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Value of travel time for home-based school tours in California

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The behavioral value of travel time is an important factor for evaluating alternative transportation facility or service improvement projects based on road user-benefit approach. This article presents the behavioral value of travel time with reference to home-based school tour in California. Initially a single value of travel time is quantified from multinomial logit and nested logit (NL) model estimate. Later random parameter logit (RPL) model is employed by specifying a random component for the travel time attribute. The values of travel time emanating from RPL model estimate are quantified across student population by assuming different types of tent-shaped random distributions such as triangular and normal. In this study the value of travel time is investigated separately for two types of home-based school tour: grade school and college-university. Overall this study examines the effect of alternative logit model specifications on quantification of value of travel time. The study is demonstrated using household travel diary data of the state of California, which is revealed preference in nature.

Keywords: value of travel time; home-based school tour; multinomial logit; nested logit; random parameter logit; random taste heterogeneity

1. Introduction

The behavioral value of travel time is one of the most important factors for the rational improvement of transportation facility or service improvement projects. It is a key to the economic feasibility analysis of most transportation projects. About 50–70% of the total benefit in a transportation improvement project is attributed to savings in the value of travel time (Rubite and Muromachi 2008). The literature shows the evidence of user benefits in the form of savings in value of travel time for a variety of contexts (Hensher 1994; Hensher and Greene 2003; Carlsson 2003) but very little information is reported on the value of travel time with respect to school travel – even though there are substantial studies available on school travel mode choice modeling.

Previous work has focused primarily on what types of policy can be undertaken to encourage the use of more active travel modes for school travel such as cycling and walking. Disaggregate models were typically employed, which accounted for various relevant attributes influencing the choice of school travel mode; the major attributes

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include distance between home and school (Ewing, Schroer, and Greene 2004; McDonald 2007; Lawrence Frank and Company 2008), child obesity (Cooper et al. 2003; Loucaides and Jago 2008), traffic safety and parental perception of crime against children and other factors (Boarnet et al. 2005; Yarlagada and Srinivasan 2008), street density and sidewalk connectivity (Ewing, Schroer, and Greene 2004), psychological and attitudinal factors of children (Black, Collins, and Snell 2001), weather conditions (Muller, Tscharaktschiew, and Haase 2008), spatial and social interaction effects (Sidharthan et al. 2010), and so on. However, none of the above studies focused on the behavioral value of travel time. Besides, most of these studies were carried out in the context of a trip-based perspective, which lacks the additional behavioral realism considered in a tour-based perspective (Ben-Akiva et al. 1998). Therefore, in the present study, a focus has been given on the estimation of value of travel time in the context of home-based school tour mode choice.

The study reported here is conducted in response to this identified lack of consideration – seeking a greater understanding of the value of travel time in the context of home-based school tour mode choice. The theoretical foundation of the value of travel time is in microeconomics, where the approach is to use a discrete choice model. In this approach, the trade-off between attributes is usually made using estimates of a fixed coefficient utility function. Several previous studies showed the lack of suitability of this approach in the quantification of the value of travel time more accurately for the population level. It was observed that the perceived value of travel time varies significantly from one individual to another based not only on the observed socio-demographic characteristics of the individual but also on unobserved characteristics, which are difficult to measure. Though the fixed coefficient discrete choice models could sometimes capture the variation in the value of travel time through systematic taste variation studies, they do not account for the taste variation due to unobserved characteristics across individuals (Hess, Bierlaire, and Polak 2005; Basu and Maitra 2007; Basu and Hunt 2012). Besides, the calculated value of travel time from a fixed coefficient logit model represents the average perceived value of travel time for a group of individuals, which is not always acceptable for the accurate estimation of benefits in cost–benefit analysis of transportation improvement projects. Fosgerau (2006) emphasized the importance of using distribution analysis for the value of travel time. Therefore, it becomes necessary to quantify the distribution of taste variations in the perceived value of travel time across individuals. Advances in simulated estimation techniques have enabled analysts to employ more complex logit models such as the random parameter logit (RPL) model that allows the simulation of broader behavioral patterns (Train 2003) through a distributional assumption of the random component of a policy variable. In this study, an attempt has been taken to empirically investigate the random taste variation in the perceived value of travel time across the student population using an RPL model. An initially fixed coefficient logit model is attempted as the base model to identify the explanatory attributes influencing the choice of school tour mode and to check the appropriate sign of the estimated coefficients, which are in agreement with the actual study area. The scope of the present work does not include the systematic taste variation analysis on the value of travel time using fixed coefficient logit models. Following this, the random taste heterogeneity is experimented with using two types of tent-shaped distributional assumption for the random component of the travel-time attribute – such as triangular and normal. Later a comparative analysis is carried out between the values of travel time emanating from the fixed coefficient logit model and the RPL model. In this study, the value of travel time is estimated separately for two groups: grade school student tours (6–18 year olds) and college-university student tours (18–21 year olds) using revealed preference observations from household travel diary data collected in the US State of California.

