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Structural equation models to analyze activity participation, trip generation, and mode choice of low-income commuters

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ABSTRACT

Low-income commuters have distinct activity-travel characteristics from non-low-income commuters. This study examines low-income commuters' activity-travel pattern for a better understanding the mechanism of activity participation and travel behaviour based on the travel survey data collected in Nanjing, China. Structural equations modelling (SEM) methodology was adopted to estimate the complex relationships among socio-demographics, accessibility, activity participation, trip generation and mode choice. Results show that strong relationships do exist among socio-demographics, activity engagement and travel behavior. Specifically, we can understand travel behaviour better by including activity participation endogenously in the model. Furthermore, it allows us to better forecast how increasing any one type of activity will affect demand for other activities, as well as trip generation and mode choice. Lastly, the results reveal the effects of accessibility variables on activity participation and travel behaviour in which population density measure has more ubiquitous effects. Findings in this study might provide insightful policy implications for improving the travel environment of the low-income commuters.

KEYWORDS

Low-income commuters; activity participation; trip generation; mode choice; accessibility; structural equation modeling

Introduction

Transportation is a critical element for everyone to accomplish tasks in daily life. However, the limited spending power of low-income residents results in relatively less out-of-home activity participation and smaller trip generation rates. Low-income residents show distinct travel characteristics from non-low-income residents (Salon and Gulyani 2010; Cheng et al. 2016). They depend heavily on non-motorized modes and transit by which they cannot travel faraway. Most of their trips are involved with subsistence activities, namely work or work-related purposes. Little maintenance and discretionary activities participation lower their quality of life and well-being. The need for low-income residents to stay active and engaged in society is an important social issue for increasingly important travel equity. We need to propose effective policies to deal with their travel difficulties. Travel is a derived demand in that the way individuals organize their lives dictates when and where they go and which travel mode they use. To better understand activity–travel pattern and evaluate possible transport policies options, it is necessary to investigate the mechanism of activity choice and travel behavior within activity-based behavioral modeling domain (Kitamura, Chen, and Pendyala 1997).

Recently, researchers have pointed out that a thorough knowledge of the causal mechanisms underlying individual activity participation behavior may help enhance the forecasting capabilities of travel demand models (Lu and Pas 1999; Yoon and Goulias 2010; Chen and Lu 2015; Gim 2017). Structural equations framework is a commonly utilized approach in these studies. The technique is able to simultaneously handle exogenous and endogenous variables, thus effectively representing the causal relationships among activity engagement and travel patterns. Structural equation model was first applied by Kitamura et al. (1992) to jointly model time allocation for activity and travel, indicating that commute time has a negative feedback on non-work activities. Gould and Golob (1997) used structural equations modeling (SEM) to explore how travel time saved by working at home or shopping close to home might be converted to other activities and other travels. Fujii and Kitamura (2000) proposed a SEM to examine the latent demand impacts of the opening of freeway lines on commuters' after-work discretionary activities and travels in which the preference indicators for in-home and out-of-home activities are used as endogenous variables. This study confirmed the usefulness of SEM in evaluating the effects of transportation planning measures and policy analysis. Golob (2000) developed a trip generation model using the time-use perspective to reveal how endogenous time use variables (including in-home work activity duration, work and non-work activity duration, travel time for trips to work and non-work activities, and travel time for return-home trips) and trip chaining variables (work tours, work/non-work tours, simple and complex non-work tours) are interrelated due to 'time-budget' effects. The model also showed how these interrelationships are affected by exogenous household characteristics. By estimating relationships among socio-demographics, activity patterns, trip generation, and travel behavior, Kuppam and Pendyala (2001) found significant trade-offs exist between in-home and out-of-home activity participation.

With regard to low-income travelers' activity–travel pattern, Chung and Ahn (2002) presented and explained the direct, indirect and total effects of relationships among socio-demographics, activity participation and travel behavior in structural equation model systems and concluded there are similar relationships between socio-demographics and travel behavior in developing and developed countries. Yang et al. (2010) modeled the time allocation of household heads to shed light on the within-personal and cross-personal interactions of activity–travel behaviors between male and female heads. Besides,

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Venter, Vokolkova, and Michalek (2007) concluded that residential location dramatically impacted the mobility conditions faced by low-income communities. Housing locations distant from the city center are associated with longer travel distances and higher transport costs.

With the scope of this brief literature review, which is by no means comprehensive, it can be seen that activity engagement and time allocation and their effects on travel behavior have been of tremendous interest to transportation researchers. Travel behavior can be explained better by including activity participation variables in travel demand models. However, most studies focus primarily on the entire population. The activity–travel pattern of low-income commuters does not receive enough attention. On the other hand, few systematic studies have explored travel mode choice as a result of activity engagement and trip generation.

The primary objective of this study is to develop model systems that would help identify and explain fundamental relationships of three sets of endogenous variables – activity participation, trip generation, and mode choice – as a function of individual exogenous socio-demographics and accessibility indices. We also want our model to determine the relationship among these endogenous variables, so that we can use the system to investigate interrelationships among activity demand, time allocation and travel patterns. This will provide a strong basis for the improved travel demand forecasting models.

The remainder of this paper is organized as follows. The next section provides a detailed description of the collected data together with the profile of activity and travel patterns. This is followed by an overview of the methodology adopted to specify and estimate structural equation models. The fourth section describes the model estimation results. Finally, conclusions and future research implications are discussed.

