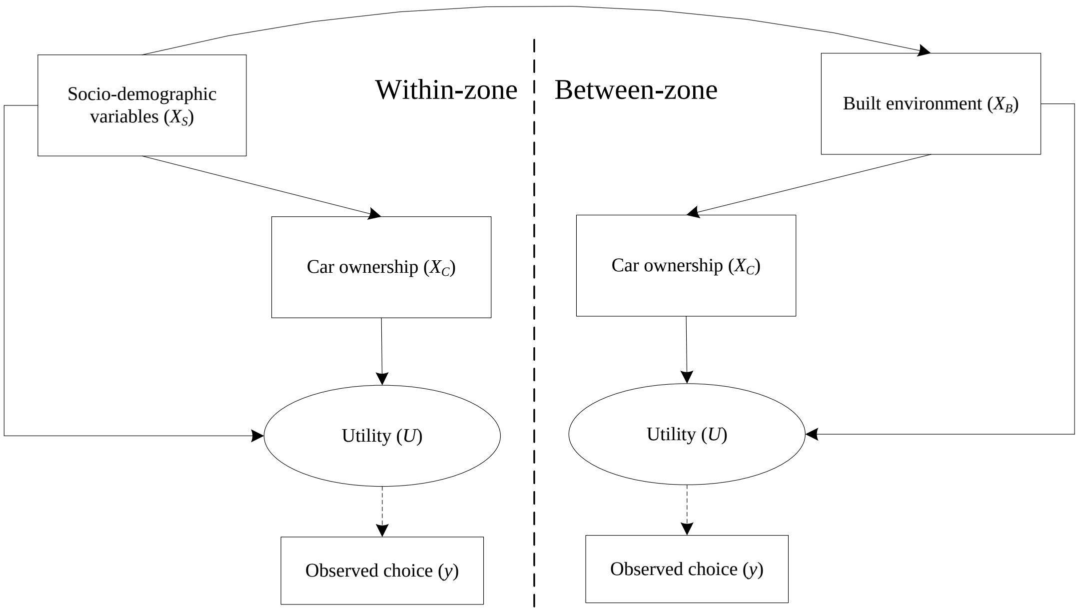

Figure 3 Framework of the multilevel integrated model of car ownership and travel mode choice

3.1 Car ownership model component

The endogenous variable CAR_{qh} that an individual i (i=1, 2, …, I) living in residence zone h (h=1, 2, …, H) associates with the number of cars (k=0, 1, 2, …, K) in a household can be written as follow:

$$CAR_{ih} = \alpha_{ih} + \beta^{\mathrm{T}} X_{ih} + \varepsilon_{ih} \tag{2}$$

And:

$$\alpha_h = \varphi + \gamma^{\mathrm{T}} Z_h + \xi_h \tag{3}$$

where X_{ih} and Z_h represent the individual associated attributes, and built environment measures at home location TAZs, respectively. α_{ih} is a varying intercept associated with the residence zone h of an individual i. β, φ, and γ are fixed effect coefficients on the different levels. ε_{ih} is an unobserved random term that represents idiosyncratic individual differences after allowing for differences due to observed individual characteristics and zone-level differences. ξ_h is the random terms that capture unobserved variations across home location zones. Here, ε_{ih} and ξ_h are assumed to be normally and identically distributed:

$$\varepsilon_{ih} \sim N(0, \sigma_{ih}^2),\ \xi_h \sim N(0, \sigma_h^2) \tag{4}$$

Then, the final model with built environment factors at residential zone level can be expressed as follows:

$$\begin{cases} CAR_{ih} \sim N(\alpha_{ih} + \beta^{\mathrm{T}} X_{ih}, \sigma_{ih}^2) \\ \alpha_h \sim N(\varphi + \gamma^{\mathrm{T}} Z_h, {\sigma_h}^2) \end{cases} \tag{5}$$

where varying intercept α_{ih} is assumed to be normally and independently distributed with the expected value $\varphi+\gamma^{\mathrm{T}}Z_h$ and standard deviation σ_h. Z_h refer to group predictors measured at home-zone level.

