Investigating Contextual Variability in Mode Choice in Chicago Using a Hierarchical Mixed Logit Model

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Urban Stud 2010 47: 2445 originally published online 18 May 2010
DOI: 10.1177/0042098009357965

Urban Studies
47(11) 2445–2459, October 2010

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[Paper first received, June 2007; in final form, August 2009]

Abstract

In this paper, a hierarchical random-coefficient mixed logit model is applied to quantify variability in commuters' mode choice in the Chicago metropolitan area, especially concerning the contextual variability by the traits of census tract of residence. It is found that individual mode choice behaviour varies considerably across residential locations. Moreover, the contextual effects are found to modify the marginal utility of mode choice. Especially, in-vehicle travel time and gasoline cost are significant covariates of census tract traits (such as percentage of blue-collar residents, ethnicity). Furthermore, random variation is present even after both contextual and individual traits are controlled for, suggesting intrinsic randomness in individual mode choice. The hierarchical structure of quantifying contextual variability proves to be a useful tool in capturing intrinsic heterogeneity in mode choice. The study findings have important implications for integrated land use and transport planning especially at the geographical levels below that of the region.

1. Introduction

There has been a large body of economic and sociological research on the role of contextual effects in economic and decision-making behaviours. The contextual effects in the literature are referred to as social interactions (Brock and Durlauf, 2001), neighbourhood effects (Brock and Durlauf, 2002) and spatial network (or spill-over) effects (Goetzke, 2008). The study findings generally agree that there is a tendency for conformity in behaviour across members in a reference group due to the social interactions (or neighbourhood or network effects). For example, Goetzke (2008) finds that social spill-over effects lead to positive demand-side network externalities which, in the context of transport mode choice, translates into 'the more people who use the mode, the more attractive this transport mode becomes for all other people'.

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0042-0980 Print/1360-063X Online

DOI: 10.1177/0042098009357965

More recently in the field of travel behaviour (in particular mode choice) studies, the contextual effects have been extended to the influence of the built environment (land use) in travel behaviour (Ewing and Cervero, 2001; Rodriguez and Joo, 2004; Handy *et al.*, 2005; Cao *et al.*, 2006; Handy *et al.*, 2006; Cao *et al.*, 2007; Frank *et al.*, 2007; Bhat and Guo, 2007; Pinjari *et al.*, 2007). Although the findings are mixed at times, intuitively one would agree that a household living in New York City may have quite different travel behaviour from its counterpart living in nearby suburban New Jersey. The behavioural differences are caused by the differences in residential environment.

On the other hand, in traditional regional travel demand forecasting where the dependent variable y (for example, number of trips, modal split) is formulated in two parts: a deterministic part as a function of household (and mode-specific) traits and a random measurement error—i.e. $y_i = \mathrm{f}(\mathbf{X}, \boldsymbol{\beta}) + \varepsilon_i$, it is common practice to assume that the model coefficients ($\boldsymbol{\beta}$) are fixed across the entire region. The important implication of that is households in the sub-regions share similar marginal effects of household/individual traits, even though they could be quite different as proven in the literature.

In this paper, we argue that this does not have to be so in demand analysis. The assumption of $\boldsymbol{\beta}$ is relaxed to allow the coefficients to vary across sub-regions. Moreover, it is hypothesised that the marginal effect of an independent variable (β) is affected by area (contextual) traits—i.e. $\boldsymbol{\beta} = \boldsymbol{\omega}\gamma + \boldsymbol{\upsilon}$, where $\boldsymbol{\omega}$ is a matrix of contextual traits; $\boldsymbol{\gamma}$ is the associated weight vector; and $\boldsymbol{\upsilon}$ is random effects due to unmeasured/unknown errors. Thus, the contextual variability in household travel behaviour is quantified and can be tested statistically as demonstrated later in the paper. This modelling approach defines a two-level—household and area—random coefficient model.

More specifically, this paper statistically quantifies and tests contextual variability in commuters' mode choice behaviour in the Chicago metropolitan area. A hierarchical random-coefficient mixed logit model is proposed. The model is formulated in two levels, individuals and census tracts. Individual characteristics form the inputs to the first level of model and the coefficients of travel impedance are associated with the contextual traits of census tracts, including socio-demography, land use and journey-to-work traits extracted from the Census Tract Planning Package (CTPP) 2000.