2. Home-based school tour

Under a tour-based travel demand modeling framework, a tour is a unit of analysis. A home-based tour represents a closed form chain of trips starting and ending at home. Each tour includes at least one destination and at least two successive trips. Figure 1 shows some typical examples of a home-based school tour. The sequence of trips from home to the school (as the primary destination) forms the outbound leg of the tour; whereas the sequence of trips from school back to home location forms the return leg of the tour. In this context, the stops made other than at the school are intermediate or

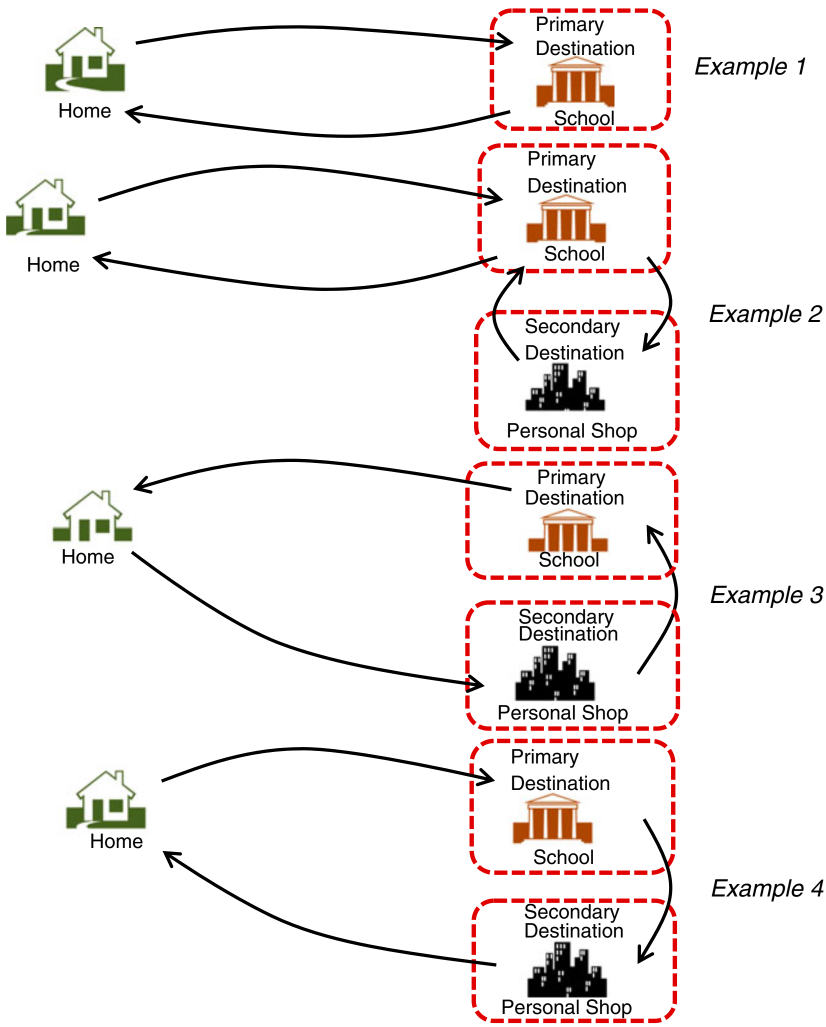

Figure 1. Some typical examples of home-based school tours.