A conventional varying intercept model can accommodate the spatial context in which individuals make travel decisions: spatial autocorrelation (correlation among individuals in the same residential zone) and spatial heterogeneity (variations in impedance measures across zonal pairs). The correlation between two individuals in the same home zone can be expressed by intra-class correlation (ICC) coefficient as follow:

$$ICC_h = \frac{\sigma_h^2}{\sigma_{ih}^2 + \sigma_h^2} \tag{6}$$

The value of *ICC* ranges from 0 to 1. This index describes the spatial heterogeneity across TAZs in the relationship between household car ownership and its determinants. It also captures spatial autocorrelations among households residing within the same zone and recognizes spatial heteroscedasticity (Bhat and Zhao, 2002). In general, if the value of *ICC* combines the range of 0.10 to 0.25 or higher, there is a need to perform a multilevel analysis (Snijder and Bosker, 2012[37]).

3.2 Mode choice model component

The random utility U_{ihm} that an individual i (i=1, 2, …, I) living in residence zone h (h=1, 2, …, H) associates with an alternative mode m (m=1, 2, …, M) can be written as follow:

$$U_{ihm} = \lambda_{ihm} + \mu^{\mathrm{T}} X_{ihm} + \rho^{\mathrm{T}} CAR_{ihm} + \zeta_{ihm} \tag{7}$$

And:

$$\lambda_{hm} = \phi + \nu^{\mathrm{T}} Z_h + \tau_{hm} \tag{8}$$

where X_{ihm}, CAR_{ihm}, and Z_h represent the individual associated attributes, car ownership, and the built environment measures at home location TAZs, respectively. λ_{ihm} is a scalar utility term for alternative m associated with the residence zone h of the individual i. μ, ϕ, and ν are fixed effect coefficients on the different levels. ζ_{ihm} is an unobserved random term and it is assumed to be independently and identically distributed (IID). In case of logit model, the random term ζ_{ihm} is assumed to have an independent and identical Gumbel distribution. In case of probit model, it is assumed that ζ_{ihm} is distributed according to a standard normal distribution with zero mean and unit variance. τ_{hm} is the random term that captures unobserved variations across home location zones. Here, τ_{hm} is assumed to be normally distributed and identically distributed:

$$\tau_{hm} \sim N(0, \sigma_{hm}^2) \tag{9}$$

Then, the zone level model with built environment factors can be transformed to form as follows:

$$\lambda_{ihm} \sim N(\phi + \nu^{\mathrm{T}} Z_h, \sigma_{hm}^2) \tag{10}$$

where varying intercept λ_{ihm} is assumed to be normally and independently distributed with the expected value $\phi+\nu^{\mathrm{T}}Z_h$ and standard deviation σ_{hm}. Z_h refer to group predictors measured at residential zone level. Therefore, the integrated individual level and zone level model can be expressed by Eq. (6) and Eq. (9). Conditional on ζ_{ihm} and

[37] Tom A B Snijders, Roel J Bosker. Multilevel analysis: an introduction to basic and advanced multilevel modeling (Second edition). Sage Press, Thousand Oaks, California, 2012.

τ_{hm} terms, the probability of choice of mode *m* for individual *i* in residence zone *h* can be written in the standard multinomial logit (MNL) model form as follows:

$$p_{ihm} \mid (\zeta_{ih1},...,\zeta_{ih2M},\tau_{h1},...,\tau_{hM}) = \frac{\exp(\phi + \mu^{\mathrm{T}} X_{ihm} + \rho^{\mathrm{T}} CAR_{ihm} + \nu^{\mathrm{T}} Z_h + \zeta_{ihm} + \tau_{hm})}{\sum_{m=1}^{M} \exp(\phi + \mu^{\mathrm{T}} X_{ihm} + \rho^{\mathrm{T}} CAR_{ihm} + \nu^{\mathrm{T}} Z_h + \zeta_{ihm} + \tau_{hm})} \quad (11)$$

Though traditional MNL model has an advantage in that probability has a simple closed form, it cannot account for unobserved similarities which exist among choice alternatives because of the independence of irrelevant alternatives (IIA) assumption. The multilevel MNL model allow more flexible pattern of error correlation structure, therefore it can overcome the IIA problem to a certain extent. A conventional varying intercept MNL model can accommodate the spatial context in which individuals make travel decisions: spatial autocorrelation (correlation among individuals in the same home zones) and spatial heterogeneity (variations in impedance measures across zonal pairs). For two individuals in the same home zone, the correlation between them for the mode *m* can be expressed as follows:

$$ICC_{hm} = \frac{\sigma_{hm}^2}{\sigma_{\zeta}^2 + \sigma_{hm}^2} \quad (12)$$

where σ_{ζ} is the standard deviation of ζ_{ihm} that has a logistic distribution, so the value of σ_{ζ} is $\sqrt{\pi^2/3}$. In case of probit model, the value of σ_{ζ} is one for a standard normal distribution (Snijder and Bosker, 2012).