Mixed-logit models are widely used in transport demand analysis (for example, Srinivasan *et al.*, 2006; Wang and Kockelman, 2006). Applications of hierarchical mixed-logit models in transport analysis are relatively few. Bhat (2000) developed a multilevel cross-classified work travel mode choice model to investigate individual heterogeneity (micro level) and place heterogeneity (macro level) for travel impedance (travel time and cost) instead of assuming the same travel impedance for all the people within the same residence and work zones when individuals make mode choice decisions. Lin and Long (2008a, 2008b) demonstrated the use of hierarchical random-coefficient models to account for geographical variability in journey-to-work vehicle trips and vehicle miles of travel. On the other hand, hierarchical models have been widely used in other fields like medicine and epidemiology (for example, Sullivan *et al.*, 1999; Greenland, 2000; Burgess *et al.*, 2000), economics (for example, Nunes Amaral *et al.*, 1997; Goodman and Thibodeau, 1998) and educational, social and behavioural sciences (for example, Kreft, 1995; Singer, 1998).

The rest of the paper is structured as follows. Section 2 describes the overall study design and data used in the study, followed by the formulation of the hierarchical mixed logit model in section 3. The model results are discussed in section 4. Finally, conclusions are drawn from the study findings and the research implications for transport planning policy and practice are discussed in section 5.

2. Study Design and Data Source

Household mode choice variability is deemed to come from two primary sources: heterogeneity in households and in their living environments (for example, good transit service, safety), which contribute to the contextual variability of household mode choice. In this paper, the contextual environment is defined by census tract and the contextual traits are those of individual census tracts. The two sources represent a two-level hierarchy—households in the lower level and census tracts in the upper level. Therefore, we apply a hierarchical mixed logit model to capture both the individual and contextual (census tract) variability in mode choice. The model structure is described in section 3.

At the household level, regional travel survey data—Pace (a suburban Chicago bus service agency) Survey 2006—are used. The survey consists of three parts

(1) Commuters' actual daily travel patterns—the commute-related (including level of service measures in terms of time, such as access and egress time, transfer time and travel time) and household demographic information were collected in this part.
(2) Attitudes towards everyday commuting—36 transit attitudinal statements towards all aspects of their travel experience were presented to the survey participants.
(3) Stated choice experiments, in which each survey participant was presented with three journey-to-work scenarios designed based on the individual's home, work and mode choice information provided in part (1) so that the scenarios were rooted in the individual's real travel patterns. In each scenario, the participants answered questions related to one of the three motorised travel mode categories: an automobile-based alternative (i.e. driving alone or sharing a ride), an existing transit alternative currently available (i.e. conventional transit service or vanpool) and a proposed bus rapid transit (BRT) service.[1] Each choice option carried its own characteristics (i.e. travel time, cost, and number of transfers). The choice experiments were designed to determine the conditions under which a respondent might change his or her mode of travel (Owen *et al.*, 2007).

A total of 1550 randomly chosen households in the Chicago metropolitan area participated in the survey and 1330 of them responded appropriately and provided valid information. In a previous analysis by Pace, these households were categorised into seven clusters, within which the households shared similar attitudes towards everyday travel (Owen *et al.*, 2007). Descriptions of the seven household clusters and their distributions are summarised in Table 1. In our mode choice modelling, to be shown later, a cluster-specific constant term is specified for each alternative to account for the heterogeneity among clusters. Furthermore, to reduce the number of cluster-specific constant terms so as to simplify the model specification without losing the meaningful grouping with respect to mode choice behaviour, we have consolidated the seven clusters into three groups—(3, 6), (1, 5, 7) and (2, 4)—based on the similarity in socioeconomic characteristics and attitudes towards transit identified by a structure equation model (SEM) output.[2] That is, respondents in clusters 3 and 6 are very sensitive to

Table 1. Household category and distribution

ID	Household category	Description	Observations: Number	Observations: Percentage
1	Million milers	Mostly well-educated male, large household size with the highest percentage of two or more workers, living and working primarily in exurban and suburban areas; 83 per cent travel by automobile	203	15.7
2	Great middle	Similar to Million milers in socioeconomic characteristics, home location and commuting patterns; however, these households are more transit-friendly and less automobile-dependent than Million milers	274	21.19
3	Demanding survivors	Tend to be women supporting small households, lowest level of education, automobile ownership and low income, transit-captive users with positive attitudes towards transit	122	9.44
4	Cautious individuals	Similar socioeconomic characteristics to Demanding survivors. Unlike the Demanding survivors, three out of four Cautious individuals drive their own cars to work; commute patterns vary considerably	178	13.77
5	Educational professionals	Highest education level, mostly male; These households have at least two cars available, reside primarily in the suburbs and many commute to the CBD; they have favourable attitudes towards commuting by transit and relatively low automobile usage	246	19.03
6	Downtown commuters	High-income households, the highest percentage of work locations in the Chicago CBD; many commute by transit	193	14.93
7	Determined drivers	Auto-dependent—95 per cent by car; majority female commuters who live in, work in and commute between exurban and suburban locations	77	5.96

Source: Owen et al. (2007).

travel time/schedule and both have a positive attitude towards transit service. Respondents in clusters 1, 5 and 7 live in the suburbs and have high automobile ownership, although cluster 5 also shows a relatively high transit propensity. On the other hand, travel patterns in clusters 2 and 4 vary considerably with no single dominant origin–destination pattern (i.e. urban-to-urban, suburban-to-urban, suburban-to-suburban, etc.). As we will show later, in the model results of section 4, this additional grouping has indeed facilitated meaningful model outputs.

