Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 7939950, 11 pages
https://doi.org/10.1155/2022/7939950

Research Article

Exploring the Impacts of Built Environment on Commute Mode Choice: Evidence from China

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Received 9 May 2022; Accepted 4 June 2022; Published 6 July 2022

Academic Editor: Hasan Dinçer

Car dependency and its negative consequences have created the urgent need for a better understanding of the determinants of car ownership and use. To get people out of their cars, great importance has been attached to the connection between the built environment and travel behaviour. However, the mediating effect of car ownership is ignored in most studies of the relationship between the built environment and travel mode. The aim of this paper is to contribute to our understanding of the influence of the built environment on commute mode choice by considering the intermediary nature of car ownership based on a nationally representative sample from China. A recursive simultaneous bivariate probit model, which allows the analysis of the mediating effect of car ownership while modelling the relationship between the built environment and commute mode choice behaviour, is employed. Results indicate that the built environment attributes at the neighbourhood level do have both direct and indirect effects on commute mode choice. For most environmental attributes, their effects on commute mode choice are greater than their effects on car ownership. Residents may be less dependent on the car if their neighbourhoods are well-designed with more balanced land use and more attractive local job opportunities are available. The research findings suggest that land use policy should be given enough consideration in strategies for car use reduction, while more case studies are needed to examine whether results from this study can be extended to other cities.

1. Introduction

The fast economic growth and urbanization in China over the past few decades have led to ballooning demand for mass motorization. In addition to a rapid increase in vehicle ownership and use, many large cities in China are experiencing severe traffic congestion, air pollution, and increased oil consumption. The issues of car dependency and its negative consequences have created the urgent need for a better understanding of the determinants of car ownership and use.

It is widely believed that well-planned transit system would play an important role in constraining car travel by reducing the need for driving and energy consumption. In most cases, travel is derived from the need to conduct an activity at a certain place. Urban form and structure fundamentally determine the spatial distribution of various infrastructures and functional areas, thus influencing individual daily travel on a long-term basis. The built environment, which comprises urban design, land use, and the transportation system and encompasses patterns of human activities within the physical environment, acts as a bridge between the urban structure and individual daily activities and travel [1]. To get people out of their cars, great importance has been attached to the linkages between the built environment and travel behaviour [2–6]. Although many studies have demonstrated the important influences of the built environment on car ownership and use, there are still a few research gaps that need to be filled. First, most existing studies focused on cities and areas in developed car-dependent countries. Conclusions drawn from studies of developed countries may not be applicable to cities in developing countries like China because of the different economic levels, urban structure, land use, and traffic conditions. Second, while car ownership is generally considered an important influential factor for car use, it is treated differently in different studies. Some studies treated car ownership and car use as two independent decision variables and investigated their connections with the built environment separately [4, 7], whereas other studies treated car ownership as one of the independent variables explaining car use just as the built environment and socioeconomic attributes [3, 8, 9]. Since travel mode is directly influenced by car ownership and the built environment and car ownership itself is influenced by the built environment at the same time, the built environment may have both a direct effect and an indirect effect through the mediating role of car ownership. Studies ignoring the dual influence car ownership plays could lead to inconsistent conclusions on the connections between commute mode choice and the built environment.

The aim of this paper is to contribute to our understanding of the influence of the built environment on commute mode choice by considering the intermediary nature of car ownership based on a nationally representative sample from China. A recursive simultaneous bivariate probit model, which allows the analysis of the mediating effect of car ownership while modelling the relationship between the built environment and commute mode choice behaviour, is employed. Two equations for the model were presented: one addressing the car ownership decision and the other addressing the commute mode choice (whether to drive or not). The two decisions were linked through a correlation coefficient; thus the direct and indirect effects of the built environment on commute mode choice were examined.

The remainder of the paper is organized as follows. In the next section, a brief review of related literature is provided. Next, the model framework and formulation of the method are described, and the data set and sample statistics are outlined, followed by the discussion of model specification, estimation, and results. Finally, in the last section, conclusions are drawn, and directions for further research are discussed.

2. Literature Review

Since the 1980s, China has seen a steadily increasing rate of urbanization, measured as the percentage of urban population to the total population. It went up from 19.39% in 1980 to 63.89% in 2020 [10], with a more than 3-fold increase. Subsequently, commuting distance and commuting time in many cities, especially in megacities such as Beijing and Shanghai, keep growing. The number of vehicles per 100 households increased from 0.51 in 2000 to 37.1 in 2020 [10], with a nearly 70-fold growth. As car commute becomes more and more common, the accompanied traffic congestion and pollution have endangered life quality and sustainable development. Therefore, it is important for policymakers and urban planners to understand the inherent mechanism by which the built environment influences car ownership and use.