To estimate the integrated car ownership and mode choice model, simultaneous estimation approach which is a full information estimation method was conducted using the software package *M*-plus to overcome the limitation of sequential approach (i.e. inconsistent and inefficient estimates) (Raveau et al., 2010[38]). Meanwhile, the direct and indirect effects of socio-demographic factors and built environment measures on car ownership as well as on travel mode choice were taken into account. Maximum likelihood (ML) method is a generally used estimating procedure in structural equation model. A basic assumption of the ML estimator is the multivariate normal distribution of all continuous endogenous variables in the model (Kline, 2005[39]). However, this assumption is not always fulfilled and, moreover, the final outcome variable travel mode choice is nominal. In order to deal with this issue, a robust maximum likelihood (MLR) estimator was used instead.

4 Data sources and description

The travel data used in this study is drawn from the household travel survey (HTS) conducted in Washington metropolitan area during the year 2007-2008 (NCRTPB-MWCOG, 2010[40]). Each household completed a travel diary that documented the activities of all household members on an assigned day, including how, where, when, and why people travel in the region. In addition to HTS data, origin-destination travel time and cost matrices by different travel modes were obtained from Maryland Statewide Transportation Model

[38] Sebastian Raveau, Ricardo Alvarez-Daziane, Maria Francisca Yanez, Denis Bolduc, Juan de Dios Ortuzar. Sequential and simultaneous estimation of hybrid discrete choice models: some new findings. Transportation Research Record: Journal of the Transportation Research Board, 2010, 2156, 131-139.

39 Rex B. Kline. Principles and practice of structural equation modeling (second edition), Guilford Press, New York, 2005.

[40] National Capital Region Transportation Planning Board Metropolitan Washington Council of Governments. 2007/2008 TPB Household Travel Survey: Technical Documentation. August 27, 2010.

(MSTM) (Mishra, 2011[41]). The sample data used for the modeling process is selected from the HTS of Washington metropolitan area, including all the trips from home to workplace in the morning (6 a.m.-12 p.m.). After removing the cases with missing data and the respondents who are less than 16 years old, the final sample comprises 6900 respondents. In the sample, 5314 respondents (77.0%) use car as commuting mode, whereas 1318 respondents (19.1%) and 268 respondents (3.9%) use transit, and non-motorized mode, respectively.

For the sample, the average household size is 2.55 and almost 20% of the respondents are single person household. Nearly 35% of the respondents have one worker and over 53.8% have two workers in their household. The lowest household income category (less than $50000) constitutes 12% of the respondents. The proportion of the respondents with students is about 41%. The average car ownership is 2.01 and 68% of the samples have two or more vehicles. Only 3.9% of the samples have no vehicles and 27.9% have a single vehicle in their household. The average sample age is 44 years. The males equal to females in our sample and nearly 75% of the respondents are white people. 6% of the respondents have more than one job. 1916 respondents (27.8%) live in suburban and rural areas, and 4984 respondents (74.2%) live in urban or central business district (CBD) areas. Household and individual characteristics of the sample data are described in Table 1.

Table 1 Descriptive statistics of sample data for the commuting trips

Variable Name	Variable Description	Mean	St. Dev.
Household characteristics			
Household size	Number of persons in household	2.55	1.256
Household workers	Number of workers in household	1.76	0.683
Household income	Income1: Household income is less than $50,000 (1=yes)	0.12	0.325
	Income2: Household income is between $50,000 and $100,000 (1=yes)	0.33	0.471
	Income3: Household income is equal to or more than $100,000 (1=yes)	0.55	0.498
Household students	Number of students in household	0.69	0.979
Car ownership	Number of household vehicles available	2.01	1.062
Individual characteristics			
Age	Age in years	44.27	12.545
Gender	Male (1=yes)	0.50	0.500
Race	Caucasian people (1=yes)	0.75	0.434
Jobs	Person has more than one job (1=yes)	0.06	0.238
Travel-related characteristics			
Travel time	Continuous variable: total time of a trip for different travel mode (min) provided by MSTM		
Travel cost	Continuous variable: total travel cost of a trip for different travel mode ($) as a function of distance provided by MSTM		

Note: 6900 persons, 1274 residential zones.