At the census-tract level, the Census Transportation Planning Package (CTPP) 2000 Part One is used to extract census-tract (contextual) variables, which are summarised in Table 2. The Pace and CTPP data are merged with a unique census-tract identifier.

3. Hierarchical Mixed Logit Structure

Building on the proposed concept in the introduction, we quantify both the individual and contextual variability in a hierarchical

Table 2. Census-tract (contextual) variables

Variable	*Definition*
Socio-demographics of a census tract	
Average household size	Average number of household members
Employment rate	Ratio of number of workers per household to household size
Vehicle count	Average number of vehicles per household
Race/ethnic (8)	Percentage of households in 8 racial/ethnic groups
Income (15)	Percentage of households in 15 income levels:
Home tenure status (2)	Percentage of homes owned, rented
Age (6)	Percentage of persons in 6 age groups
Resident industrial type (14)	Percentage of workers in 14 industries
Occupation (5)	Percentage of residents in 5 occupation categories
Land use features of a census tract	
Population density	Per square kilometre population
Worker density	Per square kilometre number of residents who work
Housing density	Per square kilometre housing units
Journey-to-work features of a census tract	
Auto usage	Fraction of workers using automobile
Transit usage	Fraction of workers using transit
Auto users	Number of workers using autos to work
Transit users	Number of workers using transit to work
Travel time to work (2)	By transit, automobile (in minutes)

random-coefficient logit model wherein 'fixed' characteristics are referred to as the observed exogenous effects (for example, household traits and level-of-service variables) and 'random effects' are the unobserved individual and contextual heterogeneities. The theoretical structure of the hierarchical random-coefficient logit model is defined as follows. Section 4 explains the final model form including what variables are included and how they are selected through the case study of Pace.

First, a typical mixed logit model has the following structure:

$$P(j|\upsilon_i) = \frac{exp(\alpha_j + \alpha_{j,s} + \boldsymbol{\theta}_{\mathbf{j}}'\mathbf{z_i} + \boldsymbol{\beta}_{\mathbf{i}}'\mathbf{x_{ji}} + \boldsymbol{\delta}_{\mathbf{i}}'\mathbf{k_{ji}})}{\sum_{n=1}^{J} exp(\alpha_n + \alpha_{n,s} + \boldsymbol{\theta}_{\mathbf{n}}'\mathbf{z_i} + \boldsymbol{\beta}_{\mathbf{i}}'\mathbf{x_{ni}} + \boldsymbol{\delta}_{\mathbf{i}}'\mathbf{k_{ji}})} \tag{1}$$

where, $P(j|\upsilon_i)$ is the probability of individual i choosing mode j (i.e., driving alone, sharing a ride, existing transit service, vanpool and BRT) given the random effects υ_i to be defined later; α_j is an alternative specific constant for alternative mode j; $\alpha_{j,s}$ is an incremental alternative specific constant for alternative j of the sth household group defined earlier in section 2 (s = 1, 2, 3); $\mathbf{z_i}$ = column vector of choice-invariant individual characteristics for individual i (for example, age, income); $\boldsymbol{\theta}_{\mathbf{j}}$ is the column vector of non-random (fixed) coefficients for $\mathbf{z_i}$; $\mathbf{x_{ji}}$ is the column vector of individual, choice-varying traits (for example, travel time and travel cost) that may exhibit contextual variability; $\boldsymbol{\beta}_i = (\beta_{ki})'$ is the random coefficient vector for $\mathbf{x_{ji}}$; $\mathbf{k_{ji}}$ is the column vector of the remaining individual, choice-varying traits that do not exhibit contextual variability (for example, headway of transit service, parking cost in Chicago CBD); and $\boldsymbol{\delta}_i = (\delta_{ki})'$ is the column vector of non-random (fixed) coefficients for $\mathbf{k_{ji}}$.