2.1. The Impacts of Built Environment on Car Dependency. In recent years, how to reduce automobile use and related social and environmental costs by changing the environment has been one of the most investigated subjects in urban planning. Characteristics of the built environment that are most heavily researched include density, diversity, design, destination accessibility, distance to transit, and demand management (including parking supply and cost), which are known as the "six Ds" [11]. Although empirical studies confirm that the built environment has a significant impact on travel mode, the results are inconsistent.

Residential density and employment density are considered the most important influences on car ownership and use. Leck [12] found that residential density is the strongest element of the built environment influencing travel mode choice. Negative associations between residential density and car ownership, VKT, and fuel consumption are further confirmed [13–15]. Increases in employment density are also found to negatively affect car ownership and use [16, 17]. Diversity, defined as the number of various land uses within a given area, is usually measured by land use mix. Research has found that a higher land use mix can result in lower car ownership [8, 16, 18], less choice of car for work [19, 20], and more choice of walking and transit modes [21, 22]. But a few studies have found that population density and employment density are not significantly associated with VKT [11] and land use mix is not closely associated with car travel [8]. Neighbourhood design elements are found to have a significant influence on car ownership and travel [23–25]. For example, Khattak and Rodriguez [26] showed that households in neo-traditional neighbourhoods make fewer automobile trips and travel fewer miles than households in conventional neighbourhoods. However, some empirical studies have found that households of neo-traditional neighbourhoods do not have lower VKT [27] because these neighbourhoods are newly built and are more attractive to households with higher vehicle ownership rates owing to residential self-selection [17].

Destination accessibility is usually represented as distance to CBD and accessibility to the job. Distance from CBD is found to be positively associated with VKT, indicating that people living further away from the CBD tend to drive more [28]. People living close to the CBD are found to own fewer cars. By using the data collected in Beijing, Li et al. [29] just got the opposite conclusion. They found the likelihood of owning a car decreases as the distance from the CBD increases. Proximity to transit stations also plays an important role in influencing car travel. Studies have found that car ownership and use are lower among people living close to transit or railway stations [19, 30, 31].

The effects of parking facilities on car ownership and use have been explored in many studies [17, 32–34]. For example, Chatman [17] mentioned that fewer parking space can discourage people from owning and using cars. Christiansen et al. [33] examined the influence of parking availability at destination and at home. They found that driving decreases with increasing distance to the parking place and parking restrictions may have the greatest effect in compact cities.

2.2. Mediating Effect of Car Ownership. Most empirical studies consider car ownership either as a travel choice to be examined or as an influential factor that explains other travel choices. According to Ben-Akiva and Atherton [35], travel-related decisions can be distinguished into long-, medium-, and short-range choices. As a medium-range decision, car ownership is influenced and restricted by long-range locational decisions of residence and work, and at the same time, car ownership influences and restricts short-range travel decisions of mode, frequency, and destination. Therefore, car ownership plays a dual role in travel mode choice modelling.

Unfortunately, only a few studies have considered the mediating effect of car ownership while modelling the relationship between the built environment and travel mode choice. Van Acker and Witlox [30] applied a structural equation model to examine the dual influence of car ownership on mode choice by assuming that car ownership mediates the relationship between the built environment and car use. Ding et al. [31] studied the relationships among the built environment, travel mode choice, travel distance, and car ownership using a framework of integrated structural equation model and discrete choice model, where the built environment affects travel mode choice through influencing car ownership and travel distance. Literature suggests that ignoring the intermediary role of car ownership may generate incorrect conclusions about the influence of the built environment on travel mode choice [36–38].

2.3. Other Factors Influencing Mode Choice. In addition to the neighbourhood-built environment, sociodemographic factors also influence car dependency behaviour. Studies suggest that households with higher income tend to own more cars and tend to use their cars more frequently [31, 39–41]. Household size and structure are also found to influence vehicle ownership and use. Large-size households with higher average age and more workers tend to prefer private car mode [4, 41]. Additionally, having more children is also positively associated with higher car ownership and higher VKT [42]. However, according to Ding et al. [31], having more children in a household is significantly associated with less car ownership since underage children cannot have driving licenses. Studies reveal that individual factors also have some impacts. For example, males and people with a higher education level are more inclined to drive more [15].

Apart from sociodemographic factors, individual preferences and attitudes can also influence car ownership and use. Kitamura et al. [43] incorporated attitudinal measures into the specification of models of travel behaviour and confirmed the role of attitudes and preferences in explaining the link between the built environment and travel behaviour. Litman and Steele [44] found that people tend to choose residential locations based on their travel abilities, needs, and preference, which is defined as “self-selection.” Handy et al. [45] found that individuals who would rather not drive choose to live in neighbourhoods conducive to driving less. Some scholars found that the effect of residential self-selection is minor in explaining travel behaviour and the built environment is significantly associated with travel mode choice even when the influence of self-selection is considered [46–48].