When exploring the relationships between the built environment and travel behavior, the built environment can be measured at different geographic scales (Handy et al., 2002[42]), and generally characterized from three aspects (i.e. density, diversity, and design) (Ewing and Cervero, 2010, 2001). In this study, according to the

[41] Sabyasachee Mishra, Xin Ye, Fred Ducca, Gerrit Jan Knaap. A functional integrated land use-transportation model for analyzing transportation impacts in the Maryland-Washington, DC Region. Sustainability: Science, Practice, & Policy. 2011, 7(2), 60-69.

[42] Susan L. Handy, Marlon G. Boarnet, Reid Ewing, Richard E. Killingsworth. How the built environment affects physical activity: views from urban planning. American Journal of Preventive Medicine, 2002, 23(2s), 64-73.

space of commuting activity, the built environment factors of residential neighborhood were measured at the geographic scale of TAZ. Using the collected land use data, the features of the built environment are measured by several types of elements, including residential density, employment density, land use mix, average block size, and distance from CBD. Density variable represents the level of sprawl and activity. Land use mix quantified the degree of balance across different land use types, representing the accessibility to various destinations. The variable of average block size represents the street network characteristic within the neighborhood. Distance from CBD measures the spatial centrality of residential location. These five measures were calculated for the total 2191 TAZs in ArcGIS 10.0 based on the method that was directly taken from author previous work (Ding et al., 2014). Table 1 presents the descriptive statistics for built environment factors in the case area. The GIS shape files of TAZ were used for spatially processing the datasets and integrating the built environment measures into the travel survey records.

Table 2 Built environment factors measured at TAZ level

Built environment measures	Definition at TAZ level
Residential density	Population/Area size (persons/ acre)
Employment density	Employment/ Area size (jobs/ acre)
Land use mix (entropy)	Mixture of residential, service, retail, and other employment land use types
Average block size	Average block size within TAZ (square mile)
Distance from CBD	Straight line distance from CBD (mile)

5 Model results

There are three potential different model structures to describe the relationship between built environment and travel behavior as specified in aforementioned part. These alternative models were estimated using the MLR estimation method and the model fit indices are reported in Table 3. In this study, four goodness-of-fit indices were used to assess the model fit, including the final log-likelihood value, likelihood ratio index (LRI), Akaike information criterion (AIC), and Bayesian information criterion (BIC). Generally, higher value of final log-likelihood and LRI, and lower values of AIC and BIC identify a better fitting model. When comparing the model fit information among the three models, it is found that the model fit of the three models improves with increasing complexity of the models. The LRI shows that the third model obtains a better fit. Specifically, the log-likelihood value of the multilevel integrated MNL and SEM model was 211.923 points higher than the other two models. The values of AIC and BIC were 417.846 points lower than the other two models. The multilevel integrated MNL and SEM model estimated both the travel mode choice parameters as well as car ownership parameters simultaneously, considering the intermediary role of car ownership played in travel behavior process and accounting for the spatial context in which individuals make travel behavior. Therefore, the model results are further discussed in detail based on the proposed multilevel integrated MNL and SEM model.

Table 3 Comparison of the model fit measurements for the three models

Model fit measurements	Model 1		Model 2	Model 3
Endogenous variables	Car ownership	Travel mode choice	Car ownership & Travel mode choice	Car ownership & Travel mode choice
Observations	6900	6900	6900	6900
Number of parameters	11	34	45	48
LL_{κ}	-8157.199	-3422.287	-11579.486	-11367.563

LRI	0.418	0.312	0.344	0.406
Akaike information criterion (AIC)	16336.398	6912.574	23248.972	22831.126
Bayesian information criterion (BIC)	16376.675	7037.066	23413.740	23006.878

Note: LRI is likelihood ratio index, LRI=1-(LLκ/LLκ0), LLκ0 is the log-likelihood value when all the parameters are set equal to zero.