Data

Data was collected from a very detailed activity-based travel survey of Nanjing, China on a typical weekday (Wednesday, October 30 2013). The survey was carried out by the local government to draw up the planning for the transportation system in the city. It includes two parts: (1) household and individual characteristics; (2) travel information of all trips made during the day (a 24 h period). Taking a whole household as a unit, a face-to-face interview was adopted for the survey to record all activities involving travel details for all individuals above six years old in the household. After the elimination of missing and erroneous data, 5504 individuals were finally obtained. Household income distribution of these samples is shown in Table 1.

The International Poverty Line Standard proposed by the Organization for Economic Cooperation and Development is used to classify the sample into a low-income subset and non-low-income subset. The standard defines poverty rate as a level of income at 50% of the regional average disposable income per capita (Mok 1993). The disposable income per capita was determined by dividing the annual household income by the household size of the family, resulting in 20,000 Yuan (1 Yuan = US$0.16 in 2013) for Nanjing City. Accordingly, 1722 low-income and 3782 non-low-income individuals are extracted from the survey data. Among these samples, students and employees are considered as commuters. Therefore, 610 low-income and 2550 non-low-income commuters are included.

Socio-demographics characteristics of the sample are shown in Table 2. The average household size of low-income commuters is 3.5 persons, which is larger than non-low-income household with 3.2 persons. The average car ownership is 0.37 cars, which is much lower than non-low-income households with 0.70 cars. This might be reflective of the limited capability of accessing goods and service within the sample. The proportion of low-income travelers having driving license and transit card is also lower than that of non-low-income travelers. People in the low-income sample tend to be less educated than people in the rest of the sample.

An overall profile of low-income commuters' activity participation, trip generation and mode choice is shown in Table 3. Activity participation indicators considered here are the amount of time allocation to different types of activities, while travel indicators considered include time spent on travel, the number of trips, the number of trip chains and travel mode choice. Activity participation was classified into three categories: subsistence activity, maintenance activity, and discretionary activity (Bowman and Ben-Akiva 2000). Subsistence activities in the Nanjing survey refer to work, school, and bureaucracy. Maintenance activities mean shopping, visiting friends, and seeing a doctor. Leisure activities refer to social recreation. In-home activities mean all activities conducted at home, such as rest and dinner.

The average amount of time spent on subsistence activity by low-income commuters is found to be longer with 8.37 h, which indicates they spend more hours making a living. The average travel time by purpose show that nearly 45% is dedicated to commuting for subsistence activities. Trip chain or tour refers to a sequence of

Table 1. Household income distribution of samples in the survey.

Category	<20	20~50	50~100	100~150	150~200	>200	Total
Percentage (%)	3.0	12.8	40.8	26.5	12.0	4.8	100.0

Notes: The unit is 1000 Chinese Yuan (RMB), 1 Yuan = US$0.16 in 2013.

Table 2. Basic summary statistics of the low-income and non-low commuter samples.

Variable	Coding	Description	Low (N = 610) (%)	Non-low (N = 2550) (%)
Household size	Size	3 persons or less	58.4	65.9
		More than 3 persons	41.6	34.1
Car ownership per household	Car	Without cars	65.4	34.8
		One car	32.5	58.6
		Two cars or more	2.1	6.6
Bicycle ownership per household	Bicycle	Without bicycles	28.7	33.7
		One bicycle	48.9	45.5
		Two bicycles or more	22.4	20.8
Moped ownership per household	Moped	Without mopeds	28.4	26.4
		One moped	44.3	55.2
		Two mopeds or more	27.3	18.4
Gender	Gender	Male (0)	51.8	53.8
		Female (1)	48.2	46.2
Occupation	Occ	Student (0)	22.6	18.2
		Employee (1)	77.4	81.8
Driving license possession	Lic	No (0)	73.9	46.7
		Yes (1)	26.1	53.3
Transit IC card possession	IC	No (0)	24.3	17.4
		Yes (1)	75.7	82.6
Age	Age	Younger than 25	25.7	24.5
		25~49 years old	60.7	63.6
		Older than 49	13.6	11.9
Education level	Edu	Under middle school	26.1	17.5
		High school	33.4	24.4
		College or above	40.5	54.9

trips that begins at home, involves visiting one or more other places, and ends at home. A simple tour involves two trips from home to a given destination and then returns home, and a complex tour involves a sequence of more than two trips that begins and ends at home. Complex work tours and nonwork tours are aggregated for the limited data. Only 0.11 nonwork tours and 0.09 complex tours are made by low-income samples. The number of tours and trips conducted by low-income commuters is smaller than that of non-low-income commuters, implying low-income sample has limited ability to pursue daily activities. Moped accounts for the largest proportion among various modes for low-income sample, which is reasonable for its flexibility and low travel costs. Car has the least dominant mode share with 0.26 car trips, much smaller than that of non-low-income commuters. The one-way analysis of variance (ANOVA) was conducted to test whether there are any statistically significant differences between the means of activity–travel profile of low-income group and non-low-income group. Results shown in Table 3 (p-value) indicate most of the activity–travel characteristics of low-income commuters are significantly different from non-low-income commuters at the 0.1 level.