Now, for those individual, choice-varying variables, $\mathbf{x_{ji}}$, suppose the coefficients, β_{ki} s, are a function of the contextual variables w_{kqm} s ($q = 1, ..., Q$) of the mth census tract—i.e.

$$\beta_{ki} = \gamma_{k0} + \sum_{q=1}^{Q} \gamma_{kq} w_{kqm} + \upsilon_{ki} \qquad (2)$$

where, γ_{kq} is the qth weight for intercept ($q = 0$) or census-tract trait ($q = 1,2,..., Q$); w_{kqm} is the qth census tract ($m = 1, ..., M$) trait associated with coefficient β_{ki}; and υ_{ki} is a random effect associated with coefficient β_{ki}.

The last term υ_{ki} defines the random effects capturing the deviation (heterogeneity) from the average effect of coefficient β_{ki} across individuals, $\gamma_{k0} + \sum_{q=1}^{Q} \gamma_{kq} w_{kqs}$. Combined with (2), Equation (1) can be rewritten in the following form:

$$P(j|u_i) = \exp\left\{\frac{\alpha_j + \alpha_{j,s} + \boldsymbol{\theta}_\mathbf{j}'\mathbf{z_i} + \left(\gamma_{k0} + \sum_{q=1}^{Q} \gamma_{kq} w_{kqs} + \upsilon_{ki}\right)' \mathbf{x_{ji}} + \boldsymbol{\delta}_\mathbf{i}'\mathbf{k_{ji}}\}}{\sum_{n=1}^{J} exp\left\{\alpha_n + \alpha_{n,s} + \boldsymbol{\theta}_\mathbf{j}'\mathbf{z_i} + \left(\gamma_{k0} + \sum_{q=1}^{Q} \gamma_{kq} w_{kqs} + \upsilon_{ki}\right)' \mathbf{x_{ni}} + \boldsymbol{\delta}_\mathbf{i}'\mathbf{k_{ji}}\right\}}\right\} \qquad (3)$$

The term

$$\left(\gamma_{k}0 + \sum_{q=1}^{Q} \gamma_{kq} w_{kqs}\right)' \mathbf{x_{ji}}$$

defines interactions between the contextual (w_{kqm}'s) and the individual/household variables ($\mathbf{x_{ji}}$). These interaction terms represent the non-linear effect of xs; and the additional effect of x_{ji} gained only when w_{kqm} is also present and vice versa (or else that effect does not exist).

To understand this, let us use the following example as an analogy. It is generally agreed that a high gasoline price suppresses vehicle miles of travel (VMT). So a policy to switch from a 5-day working week schedule to a 4-day one (10 hours a day) would likely facilitate further VMT reduction. There is clearly interaction between a high gasoline price and a 4-day work schedule. However, it is wrong to conclude that a 4-day schedule is effective in reducing VMT because without the high gasoline price a 4-day work week programme in itself may not have any effect at all on VMT. So, if we were to fit a regression with both the gasoline price and a 4-day working week schedule as individual independent variables on VMT, the coefficients of both would be completely misleading. That is, the effect of gasoline price would be overstated—i.e. $\beta(gas\ price)$ should in fact be

$$\gamma_1(gas\ price) + \gamma_2 (4 - day\ working\ schedule \times gas\ price)$$

and an individual 4-day working week term in the model would make no sense because the programme itself did not have an effect on VMT.

This hierarchical model structure is particularly desirable for modelling and statistically testing contextual variability in household mode choice behaviour. The mode choice variability is tested through the following hypothesis tests

(1) Hypothesis test of $\alpha_{j,s}$: Alternative specific constant $\alpha_{j,s}$ is designed to vary across the three household cluster groups. The null hypothesis is of the form H_0: $\alpha_{j,s}$ is equal across the cluster groups for each travel mode j. If the null hypothesis is rejected, the idea that the travel modes of interest show equal constant utility across the cluster groups must be rejected.
(2) Hypothesis test for fixed effects ($\boldsymbol{\gamma}$): Non-zero coefficients of the fixed effects, $\boldsymbol{\gamma}$, represent the average contextual effects. The fixed effects of the contextual covariates on the dependent variable are statistically zero if the null hypothesis cannot be rejected, or not if the null hypothesis is rejected. Moreover, the alternative hypothesis says that the model coefficients, $\boldsymbol{\beta}$, are significantly dependent on the contextual traits. That is, there exists interaction between the contextual and individual covariates if the null hypothesis is rejected.
(3) Hypothesis test for random effects ($\boldsymbol{\upsilon}$): Non-zero random effects, $\boldsymbol{\upsilon}$, indicate deviations from the fixed effects defined in (2) due to unmeasured random errors. When random effects ($\boldsymbol{\upsilon}$) are non-zero, $\boldsymbol{\beta}$ are indeed random coefficients and there still exists random contextual variation even after known census-tract traits are controlled for.