secondary stops. For example, a home-based school tour may have a school-based subtour as shown in Example 2 of Figure 1. In most cases, a student uses the same mode for all his/her trips of the school tour, so the trip mode and the tour mode remain the same. But it may still be possible for a student to use different modes for different chain of trips of a school tour, and in such cases the present study considers the fastest trip mode as its tour mode.

3. Methodology

In transportation planning, discrete choice models have largely been employed to represent the choice of one alternative among a set of mutually exclusive alternatives in a choice set. The choice model is developed at disaggregate-level describing behavior of an individual. In random utility maximization theory, it is assumed that an individual chooses an alternative from a set of alternatives having the highest utility. The utility (U) of an alternative is represented by a deterministic i.e. observable portion (V), which is generally a function of the attributes of alternatives and characteristics of an individual and/or household characteristics of the individual, and a random error component (ε).

$$U = V + \varepsilon \tag{1}$$

Under this condition, the choice becomes probabilistic and the alternative with the maximum utility has the highest probability of being chosen. The deterministic portion is commonly specified as a linear form of attributes.

To begin with, a multinomial logit (MNL) model is attempted, where a Gumbel distribution (independently and identically distributed [IID] across choice alternatives and individuals) is considered for the random error term ε. Under this assumption, the probability of choosing an alternative i by an individual n becomes (McFadden 1974):

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j \in j_n} e^{V_{jn}}} \tag{2}$$

The MNL model has several limitations and among them the independence of irrelevant alternatives (IIA) becomes the most prominent in the context of the mode choice model (Train 2003). Therefore, the present study also employs another fixed coefficient discrete choice model called a nested logit (NL) model to overcome partially the IIA limitation. The NL model has the ability to represent similarities among a set of alternatives considered under a specific group (also called nests). In this study, a two-level NL model as defined by Daly (1987) is attempted to reveal whether it better represents statistically the underlying data-set than the MNL model. A two-level NL structure is considered with g groups of alternatives and m_g alternatives in each group, where $\sum_g m_g = C_n$, i.e. the choice set of all alternatives faced by an individual n. Then, as per the Daly (1987) method, the probability of choosing an alternative i in group g by an individual n becomes:

$$P_{in} = P_{i/g} \times P_g \tag{3}$$

where,

$P_{i/g}$ represents the probability of choosing an alternative i in group g,

P_g represents the probability of choosing the group g,

$$P_{i/g} = \frac{e^{V_i}}{\sum_{i' \in m_g} e^{V_{i'}}} \tag{4}$$

$$P_g = \frac{e^{\mu_g \tau_g}}{\sum_{g'=1}^{g} e^{\mu_{g'} \tau_{g'}}} \tag{5}$$

$$\tau_g = \ln \sum_{m' c m_g} e^{V_{m'}}$$

and μ_g is the coefficient of nest m.

Both MNL and NL models are estimated using the maximum likelihood technique. Although these models may capture the systematic taste variation based on observed socio-demographic characteristics, they are unable to accommodate the random taste variation over a population of individuals. The RPL model overcomes this limitation by allowing random taste variations of the coefficient of attributes. In this study, the RPL model takes the following behavioral specification (Train 2003):

$$U_{in} = \alpha' x_{in} + \mu'_n z_{in} + \varepsilon_{in} \tag{6}$$

where x_{in} and z_{in} are the vectors of observed attributes relating to alternative i, α is a vector of fixed coefficients, μ is a vector of random error terms with zero mean, and ε_{in} is an error term following the Gumbel distribution, which is IID across choice alternatives and individuals.