In addition to obtaining overall descriptive profiles of activity and travel pattern, descriptive statistical analysis is performed to help guide the following model specification. Pearson's chi-squared (χ^2), one-way analysis of variance (ANOVA) and correlation analysis are conducted to test significance between those discrete and continuous variables. Detailed results of the statistical analysis are not included in the study for brevity.

Table 3. Profile of activity and travel characteristics (hours).

Characteristic	Coding	Average of the non-low-income	Average of the low-income	ANOVA p-value
Activity durations				
Subsistence activity	Sub_d	8.14	8.37	**0.091**[a]
Maintenance activity	Main_d	0.27	0.16	**0.023**[a]
Leisure activity	Lei_d	0.35	0.18	**0.060**[a]
In-home activity	Home_d	13.94	14.08	0.126
Travel time				
Subsistence activity	Sub_t	0.50	0.53	0.401
Maintenance activity	Main_t	0.08	0.04	**0.093**[a]
Leisure activity	Lei_t	0.11	0.04	**0.001**[a]
Travel for home	Home_t	0.61	0.59	0.139
Number of tours				
Simple work tours	Hwh	0.94	0.94	0.775
Simple non-work tours	Hoh	0.16	0.11	**0.098**[a]
Complex tours	Hwoh	0.09	0.09	0.783
Average number of tours	Tour	1.19	1.14	**0.087**[a]
Average number of trips	Trip	2.50	2.39	**0.092**[a]
Travel mode choice				
Frequency of car	F_car	0.65	0.26	**0.000**[a]
Frequency of public transport	F_PT	0.40	0.49	**0.025**[a]
Frequency of moped	F_moped	0.59	0.70	**0.034**[a]
Frequency of bicycle	F_bicycle	0.36	0.44	**0.012**[a]
Frequency of walk	F_walk	0.50	0.52	0.449

Notes: [a] indicates the p-value is significant at the 0.1 level.

Methodology

A typical structural equation model is applied to estimate the interrelationships among socio-demographics, accessibility variables, activity participation, trip generation, and mode choice behavior of low-income commuters. The advantage of structural equation model is the capability in simultaneously estimating the complex causal relationships among a set of observed variables based on a specified model. Basically, a structural equation model without latent variables has the form (McDonald and Ho 2002):

$$y = By + \Gamma x + \zeta \tag{1}$$

where y is a column vector of p endogenous variables, x is a column vector of q exogenous variables, and B is a matrix ($p \times p$) of direct effects between pairs of p endogenous variables, Γ is a matrix ($p \times q$) of regression effects of q exogenous variables, ζ is a column vector of error terms associated with endogenous variables.

In order to get a better understanding of the model estimation results, it is often useful to calculate the direct and indirect effects from the model (Golob 2000, 2003; McDonald and Ho 2002). A direct effect is the influence of one variable on another that is not mediated by any other variables, while an indirect effect is one that is mediated by at least one other variable. The total effect of one variable on another is the sum of the direct and indirect effects. For example, in our model, socio-demographics can have both direct and indirect effects on trip generation, where the latter is mediated by activity participation variables (see Figure 1). After estimating B and Γ in the SEM, the direct, indirect, and total effects can be derived from these coefficients.

In this paper, exogenous variables are socio-demographics and accessibility variables. Endogenous variables refer to activity participation, trip generation, and mode choice. A necessary condition for model identification is that $(I - B)$ must be nonsingular, where I denotes the identity matrix of dimension p. The total effect of the endogenous variable on one other is represented by:

$$T_{yy} = (I - B)^{-1} - I \tag{2}$$

And the total effect of the exogenous variable on the endogenous variable in the model is given by:

$$T_{xy} = (I - B)^{-1}\Gamma \tag{3}$$

In this study, the maximum likelihood method is used to estimate the SEM because it converges more rapidly, and coefficients estimated by ML are consistent even with censored endogenous variables, and estimates have been shown to be robust under violations of multivariate normality (Boomsma 1987).

Ideally, one would like to be able to develop a single model system that simultaneously incorporates all of the relationships among these five sets of variables. However, in order to develop such a comprehensive model system, one would need to have a larger sample size than that used in this study. In addition, it is felt that a single model system with so many variables may become too complex to effectively interpret. Therefore, two smaller model systems specifically aimed at identifying sets of variables are developed in the study.

Model A: trip generation as a function of socio-demographics, accessibility, and activity participation

Numerous studies in the past have modeled relationships between socio-demographics, activity participation, and travel behavior. However, few of them have included accessibility as exogenous variables. Model A attempts to explore these relationship from the time budget viewpoint. Figure 1 provides a scheme that depicts the types