5.1 Car ownership model parameter estimates

The results of car ownership model component are presented in Table 4. From the model results, we can gain that how the built environment influences car ownership after controlling for the household characteristics. The model results show that all the built environment variables were found to have significant impacts on car ownership at the 95% level, with the expected signs. Among the built environment measures, the parameter estimates indicate that people living in high residential and employment densities were more likely to own fewer automobiles, perhaps because of more alternative modes in the dense areas (Ding et al., 2015). Significant relationships were also found between land use mix and car ownership, which is consistent with the studies conducted by Zegras (2010), and Potoglou and Kanaroglou (2008). This may be due to the fact that high degree of mixed land use may shorter the commuting origin-destination distances, thereby reduce the probability of owing more automobiles. Average block size was found to have positive impact on car ownership, indicating that people in smaller block size are more likely to have fewer automobiles, potentially because of the better street connectivity. People living further from the CBD have a higher likelihood of owning automobiles. Generally, the transit service decreases with the distance from CBD increases, and the limited transit accessibility makes people living further from the CBD have to own automobiles. Among the household factors, the number of household size, workers, and household income were found to be significantly related to car ownership at the 95% level. Specifically, the parameter estimates indicate that households with more people and workers have a higher preference to own more automobiles. As expected, increasing the household income is more likely to increases the probability that households own more automobiles.

Table 4 Estimation results for car ownership component of the joint model

Variables	Multilevel integrated MNL and SEM model	
	Parameter	*t*-statistic
Constant	0.684	11.054**
Socio-demographic and control factors at individual level		
Household size	0.124	10.668**
Household workers	0.541	21.452**
Income-1	-0.242	-7.005**
Income-3	0.233	9.560**
Built environment variables at TAZ level		
Residential density	-0.014	-7.141**
Employment density	-0.002	-3.294**
Land use mix	-0.139	-2.065**
Average block size	0.061	5.289**
Distance from CBD	0.007	4.688**
Spatial heterogeneity parameters across home zones		
σ_{ih}^2	0.520	22.816**
σ_h^2	0.117	8.825**

Note: ** indicates significant values at the 95% level; * indicates significant values at the 90% level.

The spatial heterogeneity parameters of car ownership are found to be significant at 95% level, indicating that household car ownership varies significantly across TAZs. The *ICC* index can be calculated using Eq. (6), representing the degree of the spatial heterogeneity of household auto ownership at the geographic scale of TAZ:

$$ICC_h = \frac{\sigma_h^2}{\sigma_{ih}^2 + \sigma_h^2} = \frac{0.117}{0.520 + 0.117} = 0.184 \tag{12}$$

The value of *ICC* indicates that there is still about 18.4% of the total variance in the household auto ownership is due to spatial variations between the residential zones after controlling for the socio-demographic factors and built environment variables. Meanwhile, as the both spatial heterogeneity parameters are statistically significant at 95% level, we could conclude that incorporating the multilevel modeling framework into the car ownership model component is very necessary, and more other factors at individual level and zonal level should be added to explain the between-zone spatial variation of car ownership.

Estimation results of car ownership model component confirmed the important roles of built environment factors played in household car ownership decision. This is an important finding that land use planning and design can be considered as a key strategy to reduce the car ownership thereby the energy consumption and emissions, rather than only through the economical strategies (e.g. higher purchase tax and fuel taxes) and administrative intervention (e.g. vehicle-purchase restriction). From urban planning and transportation public policy perspectives, it is important to steer the planning strategies towards a denser, and well-designed built environment at the residential zones.

5.2 Travel mode choice model parameter estimates

The results of travel mode choice model component are provided in Table 5. The coefficient estimates represent the influences of exogenous the variables on commuter's travel mode choice of transit and non-motorized mode (i.e. walk and bicycling) versus car mode. From the model results we can see that commuter's travel mode choice for the journey to work would be significantly influenced by some aspects of the built environment when the socio-demographic and travel-related factors were taken into account. Among the built environment measures, residential density was found to be significantly associated with transit and non-motorized mode with the expected positive signs at the 95% level. This result suggests that people living in a high density of residential area were more willing to choose to commute by transit, walk and bicycling. As to another density variable, employment density attained a statistical significance at the 95% level. The expected positive sign shows that increasing more employment opportunities around residential neighborhood would encourage more people to choose commute by walk and bicycling. Though employment density also shows an expected sign for transit, it did not show statistical significance. These findings are consistent with previous studies in other cities (Chen et al., 2008[43]). The entropy measures of land use mix had no significant impact on commuting mode choice. This result is consistent with the studies conducted by Zhang (2004) and Cervero (2002), a balance of land use near residential neighborhood may more matter to travel for nonwork. Average block size was found to have expected negative impacts on transit and non-motorized mode, significantly at the 95% level and 90%, respectively. This may be due to the fact that a smaller block size generally means better street connectivity that is a friendly environment for choosing transit, walk and bicycling as commuting modes. Distance from CBD is another significant factor in the commuter's travel mode choice. The negative sign

[43] Cynthia Chen, Hongmian Gong, Robert Paaswell. Role of the built environment on mode choice decisions: additional evidence on the impact of density. Transportation, 2008, 35(3), 285-299.

indicates that people living further from the CBD tended to choose to commute by car.