3. Methodology

3.1. Model Development. This study investigates the influence of the built environment on commute mode. Commute mode choice behaviour is directly influenced by sociodemographics, car ownership, and the built environment. But car ownership itself is also affected by sociodemographics and the built environment at the same time, which may result in indirect influences of sociodemographics and the built environment on commute mode through the mediating effect of car ownership when modelling the influence of the built environment on commute mode. Therefore, a recursive simultaneous bivariate probit model is employed. In the model, car ownership is predetermined according to the first functional relationship, which measures the direct influences of sociodemographics and the built environment. Then the choice of car ownership is specified as a dummy variable in the second functional relationship for commute mode choice to directly measure the impact of car ownership, sociodemographics, and the built environment on commute mode choice. Thus, the mediating effect of car ownership on the relationship between commute mode choice and the built environment is measured.

The car ownership choice and commute mode choice (whether to drive or not) are treated as two binary choices. The bivariate probit model can be formulated to simultaneously analyze their probabilities with accommodation of random error correlation as follows:

$$\begin{cases} C_n^* = \alpha' Z_n + \varepsilon_n, \\ M_n^* = \beta' X_n + \eta C_n + \omega_n, \end{cases} \tag{1}$$

where C_n^* is a latent variable representing the utility of owning a car for respondent $n (n = 1, 2, \ldots, N)$. C_n^* is continuous and unobserved. But its binary realization, C_n, is observed. It takes the value $C_n = 1$ when $C_n^* > 0$ and takes the value $C_n = 0$ when $C_n^* \leq 0$. M_n^* is a latent variable representing respondent n's utility of driving to work. It is continuous and unobserved. But its binary realization, M_n, is observed. It takes the value $M_n = 1$ when $M_n^* > 0$ and takes the value $M_n = 0$ when $M_n^* \leq 0$. Z_n and X_n are vectors of explanatory variables for C_n^* and M_n^*, respectively. α and β are vectors of model coefficients associated with the explanatory variables Z_n and X_n, respectively. η is a scalar coefficient for C_n to measure the impact of car ownership on commute mode choice. ε_n and ω_n are random error terms, which are standard bivariate normally distributed with zero means, unit variances, and correlation ρ (i.e., $\varepsilon_n, \omega_n \sim \phi_2(0, 0, 1, 1, \rho)$). In model (1), car ownership is determined according to the first functional relationship. Then the choice of car ownership is specified as a dummy variable in the second functional relationship for commute mode choice to measure the mediating effect of car ownership on the relationship between commute mode choice and the built environment.

Based on the normality assumption of the model random error terms, one can derive the probability of each possible combination of binary choices for respondent n:

$$Prob(C_n = 0, M_n = 0) = \Phi_2(-\alpha' Z_n, -\beta' X_n, \rho), \tag{2}$$

$$\begin{aligned} Prob(C_n = 1, M_n = 0) =& \Phi_1[-(\beta' X_n + \eta)] \\ &- \Phi_2[-\alpha' Z_n, -(\beta' X_n + \eta), \rho], \end{aligned} \tag{3}$$

$$\begin{aligned} Prob(C_n = 0, M_n = 1) =& \Phi_1(-\alpha' Z_n) \\ &- \Phi_2(-\alpha' Z_n, -\beta' X_n, \rho), \end{aligned} \tag{4}$$

$$\begin{aligned} Prob(C_n = 1, M_n = 1) =& 1 - \Phi_1(-\alpha' Z_n) - \Phi_1[-(\beta' X_n + \eta)] \\ &+ \Phi_2[-\alpha' Z_n, -(\beta' X_n + \eta), \rho], \end{aligned} \tag{5}$$

where $\Phi_1(\cdot)$ and $\Phi_2(\cdot)$ are the cumulative distribution function for standard univariate and bivariate normal distributions, respectively.

To facilitate formulating the likelihood function, equations (3) to (5) can be rewritten in a format that includes only the cumulative distribution function of the standard bivariate normal distribution [49] as follows:

$$\begin{aligned} Prob(C_n = 1, M_n = 0) &= \mathrm{Prob}[\varepsilon_n > -\alpha' Z_n, \omega_n \le -(\beta' X_n + \eta)] \\ &= \mathrm{Prob}[-\varepsilon_n \le \alpha' Z_n, \omega_n \le -(\beta' X_n + \eta)] \\ &= \Phi_2[\alpha' Z_n, -(\beta' X_n + \eta), -\rho], \\ Prob(C_n = 0, M_n = 1) &= \mathrm{Prob}(\varepsilon_n \le -\alpha' Z_n, \omega_n > -\beta' X_n) \\ &= \mathrm{Prob}(\varepsilon_n \le -\alpha' Z_n, -\omega_n \le \beta' X_n) \\ &= \Phi_2(-\alpha' Z_n, \beta' X_n, -\rho), \\ Prob(C = 1, M = 1) &= \mathrm{Prob}[\varepsilon_n > -\alpha' Z_n, \omega_n > -(\beta' X_n + \eta)] \\ &= \mathrm{Prob}(-\varepsilon_n \le \alpha' Z_n, -\omega_n \le \beta' X_n + \eta) \\ &= \Phi_2(\alpha' Z_n, \beta' X_n + \eta, \rho). \end{aligned} \tag{6}$$