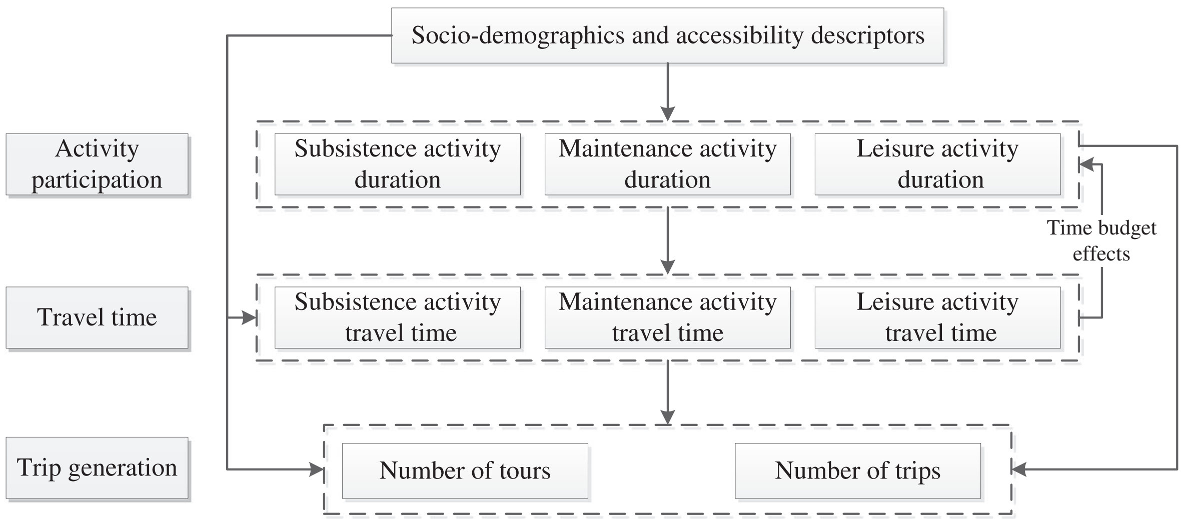

Figure 1. Trip generation as a function of socio-demographics, accessibility, and activity participation.

of relationships captured in Model A. In the model, trip generation is represented by the number of tours and the number of trips.

The effects among the activities are hypothesized based on each activity's importance and the degree of obligation. In other words, it is assumed that people allocate their time on subsistence activities first, on maintenance activities second, and then on leisure activities. Also, direct effects of travel time spent for a higher level of activities to a lower level of activity participation durations are considered. In other words, subsistence travel time affects maintenance and leisure activity durations. Similarly, travel time for maintenance activity affects leisure activity duration (Golob 2000). Accessibility descriptors include population density at residence and employment density at residence, which are calculated according to the population and the number of retail employees in the traffic analysis zones (TAZ) with the unit of 1000 persons/km^2. The natural log transformation is applied to these accessibility variables to make their distribution more symmetric and to mitigate the potential problem of heteroskedasticity.

Model B: travel mode choice as a function of socio-demographics, accessibility, activity participation, and trip chaining

Analyzing mode choice may lead to a deeper understanding of how commuters respond to different scenarios. Figure 2 represents relationships among socio-demographics, accessibility, activity participation, trip chaining, and mode choice. In the model, we assume that people have tendencies to arrive at destinations with a faster speed. Therefore, travel mode preferences are hypothesized at the order of car, public transit, moped, bicycle, and walk.

Results

Three distinct types of relationships obtained from structural equation modeling procedures are considered based on LISREL 8.80 software in this study. They are direct effects, indirect effects, and total effects. For example, it can be seen in Table 4 that subsistence activity duration has a direct effect on travel time for subsistence activity. Similarly, subsistence activity duration has an indirect effect on maintenance activity duration through subsistence activity travel time, which serves as the mediating variable. The total effect of one variable on another is the sum of its direct and indirect effects.

It is to be noted, however, that direct and indirect effects may be of different signs, thus having important implications for the overall total effects. For instance, Table 4 shows duration of subsistence activity has a positive direct effect (0.02) and a negative indirect effect (−0.09) on the number of trips. The indirect effect is caused by maintenance activity travel and leisure activity travel. That is, an increase in subsistence activity duration may indirectly decrease the number of trips by decreasing the travel time for maintenance activity (−0.03) and leisure activity (−0.02). The total effect of subsistence activity duration on the number of trips will be the sum of these two effects.

Model A: Model estimation results are shown in Table 4. The χ^2 is 69.62 with 67° of freedom, showing that the null hypothesis that sample moments are equal to implied moments cannot be rejected. The goodness-of-fit index (GFI) is 0.99, indicating that the overall fit of the model is excellent. Other measures of fit such as adjusted goodness-of-fit index (AGFI = 0.97) and the root mean square error of approximation (RMSEA = 0.0079) are also found to be acceptable by model fit criteria for structural equation models. Hoelter's Critical N (CN) statistic is found to be 849 (more than 200 is acceptable), which is the sample size at which the value of the fitting function F_{ML} would lead to the rejection of the null hypothesis, H_0 ($\Sigma = \Sigma(\theta)$), at a given significance level.

In the following paragraph, the relationship from socio-demographics to activity participation and trip generation will be discussed. The model results show that commuters from larger households make fewer tours (−0.07) and trips (−0.15). Bicycle ownership has a negative influence (−0.02) on the number of trips through the mediating variable (maintenance activity travel time). Females spend more time on maintenance and leisure activities (0.08 and 0.08). This finding corroborates earlier literature that suggests females undertake a larger share of household obligations. Older commuters may pursue more maintenance activities (0.26). Judging from the total effects, commuters with an older age or a higher education level tend to increase the propensity to make tours and trips.

With respect to relationships from activity participation to trip generation, subsistence activity duration variable has negative effects on tours (−0.03) and trips (−0.08). This implies that, if subsistence activity durations are shortened, then more trip generation are induced. Maintenance activity duration is found to indirectly increase the trips (0.09). The indirect effects mainly result from leisure activity duration variable and maintenance activity travel time variable.