The fixed and random effects hypothesis tests combined, conclusions can be made about contextual variability in household travel across the region

(1) If there are no significant fixed effects or significant random effects, there is no contextual effect on mode choice variability.
(2) If there are significant fixed effects and no random effects, the effects of a census tract on the marginal utility of household mode choice are deterministic.
(3) If the random effects are significant (regardless of the fixed effects), there is significant contextual variability.

4. Model Results

First, Table 3 summarises the variables included in the resulting model to be presented in sections 4.1 through 4.4. The model variables are chosen and retained in the model based on the following considerations

(1) Past studies have shown that work location and level of service variables are key factors influencing choice of transport mode. Household socioeconomic and demographic variables, such as vehicle availability and gender, also play an important role in the mode choice decision. In selecting the contextual variables, it is of particular interest to find out the group (neighbourhood) effect of ethnicity on mode choice, following past studies (Giuliano, 2000; Polzin *et al.*, 2000; Lin and Long, 2008b) in which residential location has been shown to be clustered ethnically in the US.
(2) Variable selection and retention are also guided by the chi-squared test. The chi-squared test is used to compare two models provided that one is a restricted version of the other by imposing restrictions (i.e. setting some parameters to zero) on parameters in the unrestricted model (Koppelman and Bhat, 2006). The chi-squared test is defined as $-2(LL_R - LL_U)$, where LL_R is the log-likelihood of the restricted model and LL_U is the log-likelihood of the unrestricted model. If the difference of the log-likelihood values between the restricted and unrestricted models is too small to accept the restricted model, then the restricted variables should indeed be dropped; otherwise the restricted model should be adopted.

Table 3. Variables included in the model

Category	*Variable*
Dependent variable	Driving alone, ride sharing, existing conventional transit service, vanpool, BRT
Individual	
Level of Service	Parking cost, access time, egress time, headway of transit service, number of transfers, transfer time, transit reliability,[a] gasoline cost for driving, transit fare, in-vehicle travel time
Work location	Urban, suburban, external urban
Socio-demographic characteristics	Vehicle ownership, gender
Census tract (contextual)	Percentage of non-Hispanic White households

[a]Transit travel-time reliability was measured by the frequency of delays in response to the question of ''You will be more than 15 minutes late...'' in the survey. The multiple choice answers range from ''once every six months'' to ''once a month''.

The model goodness-of-fit is summarised in Table 4. There are a total of 3877 observations. The log-likelihood at convergence is -3030.02, whereas the log-likelihood values with the zero-coefficients and constants-only models are -6167.40 and -3707.97 respectively. These have explained the reasonably high rho-squared value of 0.5061 with respect to (w.r.t.) zero and 0.1800 w.r.t constant and confirm an overall good performance of the fitted model. The model specification and results are discussed in sections 4.1 through 4.4 as follows.

Table 4. Model results: model goodness-of-fit (N = 3877)

Log-likelihood at zero	−6167.40
Log-likelihood at constant	−3707.97
Log-likelihood at convergence	−3030.02
Rho-squared w.r.t zero	0.5061
Rho-squared w.r.t Constant	0.1800

4.1 Constants and Variables ($\alpha_j+\alpha_{j,s}+\theta_j^{'}z_i$)

As shown in Table 5, the signs of all coefficients are intuitively correct. The constant for the drive-alone mode has been set to zero to serve as the basis for comparison with the other four modes. The constants in shared ride are all negative (-0.06 to -2.11) and statistically significant across the household clusters. A larger magnitude indicates greater difficulty in co-ordinating schedules in shared ride to work relative to other modes. Vanpool service, shows less negative utility, suggesting easier schedule co-ordination than that of the shared ride mode.

The positive overall constant in the existing transit mode suggests that existing transit service is perceived as competitive to automobile by households to whom automobile and transit offer comparable levels of service. The positive view towards transit service may be explained by the prolonged highway congestion and the relatively high level of transit service in Chicago.

A similar pattern is also found in the constants of the proposed BRT service, although slightly less positive. In particular, BRT is most appealing to the following two household clusters, Demand survivors and Downtown commuters, reflecting transit-friendly attitudes, low automobile usage and comparatively high transit usage in those households. In contrast, BRT appears to be least appealing to the Great middles and the Cautious individuals, who are clearly automobile dependent. In addition, personal