Let $\mu_n = 2C_n - 1$, $\tau_n = 2M_n - 1$, then the general formulation for the probabilities of the four combinations of the two binary choices is

$$P_n = \Phi_2[\mu_n \alpha' Z_n, \tau_n(\beta' X_n + \eta C_n), \mu_n \tau_n \rho]. \tag{7}$$

Based on equation (7), the likelihood function for model (1) can be summarized as follows:

$$L = \prod_{n=1}^{N} \{\Phi_2[\mu_n \alpha' Z_n, \tau_n(\beta' X_n + \eta C_n), \mu_n \tau_n \rho]\}. \tag{8}$$

Full information maximum likelihood estimates of the parameters are obtained using Stata [50].

The coefficients in a binary choice model can be misleading since the model is of a probability. As has been widely documented [49], to compute marginal effects in a binary choice model, one must scale the coefficients. For the commute mode choice equation in model (1), one would have

$$\begin{aligned} E(M_n | X_n, Z_n) &= E(M_n | X_n, Z_n, C_n = 1) \times Prob(C_n = 1) + E(M_n | X_n, Z_n, C_n = 0) \times Prob(C_n = 0) \\ &= \mathrm{Prob}(M_n = 1 | C_n = 1) \times Prob(C_n = 1) + \mathrm{Prob}(M_n = 1 | C_n = 0) \times Prob(C_n = 0) \\ &= \mathrm{Prob}(M_n = 1, C_n = 1) + \mathrm{Prob}(M_n = 1, C_n = 0) = \Phi_2(\alpha' Z_n, \beta' X_n + \eta, \rho) + \Phi_2[\alpha' Z_n, -(\beta' X_n + \eta), -\rho]. \end{aligned} \tag{9}$$

The marginal effect of a change in a variable in the commute mode choice equation will be a sum of terms. One will account for the direct effect of a change in that variable on the probability that M_n equals one, and the other will measure the indirect effect of change in this variable on the probability that C_n equals one in the car ownership equation, which, in turn, affects the probability that M_n equals one. Thus, for a continuous variable, y, which might appear in Z_n and/or X_n, its marginal effect in the commute mode choice equation is

$$\partial\frac{(M_n|X_n,Z_n)}{\partial y}=\partial\frac{[\Phi_2(\alpha' Z_n,\beta' X_n+\eta,\rho)]}{\partial y}+\partial\frac{[\Phi_2(\alpha' Z_n,-\beta' X_n-\eta,-\rho)]}{\partial y}. \tag{10}$$

Let $\lambda_n=\alpha' Z_n$, $\theta_n=\beta' X_n+\eta$, then

$$\begin{aligned}
&\partial E\frac{(M_n|X_n,Z_n)}{\partial y}\\
&=\left\{\frac{\partial[\Phi_2(\alpha' Z_n,\beta' X_n+\eta,\rho)]}{\partial\lambda_n}\frac{\partial\lambda_n}{\partial y}+\frac{\partial[\Phi_2(\alpha' Z_n,\beta' X_n+\eta,\rho)]}{\partial\theta_n}\frac{\partial\theta_n}{\partial y}\right\}\\
&\quad+\left\{\frac{\partial[\Phi_2(\alpha' Z_n,-\beta' X_n-\eta,-\rho)]}{\partial\lambda_n}\frac{\partial\lambda_n}{\partial y}+\frac{\partial[\Phi_2(\alpha' Z_n,-\beta' X_n-\eta,-\rho)]}{\partial(-\theta_n)}\frac{\partial(-\theta_n)}{\partial y}\right\}\\
&=\left\{\phi(\alpha' Z_n)\Phi_1\left[\frac{(\beta' X_n+\eta)-\rho(\alpha' Z_n)}{\sqrt{1-\rho^2}}\right]\alpha_y+\phi(\beta' X_n+\eta)\Phi_1\left[\frac{\alpha' Z_n-\rho(\beta' X_n+\eta)}{\sqrt{1-\rho^2}}\right]\beta_y\right\}\\
&\quad+\left\{\phi(\alpha' Z_n)\Phi_1\left[\frac{-(\beta' X_n+\eta)-(-\rho)(\alpha' Z_n)}{\sqrt{1-(-\rho)^2}}\right]\alpha_y+\phi[-(\beta' X_n+\eta)]\Phi_1\left[\frac{\alpha' Z_n-(-\rho)[-(\beta' X_n+\eta)]}{\sqrt{1-(-\rho)^2}}\right]\beta_y\right\}\\
&=\left\{\phi(\beta' X_n+\eta)\Phi_1\left[\frac{\alpha' Z_n-\rho(\beta' X_n+\eta)}{\sqrt{1-\rho^2}}\right]+\phi[-(\beta' X_n+\eta)]\Phi_1\left[\frac{\alpha' Z_n-(-\rho)[-(\beta' X_n+\eta)]}{\sqrt{1-(-\rho)^2}}\right]\right\}\beta_y\\
&\quad+\left\{\phi(\alpha' Z_n)\Phi_1\left[\frac{(\beta' X_n+\eta)-\rho(\alpha' Z_n)}{\sqrt{1-\rho^2}}\right]+\phi(\alpha' Z_n)\Phi_1\left[\frac{-(\beta' X_n+\eta)-(-\rho)(\alpha' Z_n)}{\sqrt{1-(-\rho)^2}}\right]\right\}\alpha_y\\
&=\text{effect}_1+\text{effect}_2,
\end{aligned} \tag{11}$$