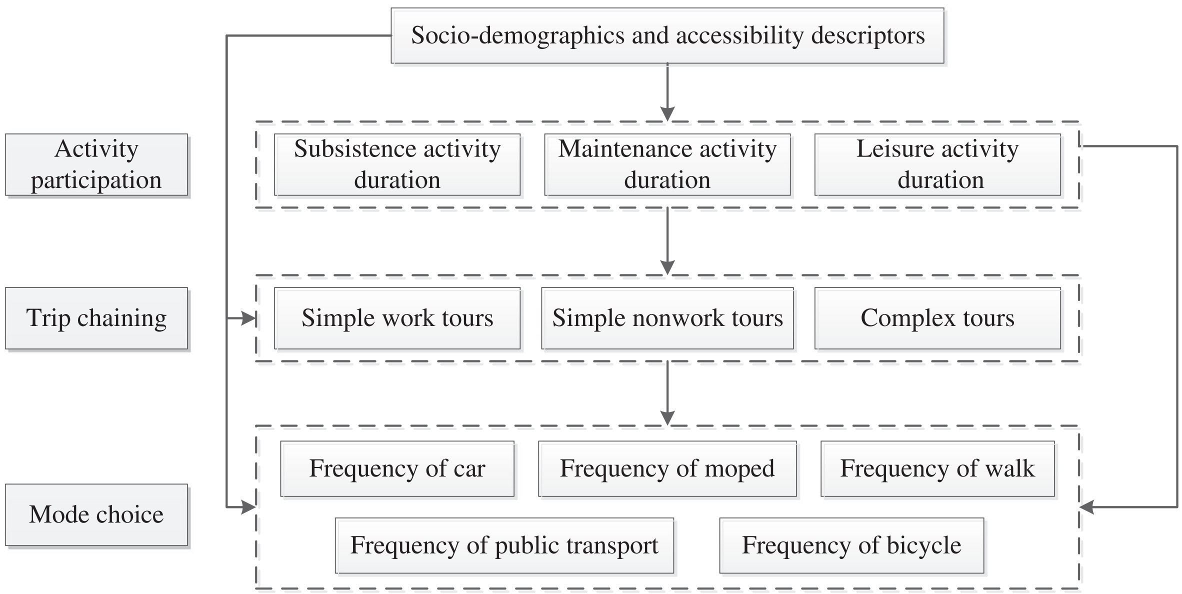

Figure 2. Mode choice as a function of socio-demographics, accessibility, activity participation, and trip chaining.

As for the relationship between activity participation, a clear trade-off is seen among subsistence duration, maintenance duration and leisure duration. That is to say, commuters who spend more time on subsistence activities may conduct fewer maintenance (−0.14) and leisure activities (−0.15) because of time budgets. In addition, travel time is affected by activity participation. For example, as subsistence activity duration increases, travel time for such activities increases (0.03); travel time for maintenance and leisure activities decreases (−0.03 and −0.02). This result is expected because increments of participation in subsistence activities decrease opportunities for participation in other activities and consequently decrease travel time for these activities.

Finally, the model shows that population density significantly affect trip generation. Higher population density contributes to more tours (0.04) and trips (0.08). However, employment density variable does not indicate any strong effects on trip generation. Also, accessibility variables show insignificant impacts on activity participation. This finding is different from Golob's research (2000). It is because accessibility primarily influences residents' non-work activity participation. And low-income commuters conduct quite a few maintenance and leisure activities, respectively, 0.16 and 0.18 h during a day (see Table 3).

Overall, Model A shows that socio-demographics, accessibility and activity participation variables exert significant influences on trip generation. There is also a clear trade-off between activity participation. Results that low-income commuters allocate their time with respect to an activity's level of importance and obligation are also demonstrated in the model system.

Model B: Model estimation results are shown in Tables 5 and 6. As in the case of Model A, all statistical goodness-of-fit measures are acceptable. The model is primarily intended to capture the relationship between socio-demographics, accessibility, activity participation, trip chaining and mode choice.

The model offers very similar indications with Model A on the effects of various socio-demographics variables on activity durations. In terms of the relationship from socio-demographics to trip chaining (Table 5), one would expect fewer complex tours (−0.06) as household size gets larger. Female commuters conduct fewer simple work tours (−0.04), more simple nonwork tours (0.04) and complex tours (0.01). Age variable has a positive impact on complex tours (0.06). In other words, older commuters are more inclined to chain activities in a tour.

Table 5 also indicates that socio-demographics significantly affect commuters' mode choices both directly and indirectly. Commuters from larger households have fewer tendencies to non-motorized travel modes, indicated by the negative total effects of frequency of moped, bicycle, and walk (−0.08, −0.06 and −0.06). When travel mode ownership increases, its corresponding mode choice probability increases, but other mode use is more likely to decrease. For example, with the increase of car ownership, commuters have more tendencies to use cars (0.61) and fewer tendencies to public transit (−0.15), moped (−0.21), and bicycle (−0.34). Females show higher propensities to use public transit (0.07), moped (0.08), bicycle (0.05), and walk (0.12). The results are similar to the research by Yang et al. (2013). Age variable is shown to be associated with less public transit use (−0.19) and more moped use (0.31). As expected, commuters with a higher education level use motorized modes more often, shown by the total positive effects of car and public transit (0.13 and 0.13). On the other hand, when commuters possess transit IC card, they are more apt to reduce car use (−0.15) and increase public transit use (0.44).