With respect to the socio-demographic variables, people from large household size were significantly more likely to choose walk and bicycling as commuting mode at the 95% level. As the number of household workers increase, the probabilities of choosing transit, walk and bicycling significantly increase, potentially because of the expensive and difficult parking in Washington metropolitan area. This finding is consistent with the study conducted by Ding et al. (2014). People from high household income were found to be significantly more likely to choose to commute by transit, walk and bicycling. Households with more students, old people and the people who have more than one job tended to choose car to work significantly at the 95% level, compared with transit. Caucasian people were found to be more likely to choose to commute by walk and bicycling, compared with other races. As to the level-of-service of travel-related variable, travel cost and travel time shows expected negative signs significantly at the 95% level.

Table 5 Estimation results of travel mode choice component of the joint model

Variables	Multilevel integrated MNL and SEM model			
	Transit		Walk and bicycling	
	Parameter	*t*-statistic	Parameter	*t*-statistic
Constant	0.694	2.642**	-1.321	-2.089**
Socio-demographic and control factors at individual level				
Household size	0.065	1.103	0.255	2.093**
Household workers	0.271	3.252**	0.325	1.939*
Income-1	-0.001	-0.006	-0.042	-0.179
Income-3	0.310	3.644**	0.366	1.977**
Household students	-0.143	-2.182**	-0.074	-0.576
Car ownership	-0.979	-12.560**	-1.047	-6.470**
Age	-0.007	-2.442**	-0.004	-0.686
Gender	0.212	2.982**	0.799	5.137**
Race	-0.060	-0.676	0.952	4.371**
Jobs	-0.461	-2.805**	-0.286	-0.969
Built environment variables at TAZ level				
Residential density	0.012	2.908**	0.012	2.447**
Employment density	0.002	1.012	0.007	2.231**
Land use mix	-0.090	-0.425	0.561	1.299
Average block size	-0.254	-4.768**	-0.448	-1.840*
Distance from CBD	-0.043	-8.383**	-0.054	-3.844**
Travel-related characteristics				
Travel cost	-0.204	-10.276**	-0.204	-10.276**
Travel time	-0.061	-8.637**	-0.061	-8.637**
Spatial heterogeneity parameters across home zones				
σ^2_{hm}	0.423	4.534**	0.546	1.688*

Note: Car is the base alternative; ** indicates significant values at the 95% level; * indicates significant values at the 90% level.

As shown in Table 5, the spatial heterogeneity parameters of transit and non-motorized mode are found to be significant at 95% level and 90% level, respectively. This finding indicates that commuter's travel mode choice among car, transit, and non-motorized mode varies significantly across TAZs. Using the formulation of

Eq. (12), the *ICC* index can be calculated as below, representing the degree of the spatial heterogeneity of transit and non-motorized mode relative to car mode at the geographic scale of TAZ:

$$ICC_{ht} = \frac{\sigma_{ht}^2}{\sigma_{\zeta}^2 + \sigma_{ht}^2} = \frac{0.423}{3.290 + 0.423} = 0.114 \tag{13}$$

$$ICC_{hn} = \frac{\sigma_{hn}^2}{\sigma_{\zeta}^2 + \sigma_{hn}^2} = \frac{0.546}{3.290 + 0.546} = 0.142 \tag{14}$$

The value of *ICC* indicates that after accounting for the socio-demographic factors and built environment variables, there is still about 11.4% and 14.2% of the total variance in the commuter's travel mode choice is due to spatial variations between the residential zones. Similar to car ownership, the significant spatial variation of commuter's travel mode choice was found. In this case, it is necessary to accommodate the spatial issues in the context of travel mode choice by incorporating the multilevel modeling framework into the travel mode choice model component. To explain the remained between-zone spatial variation of travel mode choice, more other factors at individual level and zonal level should be included.