where $\phi(\cdot)$ is the density function of the standard normal distribution. α_y and β_y are coefficient on y in the car ownership equation and the commute mode equation, respectively. effect_1 and effect_2 are the direct and indirect effect of explanatory variable y on commute mode choice, respectively.

When y is a binary variable, its marginal effect in the commute mode choice equation is defined as follows:

$$\begin{aligned}
&E(M_n|X_n,Z_n,y=1)-E(M_n|X_n,Z_n,y=0)\\
&\quad=[\text{Prob}(M_n=1|C_n=1)\times\text{Prob}(C_n=1)+\text{Prob}(M_n=1|C_n=0)\times\text{Prob}(C_n=0)]_{y=1}\\
&\qquad-[\text{Prob}(M_n=1|C_n=1)\times\text{Prob}(C_n=1)+\text{Prob}(M_n=1|C_n=0)\times\text{Prob}(C_n=0)]_{y=0}\\
&\quad=[\text{Prob}(M_n=1,C_n=1)+\text{Prob}(M_n=1,C_n=0)]_{y=1}\\
&\qquad-[\text{Prob}(M_n=1,C_n=1)+\text{Prob}(M_n=1,C_n=0)]_{y=0}\\
&\quad=\{\Phi_2(\alpha' Z_n,\beta' X_n+\eta,\rho)+\Phi_2[\alpha' Z_n,-(\beta' X_n+\eta),-\rho]\}_{y=1}\\
&\qquad-\{\Phi_2(\alpha' Z_n,\beta' X_n+\eta,\rho)+\Phi_2[\alpha' Z_n,-(\beta' X_n+\eta),-\rho]\}_{y=0}.
\end{aligned} \tag{12}$$

For the endogenous binary variable C_n, its marginal effects is

$$E(M_n|X_n, Z_n, C_n = 1) - E(M_n|X_n, Z_n, C_n = 0) = \Phi_1(\beta' X_n + \eta) - \Phi_1(\beta' X_n). \tag{13}$$

The marginal effects in the car ownership equation of model (1) is much simpler. For a continuous variable x, which might appear in X_n, its marginal effect in car ownership equation is

$$\partial E\frac{(C_n|X_n)}{\partial x} = \partial\Phi_1\frac{(\alpha' Z_n)}{\partial x} = \phi(\alpha' Z_n)\alpha_x, \tag{14}$$

where α_x is coefficients on x in the car ownership equation. If x is a binary variable, its marginal effect is

$$E(C_n|X_n, x = 1) - E(M_n|X_n, x = 0) = \Phi_1(\alpha' Z_n)_{x=1} - \Phi_1(\alpha' Z_n)_{x=0}. \tag{15}$$

3.2. Data and Variables. The research data come from the 2014 wave of the China Labour-force Dynamics Survey (CLDS), which is a large-scale, nationally representative, longitudinal, multidisciplinary survey administered by the Centre for Social Survey at Sun Yat-sen University (https://css.sysu.edu.cn for detail). First carried out in 2012, the survey is conducted every two years using a stratified multistage sampling design. Respondents were selected from 29 out of China's 31 provinces and autonomous regions (excluding Hainan and Tibet) by the survey's multilevel (neighbourhood, household, and individual) sampling frames. The raw 2014 CLDS database consists of 23,594 individuals within 401 neighbourhoods from 106 cities. In the data, 14,783 respondents have a job. Given the study focus of this research, the sample was restricted to employees aged 16–65, which is the common age range for the Chinese working-age population. After data cleaning and processing, a final sample of 7,287 working individuals within 236 neighbourhoods from 102 cities was used for analysis.

A comprehensive set of variables including individual and household sociodemographic factors, travel characteristics, and built environment measurements were examined in the empirical analysis. Table 1 presents the variable definition and the statistical description. Approximately 54.1% of the respondents are male. The average age is 43.1 years. About 16.8% of the respondents have a college degree or above. In the sample, the average household size is about 4 members, and about 26.5% of the households have children under 6 years old. The average yearly household income is close to 60,520 RMB. Almost 20% of the sample households own at least one car. The percentage of car commuting is found to be 7.4% for the whole sample and 30.2% and 1.7% for car owners and noncar owners, respectively.