Another noteworthy result is that two accessibility variables show significant impacts on trip chaining and mode choice. Higher population density is associated with more simple nonwork tours (0.02) and complex tours (0.02). Population density variable indirectly contributes to moped, bicycle, and walk use. These indirect effects mainly come from trip chaining variables. Employment density variable positively affects public transit use (0.06). It is plausible for the reason that high employment density at residence implies mixed land use. Mixed land use is helpful in attracting transit riders (Cervero 2002).

Next, we want to look at the relationships among activity engagement, trip chaining, and mode choice (Table 6) in the following two paragraphs. Subsistence activity duration has positive effects on simple work tours (0.07) and negative effects on simple nonwork tours (−0.07) and complex tours (−0.02). Commuters who spend more time on maintenance activity are more apt to conduct complex tours (0.09). Leisure activity duration variable shows negative impacts on simple work tours (−0.13) but positive on simple nonwork (0.08) and complex (0.03) tours. This suggests that if leisure activity duration is lengthened, commuters conduct more nonwork activities and chain more activities in a tour.

Table 4. Estimation results of Model A.

	Effects	Size	Bicycle	Gen	Age	Edu	Popud	Employd	Sub_d	Main_d	Lei_d	Sub_t	Main_t	Lei_t	Tour
Sub_d	Total	–	–	−0.55*	−0.95**	–	–	–	–	–	–	–	–	–	–
	Direct	–	–	−0.55*	−0.95**	–	–	–	–	–	–	–	–	–	–
	Indirect	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Main_d	Total	–	–	0.08*	0.26**	−0.03*	–	–	−0.14**	–	–	−0.22**	–	–	–
	Direct	–	–	–	0.13**		–	–	−0.13**	–	–	−0.22**	–	–	–
	Indirect	–	–	0.08*	0.13**	−0.03*	–	–	−0.01*	–	–	–	–	–	–
Lei_d	Total	–	–	0.08*	–	–	–	–	−0.15**	−0.24**	–	–	–	–	–
	Direct	–	–	–	−0.16**	–	–	–	−0.17**	−0.24**	–	−0.20*	–	–	–
	Indirect	–	–	0.08*	0.11**	–	–	–	0.03**	–	–	0.06*	–	–	–
Sub_t	Total	–	–	−0.02*	−0.03**	0.13**	–	–	0.03**	–	–	–	–	–	–
	Direct	–	–	–	–	0.13**	–	–	0.03**	–	–	–	–	–	–
	Indirect	–	–	−0.02*	−0.03**	–	–	–	–	–	–	–	–	–	–
Main_t	Total	−0.02*	−0.02*	0.01*	0.06**	0.00*	0.01*	–	−0.03**	0.11**	–	−0.02**	–	–	–
	Direct	−0.02*	−0.02*	–	0.02*	–	0.01*	–	−0.01**	0.11**	–	–	–	–	–
	Indirect	–	–	0.01*	0.04**	0.00*	–	–	−0.01**	–	–	−0.02**	–	–	–
Lei_t	Total	–	–	0.01*	–	–	–	–	−0.02**	−0.02**	0.07**	–	–	–	–
	Direct	–	–	–	–	–	–	–	−0.01**	–	0.07**	0.03*	–	–	–
	Indirect	–	–	0.01*	–	–	–	–	−0.01**	−0.02**	–	–	–	–	–
Tour	Total	−0.07*	–	0.01*	0.09**	0.01**	0.04**	–	−0.03**	–	–	0.11**	–	0.47**	–
	Direct	−0.07*	–	–	0.06**	–	0.04**	–	−0.03**	–	−0.04*	0.10*	–	0.47**	–
	Indirect	–	–	0.01*	0.03**	0.01**	–	–	–	–	0.03**	0.02*	–	–	–
Trip	Total	−0.15**	−0.02*	0.04*	0.21**	0.04**	0.08**	–	−0.08**	0.09**	–	0.33**	0.93**	2.61**	1.93**
	Direct	–	–	–	–	–	–	–	0.02**	–	−0.06**	0.09*	0.93**	1.71**	1.93**
	Indirect	−0.15**	−0.02*	0.04*	0.21**	0.04**	0.08**	–	−0.09**	0.09**	0.10**	0.24**	–	0.90**	–

Note: Popud and Employd refers to population density at residence and employment density at residence.
**$p < 0.01$; *$p < 0.05$.

Table 5. Estimation results of Model B (I).