Estimation results of travel mode choice model component showed that built environment played important roles in commuter's travel mode choice. Planning strategies such as creating much higher residential and employment densities, designing smaller block size, and layouting more housing opportunities in an employment area can be significantly effective in reducing car driving and increasing the share of transit, walk and bicycling commuting, rather than only through the economical strategy (e.g. congestion charging) and administrative intervention (e.g. odd-and-even license plate rule). The findings suggested more attention should be paid to the attributes at residential location to change the commuter's driving behavior.

5.3 Indirect and total effects

Only the direct effects can be captured in the traditional discrete choice model. When investigating the effects of planning strategies and transport policies on travel behavior, only focusing on the direct effects would result in inconsistent conclusions in some cases (Ding et al., 2014[44]; Aditjandra et al., 2012[45]). In this study, by integrating MNL and SEM model, the indirect effects of household characteristics and built environment on travel mode choice through the mediating variable car ownership were recognized. Hence, the total effects can be obtained by summing of the direct and indirect effects. Table 6 presents the detailed indirect effects and total effects of household characteristics and built environment on transit, walk and bicycling.

As shown in Table 5, household size was not found to be significantly associated with transit mode choice if only the direct effect was focused on. However, as shown in Table 6, the indirect effect of household size on transit mode choice was significantly found at the 95% level, indicating that transit mode choice was more likely to be impacted by household size mainly in an indirect way through the mediating variable car ownership. As to the built environment, similar example relates to the effects of employment density and land use mix on transit mode choice. Generally speaking, higher employment density and land use mix increase the probabilities of choosing transit as the commuting mode. However, we can see that the direct effects of employment density and land use mix on transit mode choice were not significant. The mode results in Table 6 suggested that the

[44] Chuan Ding, Chao Liu, Yaoyu Lin, Yaowu Wang. The impact of employer attitude to green commuting plans on reducing car driving: a mixed method analysis. Promet Traffic & Transportation, 2014, 26(2), 109-119.
[45] Paulus Teguh Aditjandra, Xinyu Cao, Corinne Mulley. Understanding neighbourhood design impact on travel behaviour: an application of structural equations model to a British metropolitan data. Transportation Research Part A, 2012, 46(1), 22-32.

significant effects of these two built environment factors on travel mode choice were mainly through the indirect way, caused by the interaction between car ownership and travel mode choice. These findings could give us the inspiration that commuter's travel mode choice was not mainly directly influenced by employment density and land use mix but rather by their household car ownership.

Table 6 Estimation results for the indirect and total effects of socio-demographic variables and built environment variables on travel mode choice behavior through mediating variable car ownership

Variables	Multilevel integrated MNL and SEM model							
	Transit				Walk and bicycling			
	Indirect effect		Total effect		Indirect effect		Total effect	
	Parameter	*t*-statistic	Parameter	*t*-statistic	Parameter	*t*-statistic	Parameter	*t*-statistic
Socio-demographic and control factors at individual level								
Household size	-0.124	-8.115**	-0.060	-1.020	-0.130	-5.743**	0.125	1.054
Household workers	-0.541	-11.118**	-0.271	-3.364**	-0.567	-6.165**	-0.241	-1.405
Income-1	0.242	5.924**	0.241	1.987**	0.253	4.875**	0.212	0.922
Income-3	-0.233	-7.928**	0.077	0.883	-0.244	-5.333**	0.122	0.669
Built environment variables at TAZ level								
Residential density	0.014	6.389**	0.025	4.680**	0.014	4.973**	0.026	4.672**
Employment density	0.002	3.190**	0.004	1.776*	0.002	2.849**	0.009	2.627**
Land use mix	0.139	2.019**	0.049	0.219	0.146	1.978**	0.706	1.642*
Average block size	-0.061	-4.853**	-0.315	-5.741**	-0.064	-4.028**	-0.512	-2.114**
Distance from CBD	-0.007	-4.258**	-0.050	-9.551**	-0.007	-3.690**	-0.061	-4.342**

Note: ** indicates significant values at the 95% level; * indicates significant values at the 90% level.