In this study, built environment factors were measured at the neighbourhood committee juweihui level, which is the smallest administrative unit in urban China [51]. Built environment characteristics available from the 2014 CLDS, which were selected for analysis, include distance to transit, distance to CBD, residential density, land use mix, green coverage ratio, street lighting, and hard-surface road ratio. The population density was used to represent the fact that residents in denser neighbourhoods often use nonmotorized modes of transport as their destinations are close by [52, 53]. Distance to transit was used to measure transit accessibility of the neighbourhood, and distance to CBD was selected to measure residential location. Land use mix was used as an indicator of destination diversity and heterogeneity of different neighbourhoods. In this study, seven categories of facilities were examined, including hospitals, banks, playgrounds, libraries, sports facilities, parks or squares, and senior activity centres. The land use mix for neighbourhood i, LUM_i, which denotes the entropy value of land use, was calculated as follows [54]:

$$LUM_i = \frac{-\sum_{j=1}^{J_i} R_{ij}\ln\left(R_{ij}\right)}{\ln J_i}, \tag{16}$$

where J_i indicates the number of different categories of facilities available in neighbourhood i. R_{ij} indicates the quantity percentage of the j-th facility type for neighbourhood i. The value of the land use mix ranges from 0 to 1. Higher levels of land use mix mean higher mix level and thus higher destination diversity. The green coverage ratio, streetlights, and hard-surface road ratio indicate the walkability and cycling-friendliness of the neighbourhood environment, which are believed to encourage residents to choose nonmotorized commute modes.

4. Results

Estimation results of the recursive simultaneous bivariate probit model are presented in Table 2. The marginal effects of explanatory variables for the two equations are computed and listed in Table 3. First, it is found that the dummy variable representing car ownership (car) significantly affects the choice of car for commute travel. The coefficient is positive, indicating that car owners are more likely to choose a car than other modes of commuting. As expected, the random error correlation is positive and statistically significant, which further confirms the positive correlation between car ownership and commuting by auto and supports the paradigm of simultaneity embodied in the bivariate probit model specification adopted for this study.

4.1. Auto Ownership. For the car ownership choice model, it is found that most sociodemographics at the household level are statistically significant, suggesting that car ownership decision is made at the household level and are significantly associated with household structure and household income. This is consistent with the prevailing belief that car ownership decision is mainly determined by sociodemographics [55, 56]. Of all sociodemographic attributes, household income shows the most important effect on car ownership. For every 10,000 yuan increase in household income, the probability of buying a car increases by about 2.5%.

The neighbourhood-built environment attributes are also important influential factors. It shows that population density has a significantly negative effect on car ownership.

Table 1: Variable definitions and statistical description.

Variable	Description	Mean	SD
Sociodemographic factors			
Male	1, if the respondent is male; 0, otherwise	0.541	0.498
Age	Age in years	43.144	11.598
College	1, if the respondent completed college; 0, otherwise	0.168	0.374
Hsize	Number of household members	4.185	1.763
Chlild6	Number of preschoolers under 6 years old	0.265	0.540
Hinc	Household yearly income (10,000 RMB)	6.052	8.882
Travel characteristics			
Car	1, if the household owns at least one car; 0, otherwise	0.199	0.399
Cmode	1, if the respondent uses car as commute mode; 0, otherwise	0.074	0.262
Built environment factors			
ResDenH	1, if residential density is above 15,000 persons/km^2; 0, otherwise	0.129	0.336
ResDenM	1, if residential density is above between 8,000 and 15,000 persons/km^2; 0, otherwise	0.077	0.266
ResDenL	1, if residential density is below 8,000 persons/km^2; 0, otherwise	0.794	0.404
DisTransit	Distance from residence to the nearest transit station (km)	2.380	6.087
DisCBD	Distance from residence to the nearest CBD (km)	4.875	7.193
Lum	Land use mixture, a measurement of the composition of seven land use categories including hospitals, banks, playgrounds, libraries, sports facilities, parks or squares, and senior activity centres	0.857	0.224
GreenCov	Green coverage ratio in the neighbourhood	0.469	0.283
StrLght	1, if all roads have streetlights; 0, otherwise	0.577	0.494
PavedRds	Hard-surface road ratio in the neighbourhoods	0.714	0.309

Table 2: Simultaneous bivariate probit model estimation results.