Table 5. Model results: constants and variables, level 1—individual

Effect	*Estimate*	*T-value*	*Pr* >|*t*|
Intercept (α_j)			
Drive alone	0		
Shared ride	−1.97	−4.243	<0.0001***
Existing transit	2.30	6.952	<0.0001***
BRT	1.73	5.813	<0.0001***
Vanpool service	−0.70	−2.229	0.0258**
Intercept by clusters ($\alpha_{j,s}$)			
Drive alone	0		
Shared Ride			
Clusters 3, 6	0		
Clusters 1, 5, 7	1.02	2.955	0.0031***
Clusters 2, 4	−0.14	−0.443	0.6576
Existing transit			
Clusters 3, 6	0		
Clusters 1, 5, 7	−0.39	−2.498	0.0125**
Clusters 2, 4	−0.60	−3.590	0.0003***
BRT			
Clusters 3, 6	0		
Clusters 1, 5, 7	−0.47	−3.535	0.0004***
Clusters 2, 4	−0.92	−6.483	<0.0001***
Zero vehicle respondents ($\theta_{1,j}$)			
Drive alone	0		
Shared ride	0.60	0.891	0.3729
Existing transit	1.71	2.888	0.0039***
BRT	1.49	2.468	0.0136**
Vanpool	0.11	0.062	0.9508
Female respondents ($\theta_{2,j}$)			
Drive alone	0		
Shared ride	0.29	1.118	0.2637
Existing transit	−0.45	−3.612	0.0003***
BRT	−0.25	−2.330	0.0198**
Vanpool	−0.13	−0.712	0.4764
Urban work location ($\theta_{3,j}$)			
Drive alone	0		
Existing Transit	−1.25	−6.767	<0.0001***
BRT	−0.96	−5.056	<0.0001***
Suburban work location ($\theta_{4,j}$)			
Drive alone	0		
Existing transit	−1.54	−8.751	<0.0001***
BRT	−1.29	−7.695	<0.0001***
External urban Work Location ($\theta_{5,j}$)			
Drive alone	0		
Existing transit	−1.72	−5.705	<0.0001***
BRT	−0.91	−4.628	<0.0001***

Notes: ***significant at the 0.01 level; **significantat the 0.05 level; *significant at the 0.10 level.

Table 6. Model results: alternative specific level of service variables

Effect	*Estimate*	*T-value*	*Pr >|t|*
Parking cost (δ_1)	−0.0009	−0.460	0.6453
Access time (δ_2)	−0.03	−3.013	0.0026***
Egress time (δ_3)	−0.04	−3.527	0.0004***
Headway of transit service (δ_4)	−0.01	−5.649	<0.0001***
Transfer time for transit modes (δ_6)	−0.03	−4.596	<0.0001***
Reliability for Travel by Transit (δ_7)	−0.05	−2.165	0.0304**

Notes: ***significant at the 0.01 level; **significantat the 0.05 level; *significant at the 0.10 level.

safety is a major concern for the Cautious individuals. BRT, although it may provide a comparable level of service, may not be perceived as a safe alternative to automobile by this particular group of households.

There is also the incremental effect of work location on transit mode choice. With the Chicago CBD as the base for comparison, the constant utility of the existing transit service is reduced by 1.25 in an urban work location other than the CBD, 1.54 less in a suburban work location and 1.72 less in an exurban location. This result suggests that the transit service is less preferred as the work location moves farther away from the CBD.

Not surprisingly, respondents who owned zero vehicles favoured transit modes (including BRT) strongly and female respondents favoured automobile modes (driving alone or sharing a ride).

4.2 Alternative Specific Level of Service Variables ($\delta_i' k_{ji}$)

Among all level of service variables, the coefficients for *access time*, *egress time*, *transit headway*, *transfer time* and *reliability for travel by transit* are all strongly significant below the 0.05 level and negative as expected (Table 6). *Parking cost* is commonly viewed as an important explanatory variable for mode choice in the literature. Interestingly, it has an expected negative but insignificant coefficient in this case study. Further investigation was performed and it was found that the coefficient of *parking cost* became statistically significant (at the 0.1 level) after work location variables were removed from the model. This suggests that work location may have partially explained the effect that parking cost had on mode choice. *Number of transfers* was not found to be statistically significant—this is likely to be due to the high correlation with *transfer time*—thus it was dropped from the model.

4.3 Fixed effects with interactions $((\gamma_{k0} + \sum_{q=1}^{Q} \gamma_{kq} w_{kqs})' x_{ji})$

Three explanatory variables (x_{ij} s), *gasoline cost for driving alone/shared ride*, *transit fare* and *in-vehicle travel time*, are very highly significant below 0.0001 and all negative as expected.