	Effects	Size	Car	Moped	Bicycle	Gen	Age	Edu	IC	Popud	Employd
Sub_d	Total	–	–	–	–	−0.55*	−0.95**	–	–	–	–
	Direct	–	–	–	–	−0.55*	−0.95**	–	–	–	–
	Indirect	–	–	–	–	–	–	–	–	–	–
Main_d	Total	–	–	–	–	0.08*	0.26**	–	–	–	–
	Direct	–	–	–	–	–	0.13**	–	–	–	–
	Indirect	–	–	–	–	0.08*	0.13**	–	–	–	–
Lei_d	Total	–	–	–	–	0.08*	–	–	–	–	–
	Direct	–	–	–	–	–	−0.16**	–	–	–	–
	Indirect	–	–	–	–	0.08*	0.11**	–	–	–	–
Hwh	Total	–	–	–	–	−0.04*	−0.06**	–	–	–	–
	Direct	–	–	–	–	–	–	–	–	–	–
	Indirect	–	–	–	–	−0.04*	−0.06**	–	–	–	–
Hoh	Total	–	–	–	0.05**	0.04*	0.06**	–	–	0.02*	–
	Direct	–	–	–	0.05**	–	–	–	–	0.02*	–
	Indirect	–	–	–	–	0.04*	0.06**	–	–	–	–
Hwoh	Total	−0.06**	–	–	−0.02**	0.01*	0.06**	0.03*	–	0.02**	–
	Direct	−0.06**	–	–	–	–	0.04*	0.03*	–	0.03**	–
	Indirect	–	–	–	−0.02**	0.01*	0.03**	–	–	−0.01*	–
F_car	Total	–	0.61**	–	0.01*	−0.27**	0.01*	0.13**	−0.15*	–	–
	Direct	–	0.61**	–	–	−0.27**	–	0.13**	−0.15*	–	–
	Indirect	–	–	–	0.01*	–	0.01*	–	–	–	–
F_PT	Total	–	−0.15**	−0.22**	−0.17**	0.07**	−0.19**	0.13**	0.44**	–	0.06*
	Direct	–	–	−0.22**	−0.15**	–	−0.20**	0.16**	0.40**	–	0.06*
	Indirect	–	−0.15**	–	−0.02*	0.07**	–	−0.03**	0.04*	–	–
F_moped	Total	−0.08**	−0.21**	0.56**	−0.15**	0.08**	0.31**	–	0.12**	0.03**	−0.02*
	Direct	–	–	0.46**	−0.20**	–	0.19**	0.12*	–	–	–
	Indirect	−0.08**	−0.21**	0.09**	0.05*	0.08**	0.12**	−0.08**	0.12**	0.03**	−0.02*
F_bicycle	Total	−0.06**	−0.34**	−0.16**	0.31**	0.05**	–	−0.09**	0.10**	0.03**	−0.02*
	Direct	–	−0.26**	–	0.15**	–	–	–	–	–	–
	Indirect	−0.06**	−0.08**	−0.16**	0.16**	0.05**	–	−0.09**	0.10**	0.03**	−0.02*
F_walk	Total	−0.06**	–	−0.18**	–	0.12**	–	−0.12**	0.07*	0.05**	−0.02*
	Direct	–	–	–	–	–	–	–	–	–	–
	Indirect	−0.06**	–	−0.18**	–	0.12**	–	−0.12**	0.07*	0.05**	−0.02*

Notes: $\chi^2 = 117.25$ with 103 degrees of freedom, GFI = 0.98, AGFI = 0.96, RMSEA = 0.014, CN = 733.
Popud and Employd refers to population density at residence and employment density at residence.
$^{**}p < 0.01$; $^{*}p < 0.05$.

Table 6. Estimation results of Model B (II).

	Effects	Sub_d	Main_d	Lei_d	Hwh	Hoh	Hwoh	F_car	F_PT	F_moped	F_bicycle
Sub_d	Total	–	–	–	–	–	–	–	–	–	–
	Direct	–	–	–	–	–	–	–	–	–	–
	Indirect	–	–	–	–	–	–	–	–	–	–
Main_d	Total	−0.14**	–	–	–	–	–	–	–	–	–
	Direct	−0.14**	–	–	–	–	–	–	–	–	–
	Indirect	–	–	–	–	–	–	–	–	–	–
Lei_d	Total	−0.15**	−0.23**	–	–	–	–	–	–	–	–
	Direct	−0.18**	−0.23**	–	–	–	–	–	–	–	–
	Indirect	0.03**	–	–	–	–	–	–	–	–	–
Hwh	Total	0.07**	−0.11**	−0.13**	–	–	–	–	–	–	–
	Direct	0.03**	−0.14**	−0.13**	–	–	–	–	–	–	–
	Indirect	0.04**	0.03**	–	–	–	–	–	–	–	–
Hoh	Total	−0.07**	–	0.08**	−0.10**	–	–	–	–	–	–
	Direct	−0.06**	–	0.06**	−0.10**	–	–	–	–	–	–
	Indirect	−0.02**	–	0.01**	–	–	–	–	–	–	–
Hwoh	Total	−0.02**	0.09**	0.03**	−0.41**	−0.33**	–	–	–	–	–
	Direct	−0.01*	0.04**	–	−0.44**	−0.33**	–	–	–	–	–
	Indirect	−0.01**	0.05**	0.03**	0.03**	–	–	–	–	–	–
F_car	Total	−0.01**	–	0.01*	−0.02*	0.19**	–	–	–	–	–
	Direct	–	–	–	–	0.19**	–	–	–	–	–
	Indirect	−0.01**	–	0.01*	−0.02*	–	–	–	–	–	–
F_PT	Total	–	0.12**	0.09*	0.04*	−0.36**	–	−0.24**	–	–	–
	Direct	–	0.14**	0.12**	–	−0.32**	–	−0.24**	–	–	–
	Indirect	–	−0.03**	−0.03**	0.04*	−0.05**	–	–	–	–	–
F_moped	Total	0.03**	–	−0.09**	–	−0.34**	1.24**	−0.35**	−0.42**	–	–
	Direct	–	–	–	0.67**	–	1.24**	−0.45**	−0.42**	–	–
	Indirect	0.03**	–	−0.09**	−0.51**	−0.34**	–	0.10**	–	–	–
F_bicycle	Total	−0.03**	–	–	–	0.40**	0.92**	−0.13*	−0.29**	−0.48**	–
	Direct	–	–	–	0.84**	0.64**	1.51**	−0.42**	−0.49**	−0.48**	–
	Indirect	−0.03**	–	–	−0.77**	−0.24**	−0.59**	0.28**	0.20**	–	–
F_walk	Total	−0.06**	−0.05*	–	–	1.03**	1.06**	−0.30**	−0.30**	−0.52**	−0.99**
	Direct	–	−0.03**	–	1.92**	1.98**	3.20**	−1.02**	−1.01**	−1.00**	−0.99**
	Indirect	−0.06**	–	–	−1.76**	−0.94**	−2.14**	0.72**	0.71**	0.47**	–