Variable	Coefficient	t-statistic
Car ownership equation		
Constant	−1.1828	−15.0189**
Hsize	0.0824	2.6778**
Child6	0.1188	3.6392**
Hinc	0.1392	9.0122**
ResDenH	−0.0868	−1.6832*
DisTransit	0.0941	0.9277
DisCBD	0.0141	5.1860**
Lum	−0.0708	−1.8872**
GreenCov	−0.2804	−4.1664**
StrLght	0.3437	7.7561**
PavedRds	0.3500	5.5374**
Commute mode choice equation		
Constant	−1.5722	−9.9269**
Male	0.1923	9.8199**
Age	−0.0127	−5.3543**
College	0.2030	4.9490**
Hinc	0.0305	1.7826*
ResDenH	−0.1482	−1.4158
DisTransit	0.1180	1.6916*
DisCBD	0.0819	1.6507*
Lum	−0.1238	−1.8808**
GreenCov	0.1601	1.5519
StrLght	0.1625	1.5521
PavedRds	0.0824	1.0203
Car	1.2387	5.6738**
ρ (error correlation)	0.5933	4.0019**
Log-likelihood		
At convergence	−5,040.0623	
At market share	−4,099.6787	
At zero	−10,101.9270	
Likelihood-ratio comparison		
No. of parameters	26	
$\overline{\rho}_0^2$	0.5916	
$\overline{\rho}_c^2$	0.1824	

Table 3: Marginal effects.

Variable	Direct effect	Indirect effect	Total effect
Car ownership model			
Hsize (continuous)	0.0146		0.0146
Child6 (dummy)	0.0149		0.0149
Hinc (continuous)	0.0247		0.0247
ResDenH (dummy)	0.0154		0.0154
DisTransit (continuous)	0.0167		0.0167
DisCBD (continuous)	0.0025		0.0025
Lum (continuous)	−0.0125		−0.0125
GreenCov (continuous)	−0.0497		−0.0497
StrLght (dummy)	0.0446		0.0446
PavedRds (continuous)	0.0620		0.0620
Commute mode model			
Male (dummy)	0.0572		0.0572
Age (continuous)	−0.0039		−0.0039
College (dummy)	0.0602		0.0602
Hinc (continuous)	0.0088	0.0035	0.0123
ResDenH (dummy)	−0.0453	−0.0032	−0.0485
DisTransit (continuous)	0.0361	0.0035	0.0396
DisCBD (continuous)	0.0251	0.0005	0.0256
Lum (continuous)	−0.0379	−0.0262	−0.0641
GreenCov (continuous)	0.0494	−0.0104	0.0390
StrLght (dummy)	0.0619		0.0619
PavedRds (continuous)	0.0252	0.0129	0.0381
Car (dummy)	0.3113		0.3113

This indicates that people from high-density neighbourhoods are significantly less likely to own cars, which is consistent with previous studies [57, 58]. One possible reason for this result may be that high residential density is usually accompanied by fewer parking space and better public transport service and living infrastructures around the neighbourhood, making public transport and nonmotorized travel more attractive and thus lower vehicle ownership propensity. Distance to the nearest transit stop has a slightly positive influence on car ownership, which is consistent with the results from some previous studies that a well-developed transit system can significantly reduce the propensity for car ownership [16, 59]. It shows that for every 1 km increase in the distance to transit, the probability of owning a car increases about 1.7%. Distance to CBD also shows a significant positive effect on car ownership. One possible reason for this may be that more and better job opportunities, more education and living infrastructures exist close to the city centre. Residents living far away from the city centre have a higher propensity to own a car for their long-distance travel to these infrastructures. It also shows that land use mix is negatively associated with car ownership, which is consistent with some previous research [4, 60]. This is because neighbourhoods with higher land use mix usually provide residents with diverse living amenities nearby. So residents' daily travels are mostly within cycling and walking distance and less dependent on the car. The green coverage rate is negatively correlated with car ownership. A possible reason for this result may be that neighbourhoods with high green coverage are more walking and cycling friendly, thus making residents less dependent on cars. Street lighting and hard-surface road ratio are found to be positively associated with car ownership. The probability of owning a car for residents from neighbourhoods with street lighting is about 4.5% higher than that for residents from neighbourhoods without street lighting.

4.2. Commute Mode Choice. The recursive simultaneous bivariate probit model, which allows the analysis of the mediating effect of car ownership on commute mode choice, provides the direct and indirect influences of explanatory factors on commute mode choice behaviour.

Some sociodemographic attributes at the individual level are important explanatory factors. Consistent with previous studies [20, 61], results show that gender is significantly positive with car mode. When other attributes are the same, the probability of males choosing car mode is 5.7% higher than that of females. Age negatively influences the propensity of car commuting, indicating that older residents are more willing to take transit or active modes to work. It is also found that highly educated groups are more dependent on car commuting. Compared with less-educated residents, people with a college education and above are 6% more likely to drive to work. This result can be explained by the fact that well-educated travellers often work with more social and business activities, therefore having higher demand for more flexible commute modes [31]. As expected, household income is significant for both car ownership choice and commute mode choice. It determines daily car use besides its positive effect on car purchasing. The direct effect of household income on car mode choice is 0.0088, and its indirect effect through the choice of car ownership on car mode choice is 0.0035. For every 10,000 yuan increase in household income the probability of car commute increases by about 1.2%.