All interaction terms, statistically significant or not, have been retained in Table 7 for illustration purposes. The interaction term between *gasoline cost for driving alone/shared ride* and *percentage of White non-Hispanic households*, γ_{11}, is insignificantly positive (0.09, $\Pr > |t| = 0.1548$). Similarly, the interaction between *transit fare* and *percentage of White non-Hispanic households*, γ_{21}, is insignificantly positive (0.01, $\Pr > |t| = 0.8836$), suggesting that

Table 7. Model results: fixed effects with interaction terms at the level 2, census-tract level

Effect	*Estimate*	*T-value*	*Pr* $>|t|$
Gasoline cost for driving alone/Shared Ride (γ_{10})	-0.29	-7.094	$<0.0001^{***}$
Interaction with Percentage of White-non Hispanic households (γ_{11})	0.09	1.423	0.1548
Transit Fares (γ_{20})	-0.22	-4.771	$<0.0001^{***}$
Interaction with Percentage of White-non Hispanic households (γ_{21})	0.01	0.146	0.8836
In-vehicle travel time (γ_{30})	-0.03	-9.004	$<0.0001^{***}$
Interaction with Percentage of White-non Hispanic households (γ_{31})	-0.01	-1.851	0.0642^{*}

Notes: ***significant at the 0.01 level; **significantat the 0.05 level; *significant at the 0.10 level.

transit fare has negligible effect on non-Hispanic White households. On the other hand, *percentage of non-Hispanic White households* has a significant negative effect (at the 0.10 level) on the marginal utility associated with *in-vehicle travel time* in all modes (-0.01, $\Pr > |t| = 0.0642$). This indicates that the non-Hispanic White view long in-vehicle travel time as a strong disutility. (This is likely to be because of the high perceived value of time by this ethnic group.) Other level-of-service variables, such as access time and transit time, were not found to be affected by the contextual traits either.

The model result indicates that, all other individual traits being equal, identical travel time or cost of a mode does not render the same marginal utility value due to the contextual effects. The conventional assumption of constant marginal utility in mode choice modelling does not hold.

It is worth mentioning the possible endogeneity caused by the simultaneity of mode choice and residential location choice (and consequently the social or neighbourhood effects; Manski, 1993). Indeed, there have been recent studies aimed at understanding what is called the 'residential sorting effects' on mode choice (Boarnet and Sarmiento, 1998; Cervero and Duncan, 2002, 2003; Schwanen and Mokhtarian, 2005; Zhang, 2006; Bhat and Guo, 2007; Pinjari *et al.*, 2007). Modelling the endogenous decision-making often involves simultaneous equations and instrumental variables or joint choice modelling (for example, Salon, 2009). In our study, we did not model the residential location choice simultaneously or jointly because of the original design of the Pace survey and the consequent data limitations, which prevented us from developing discrete joint choice/simultaneous structures models. Nevertheless, we have tested for endogeneity of neighbourhood choice by adopting an operationable definition and identification, given the data limitations, of endogeneity from Manski (1993). That is, 'the propensity of an individual to behave in some way varies with the behaviour of the [reference] group', or mathematically in the case of a choice model with social effects

$$\mathrm{P}(y = 1|\mathbf{w}, \mathbf{z}) = H\left[\alpha + \theta P(y = 1|\mathbf{w}) + \mathbf{z}'\boldsymbol{\eta}\right]$$

where, $H(\cdot)$ is a logit model; $\mathbf{w}$ are attributes of an individual's reference group—i.e. residential location (urban, suburban and exurban) in this test; and $\mathbf{z}$ are individual attributes listed in Table 3.

If the coefficient $\theta \neq 0$, then there exist endogenous residential location effects on the choice outcome. The analysis results show a mixed outcome—i.e. automobile

Table 8. Model results – random effects (heterogeneity)

Effect	*Estimate*	*T-value*	*Pr >|t|*
Gasoline cost for driving alone/shared ride (v_1)	0.33	1.754	0.0794*
Transit fares (v_2)	0.39	2.392	0.0168**
In-vehicle travel time (v_3)	0.05	5.068	<0.0001***

Notes: ***significant at the 0.01 level; **significantat the 0.05 level; *significant at the 0.10 level.

modes demonstrating endogenous effects of residential location ($\theta_{drive\_alone} = 6.36$, $\Pr > |t| = 0.0032$; $\theta_{shared\_ride} = -11.34$, $\Pr > |t| = 0.0338$) and transit modes showing no such effects ($\theta_{existing\_transit} = -0.86$, $Pr > |t| = 0.5007$; $\theta_{vanpool} = -0.13$, $\Pr > |t| = 0.9262$).[3] That transit mode choice showed no neighbourhood effect suggests no coupling of transit mode choice and residential location choice. This is consistent with the earlier findings in the interaction effects of transit fare and the contextual variables. On the other hand, this is in contrast to the finding in some studies (for example, Goetzke, 2008) and may be unique to the study area. Further work on the identification of endogenous social effects is necessary. The endogeneity finding of residential location in automobile mode choice suggests the need for simultaneous modelling of residential and mode choice decisions. While it is outside the scope of this paper given the original design of the survey, future investigation with simultaneous modelling is nonetheless warranted for the study area. Furthermore, in light of the major goal of this paper, which is to present a new framework to account for contextual effects in mode choice decisions, the analyses and findings are believed to have provided valuable technical and practical insights for contextual effects modelling.