According to the direct, indirect, and total effects as shown in Table 5 and Table 6, we can see that the total effects of built environment variables had larger magnitudes than the direct effects due to the synergism of the indirect effects, except the effect of land use on transit mode choice. This finding suggested that the effects of built environment on travel mode choice exist not only in a direct way but also in an indirect way through the mediating variable car ownership, which provides insights that support the importance of the built environment in reducing commuter's driving behavior. While the total effects of household characteristics were the net outcome of the direct and indirect effects because of the different effect signs. For example, it was found that the variable of household workers was significantly associated with transit, walk and bicycling with positive signs. However, as shown in Table 6, the total effects of household worker had negative signs. It indicated that the magnitude of the negative indirect effect of household workers was larger than its positive direct effect, thereby leading to a negative sign on total effect. Based on the aforementioned results we can see that biased conclusions may be obtained when ignoring intermediary nature of car ownership. The model results confirm that when investigating the effects of built environment on travel behavior, car ownership should be considered as a mediating variable in the modeling framework which is consistent with previous studies (Ding et al., 2014; Van Acker and Witlox, 2010, 2011[46]).

Given the increasing debates concerning on the effectiveness of land use planning strategies to reduce transport energy consumption and emissions, the model results provide insight into how the built environment impacts commuter's driving behavior. Our findings point out that it is essential to realize that built environment

[46] Veronique Van Acker, Frank Witlox. Commuting trips within tours: how is commuting related to land use? Transportation, 2011, 38(3), 465-486.

can play a pivotal role in reducing driving, thereby energy consumption and emissions.

6 Conclusions

This study contributes to investigate the influences of the built environment on car ownership and travel mode choice simultaneously by making use of a multilevel integrated MNL and SEM model that jointly accommodates the spatial context in which individuals make travel decisions and considers the intermediary of car ownership. Moreover, a comparison among the separate model, single level, and multilevel integrated MNL and SEM models was conducted. Finally, the spatial heterogeneities of car ownership and travel mode choice across TAZs were recognized, and the direct, indirect and total effects of the built environment on car ownership and travel mode choice were obtained.

In this study multi-source data (i.e. travel survey and land use) was collected in Washington metropolitan area. The built environment was measured at the geographic scale of TAZ, specifically presented by residential density, employment density, land use mix, average block size, and distance from CBD. All the trips from home to workplace in the morning were taken as the analysis unit in travel mode choice decisions. Using the entire dataset, the impacts of built environment on car ownership and travel mode choice were examined by using different model structures. By comparing the model fit measurements of different models, the empirical results suggested that multilevel integrated MNL and SEM model significantly outperforms other models. Meanwhile, this model also provides great benefits in recognizing the spatial heterogeneities of car ownership and travel mode choice across TAZs. It was found that car ownership mediates the link between the built environment and travel mode choice, therefore car ownership should be considered as a mediating variable when investigating the impacts of built environment on travel mode choice. The calculated *ICC* indexes showed that the unobserved spatial variations of car ownership and travel mode choice both significantly existed. There were relatively small correlations among households and commuters living in the same TAZ due to the explanatory power from the household, individual, travel-related characteristics, and built environment factors in the model.

Given the increasing debates concerning on the effectiveness of land use planning strategies to reduce transport energy consumption and emissions, the empirical results provide additional insight into how the built environment impacts commuter's driving behavior. The model results confirmed the important roles that the built environment played in household car ownership and travel mode choice. Household car ownership was found to be significantly associated with residential density, employment density, land use mix, average block size, and distance from CBD. The factors of residential density, average block size, and distance from CBD were found to have significant effects on commuter's transit, and walk and bicycling mode choice. Meanwhile, the mode of walk and bicycling was also influenced by employment density around residential location. The direct effects of land use mix on commuter's travel mode choice were not significant. The empirical results indicated that land use mix influenced commuter's travel mode choice mainly in indirect ways through the mediating variable car ownership. The indirect effects of land use mix on commuter's transit, and walk and bicycling mode choice were found to be significant at the level 95%, with the expected signs. Similar results related to the effect of employment density on transit mode choice. Therefore, ignoring the mediating effect from car ownership is likely to lead to imprecise conclusions. Accurately, the effects of built environment on travel mode choice exist not only in a direct way but also in an indirect way through the mediating variable car ownership, which provides insights that support the importance of the built environment in reducing commuter's driving behavior. From urban planning and transportation public policy perspectives, creating much higher residential and employment densities, designing smaller block size, and layouting more housing opportunities in an employment area can be significantly effective in reducing household car ownership and car driving, and increasing the share of transit, walk and bicycling commuting.

One limitation in this study should be noted that the influence of residential self-selection on travel behavior was just partly captured. To solve this problem, more attitudes and preferences data or other modeling techniques are required to disentangle the influences of built environment and self-selection on car ownership and commuting mode choice in future studies.

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