In terms of built environment attributes, the results show that some attributes have significant effects on commute mode choice. Distance to transit has significantly positive direct and indirect effects on commute mode, and the total marginal effect is about 0.04. This means that convenient transit services can significantly reduce car dependency. Distance to CBD shows both significant direct and indirect association with commute mode choice. The longer the distance from the neighbourhood to CBD, the more likely the residents are to drive to work. Land use diversity is another built environment attribute whose direct and indirect influence on commute mode choice are both significantly negative. The result suggests that residents living in neighbourhoods with more balanced land use are significantly less likely to commute by car. As for the green coverage effect, it has completely opposite effects on car ownership and commute mode choice. Although the direct effect is weakened by the negative indirect effect, the total effect of the green coverage rate on commute mode choice is positive. A possible reason for this may be that neighbourhoods with high green coverage are usually located in suburban areas with less job opportunities. Residents living in these neighbourhoods have to accept long-distance commutes to deal with the imbalance between jobs and housing. Therefore, they become more dependent on car commute.

5. Conclusions

With the acceleration of the urbanization process in China, car dependency has already become one of the most important contributors to many social, economic, and environmental problems such as traffic congestion, air pollution, and energy consumption. In many large cities, restriction policies on private vehicle ownership and use have been implemented in the name of reducing car dependency and promoting public transit use. Therefore, the determinants of car ownership and use are important for urban planning and transportation. By using the 2014 wave of the CLDS data, this study has explored the linkages between the built environment, car ownership, and commute mode choice. To account for the intermediary nature of car ownership, a recursive simultaneous bivariate probit model was applied. Two equations for the model were presented: one addressing the car ownership decision and the other addressing the commute mode choice. The two decisions were linked through a correlation coefficient; thus, the direct and indirect effects of the built environment on commute mode choice were examined. This study has contributed to the literature in terms of both methodology implementation and policy implications.

Methodologically, the recursive simultaneous bivariate probit model provides a convenient way to examine the complex relationship between the built environment and commute mode choice while considering the mediating effect of car ownership simultaneously. The model results show that some explanatory variables have both direct and indirect effects on commute mode choice. Their direct influences on commute mode choice can either be strengthened or weakened by the indirect effect owning to the mediating role of car ownership. Therefore, methods on the links between environment and commute mode choice may lead to inconsistent or even misleading conclusions if they ignore the mediating effect of car ownership. This is consistent with some existing research that car ownership should be considered as a mediating variable in order to correctly determine the usefulness of urban planning policies that intend to discourage car use [30].

The results confirm that the built environment at the juweihui level has significant effects on car ownership and car owners' commute mode choice. Marginal effects analysis demonstrates that the built environment does have both direct and indirect effects on commute mode choice. For most environmental attributes, their effects on commute mode choice are greater than their effects on car ownership, which may indicate that car owners may not be as addicted to driving, as they seem to be. Therefore, land use policy should be given enough consideration in strategies for car use reduction. Based on the total effects, higher population density is found to significantly reduce the probability of driving to work. The decrease in the probability of driving to work also comes with well-designed compact neighbourhoods with convenient transit and living infrastructures that support noncar travel. Distance to transit has significantly positive direct and indirect effects on commute mode, which means that convenient transit service can significantly reduce car dependency. The longer the distance from the neighbourhood to CBD, the more likely the residents are to drive to work. The effect of land use diversity suggests that residents living in neighbourhoods with more balanced land use are significantly less likely to commute by car. As for the green coverage effect, its total effect on commute mode choice is positive. Since neighbourhoods with high green coverage are usually located in suburban areas with less job opportunities, residents living in these neighbourhoods have to accept long-distance commutes to deal with the imbalance between jobs and housing and thus become more dependent on the car. These research findings are consistent with many existing studies suggesting that compact land use with high density, convenient transit service, and balanced land use is good for car use reduction. However, more case studies are needed to examine whether these results can be extended to other cities and workable TDM strategies and policies should be combined to make land use planning more effective.

In addition, several directions for further research can be identified. First, owing to limited data availability, some important attributes of the built environment not included in the current study should be examined further, such as bus route coverage, bus network density and bus station density for public transport, street network density, four-way, and *T* type intersection density for neighbourhood design. Second, owing to the lack of attitude data, residential self-selection is not considered in this study. Further research should apply a more advanced modelling method to include the effect of self-selection. Third, only the effect of the built environment at the residential location is considered in this study. Further study should pay more attention to the spatial heterogeneity of the built environment at both residential and work locations and its influences on commute mode choice. Fourth, further studies should pay more attention to the causal relationships between the built environment and travel choices if panel data are available.

Data Availability

Data used in this paper are from the China Labour-Force Dynamics Survey (CLDS) by the Centre for Social Science Survey at Sun Yat-sen University in Guangzhou, China. Please refer to https://css.sysu.edu.cn for more information about the CLDS data.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (52002243).

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