$^{**}p < 0.01$; $^{*}p < 0.05$.

Then, the effects of activity on mode choice are discussed. Table 6 illustrates that commuters' choice probability of car, bicycle and walk decreases as the amount of time spent on subsistence activity increases. On the other hand, both maintenance activity duration and leisure activity duration have positive influences on public transit use (0.12 and 0.09). When low-income commuters make simple work tours, they have tendencies to choose public transit (0.04). However, if they make simple nonwork tours, they are more likely to use car, bicycle and walk (0.19, 0.40, and 1.03). Complex tours are shown to be involved with more frequencies of moped, bicycle, and walk for the flexibility of these modes. Furthermore, clear trade-off effects are seen in different mode use, indicating these modes are quite competitive. Indicated by the total effects, bicycle and walk are the most competitive (−0.99) while car and bicycle are the least competitive (−0.13).

Overall, the model has shown that socio-demographics, accessibility, activity participation and trip chaining affect mode choice pattern. In general, females and commuters with higher education level show a greater inclination towards public transit. High employment density also contributes to public transit use. Positive effects of moped use come from subsistence activity duration and complex tours. Simple nonwork tours are associated with more bicycle and walk use.

Conclusions

The paper utilized the Nanjing activity-based travel data-set to investigate and estimate structural relationships among socio-demographics, accessibility, activity participation, trip generation, and mode choice of low-income commuters. We specified simultaneous equation models in which all of the activity participation and trip generation variables are function of themselves and of exogenous household characteristics, including location-specific accessibility.

There are four main contributions in this study. (1) The usefulness of structural equation models in modeling the complicated relationships addressed in this research has been demonstrated. (2) We specifically examine low-income commuters' activity–travel pattern for a better understanding the mechanism of activity participation and travel behavior. (3) Relationships between activity participation and trip generation from the time budgets viewpoint are investigated for an improved travel demand forecasting model. (4) Travel mode choice as a function of socio-demographics, accessibility, activity participation and trip chaining is modeled for a better understanding the mode choice mechanism.

Our general findings can be summarized as follows. First, by descriptive analysis, it is found that the activity–travel pattern of low-income commuters is significantly different from that of non-low-income commuters. Then, we estimated models that subdivided activity participation into (1) subsistence, (2) maintenance, and (3) leisure activities. In an extension, time allocations are added as constraints. The model structure allows us to better forecast how increasing any one type of activity (for instance, working) will affect demand for other activities, as well as trip generation and mode choice. Third, we can better capture and understand travel behavior better than through socio-demographics alone, by including activity participation endogenously in the model. Last, we considered location-specific accessibility variables. Two of these indices, i.e. population density and employment density, focused on the immediate neighborhood of each household and were generated by GIS using zone-based data. Each index added significant explanatory power, and the results show how accessibility influences activity participation and travel behavior. The population density measure has more ubiquitous effects.

Joint models of activity participation and trip generation can be used to forecast the effects of exogenous shocks to the endogenous variables, because they capture the effects of activity participation, trip chaining, and mode choice on all the endogenous variables. For example, we can trace the effects of increases in telecommuting on demand for all other activities, trip generation, and mode choice. Or, we can expand the model to adding network-based level-of-service as exogenous variables, thus addressing the issue of induced travel in the context of increasing road network capacity in the neighborhood of low-income residents. The impacts of commuting time savings on activity engagement (and therefore travel) can be determined using models such as those provided in this study. These insights form the basis for the development of robust travel behavior models that are responsive to a host of transportation policy scenarios being considered to improve the travel environment of low-income commuters.

Empirically, findings in this study will lead to a better understanding of the influencing factors on low-income commuters' travel behavior, which provides useful policy implications for policy-makers. Nowadays, public transit is thought be a good way to improve the mobility of low-income commuters. Due to the fact that females are more likely to travel by public transit then males, priority policies should be given to women to solve their travel problems. For example, more low-floor buses are available to make women wearing high-heeled shoes get on/off the bus easily. In terms of the phenomenon that IC card holders prefer using public transit, it is necessary for public transport agencies to implement measures for increasing transit card ownership, such as free processing fees when low-income residents apply and a higher fare discount when they use their cards.

The findings in this paper might offer further insights into understanding low-income commuters travel behavior on a weekday. Firstly, we can measure accessibility using other indices to reflect the transportation network characteristics and services quality. Secondly, the study just considers one mode in each trip. Future research can focus on multi-mode in each trip consider transferring for deeply exploring mode choice pattern.

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