Finally, the final fixed-effects portion of the model is shown in the following form

$$\begin{cases} Utility = \hat{\beta}_1(\text{Gasoline cost}) + \hat{\beta}_2(\text{Transit fare}) + \hat{\beta}_3(\text{IVTT}) + \ldots \\ \quad \hat{\beta}_1 = -0.289 + (0.6495)\ (\text{percentage of blue-collar residents}) \\ \quad \hat{\beta}_2 = -0.21 \\ \quad \hat{\beta}_3 = -0.029 + (-0.0152)\ (\text{percentage of non-Hispanic White households}) \end{cases} \tag{6}$$

4.4. Random effects (v_{ki} s)

The random effects, v_{ki} s, capture the unobserved individual and contextual heterogeneities from the average contextual effects. If the estimated random effect is significantly different from zero, there are significant heterogeneities from the average contextual effects across census tracts. As shown in Table 8, the random effect associated with gasoline cost (v_1) is only significant at the 0.10 level, suggesting that the contextual effects of gasoline cost are quite well explained by the contextual variables. The random effect associated with in-vehicle travel time (v_3) is highly significant, below the 0.0001 level, suggesting that the deviations from the mean βs cannot be ignored across census tracts. The random effect associated with transit fare (v_2) is statistically significant at the 0.05 level and hence there is some degree of deviation across census tracts in transit fares.

5. Conclusion

This paper has demonstrated that contextual variability in individual mode choice can be quantified and statistically tested in a two-level random-coefficient mixed logit model. The random-coefficient model structure is particularly desirable in studying the contextual effect of the built environment on travel behaviour. By incorporating both fixed and random effects in the model coefficients, the model allows incorporation of environmental covariates associated with the geographical areas and accounts for their interaction with individual characteristics.

It is found that individual mode choice behaviour varies considerably across different residential census tracts even after individual/household traits are controlled for. Moreover, the contextual effects are found to modify the marginal utility of mode choice. In particular, in-vehicle travel time and gasoline costs are strongly geographically variable and are significant covariates of census-tract traits. Significant variability in the effects of those two variables is still present even after both contextual and individual traits are controlled for, suggesting intrinsic randomness in individual mode choice. It is also found that automobile mode and residential location choices are endogenous processes, while such endogeneity is not exhibited in transit modes. This finding may be specific to the study area. Due to the limitation of the currently available data, future investigation on this subject is necessary.

The proposed model and study findings have important implications for integrated land use and transport planning. It is generally agreed in the literature that there is a two-way effect between the built environment and travel behaviour; however, this knowledge has not been fully transferred to transport planning practice. For example, most regional travel forecasting models in practice assume constant marginal utility in mode choice modelling, which has been proved in this study to be deficient in capturing heterogeneity in mode choice due to the built environment/travel behaviour dynamics. This study has also shown that, with a hierarchical structure, much of the heterogeneity can be properly accounted for. Moreover, conventional regional transport forecasting models are not sensitive to the environmental factors at the local or neighbourhood level and thus are unlikely to adequately address induced travel demand at those geographical levels—for example, due to an alteration of a highway section or a new subway station. Since the local or neighbourhood built environment has been shown to shape personal mode choice (and probably vice versa), local and neighbourhood land use/transport planning efforts must work in co-ordination with the regional planning effort to improve travel demand management and provide more coherent land use/transport planning at both local and regional levels. To do so, necessary policies and institutional incentives must be put in place to facilitate integrated land use and transport planning practice and to encourage co-operation across local and regional levels.

Finally, it is important to point out that the study findings must be interpreted within the context of the study limitations, owing to the complexity of the causal relationships between the built environment and travel behaviour. Most noteworthy, we assembled a set of household and census-tract variables that were available to us for analysis. However, we do not intend to imply that the assembled variables, especially at the census-tract level, have fully characterised the households or the built environment. Other unavailable measures—for example, proximity to highway/transit and more detailed land use categorisation—would be of great interest. Moreover, the area size of census tracts varies widely depending on the density of settlements. There may be variability due to micro level factors that are not captured at the census-tract level. Further research effort is needed.

Notes

1. Pace provides vanpool service that ranges from traditional vanpool to an employer shuttle service to Metra (regional commuter rail) feeder service and others. Employees that live and work near one another and share similar schedules can form a group that conveniently gets them between home and work.
2. The SEM results are not included in the paper as they are minor to the objective of the entire paper. They are available upon request.
3. The coefficients were based on the assumption that the effect on BRT was zero. The model results are available upon request.

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