The coefficients in z_{in} are random components that along with ε_{in} define the stochastic portion of the utility function. Therefore, the unobserved part of the utility function is $\mu'_n z_{in} + \varepsilon_{in}$, which may be correlated over alternatives. In a fixed coefficient logit model z_{in} is identically zero, so there is no correlation in utility over the alternatives. This lack of correlation gives rise to the IIA property and its restrictive substitution patterns. The vector of coefficients μ'_n vary over individuals in the population with a density function $f(\mu)$. The individual knows the value of his/her own α', μ'_n, and ε_{in} for j and chooses alternative i, if and only if:

$$U_{in} > U_{jn} \text{ for } j \in C_n \text{ and } j \neq i$$

However, the analyst only observes x_{in} and z_{in}. If the analyst observed α' and μ'_n, then the choice probability would be the standard logit, since the error term ε_{in} follows the IID extreme value distribution. Under this circumstance, the choice probability conditional on μ'_n is:

$$L_{in}(\mu_n) = \frac{e^{\alpha' x_{in} + \mu'_n z_{in}}}{\sum_j e^{\alpha' x_{jn} + \mu'_n z_{jn}}} \tag{7}$$

In reality, however, the analyst does not know about μ'_n. Therefore, the unconditional choice probability is the integral of $L_{in}(\mu_n)$ over all possible values of μ'_n:

$$P_{in} = \int \frac{e^{\alpha' x_{in} + \mu'_n z_{in}}}{\sum_j e^{\alpha' x_{jn} + \mu'_n z_{jn}}} f(\mu) d\mu \tag{8}$$

The above model can be estimated using the simulated maximum log-likelihood technique (Train 2003).

3.1. Quantification of the value of travel time

The quantification of the value of travel time from a fixed coefficient logit model estimate is straightforward, which is carried out using the marginal rate of substitution at constant utility. But in the case of the RPL model estimate, quantification depends on the distributional assumption of the random component of an attribute. In this study, the valuing of travel time is constructed using an unconditional parameter estimate. Here each sampled student is randomly assigned along the continuous distribution. In such a case, the value of travel time is constructed as follows:

$$\text{Value of travel time} = \left(\alpha'_{TT} + \mu'_{TT} \times D_r\right) / \alpha'_{TC} \tag{9}$$

where, the coefficient of travel cost is considered to have a fixed component only, α'_{TC}. Ruud (1996) pointed out that the RPL model has a tendency to be unstable when all parameters are allowed to vary. Fixing the travel-cost coefficient resolves this instability. Besides this, the other reasons for keeping the travel-cost coefficient fixed are, first, that it simplifies the quantification of the value of travel time and, second, the distribution of the value of travel time follows the same distributional pattern of the travel-time attribute (Hensher 2001a; Hensher, Rose, and Greene 2005). The coefficient of the travel-time attribute is split into two components: a fixed component, α'_{TT}, and a random component with mean zero and standard deviation/spread, μ'_{TT}. D_r is a random draw either from a triangular or from a standard normal distribution. It should be noted that a random draw (say D_r) of a population from a triangular distribution can be obtained from a standard uniform distribution, U_r, as follows:

$$D_r = \sqrt{2V_r} - 1 \text{ if } V_r < 0.5 \text{ else } D_r = 1 - \sqrt{2(1 - V_r)} \text{ where } V_r \sim U_r[0, 1] \tag{10}$$

4. Database

The home-based school tour mode choice models are demonstrated using household travel diary data for the US State of California. The choice model considers the year 2000 as base year. The database consists primarily of statewide household travel survey data for the years 2000–2001 (NuStats 2002). This database is augmented by a similar type of household travel survey data conducted over the years 2001–2006 for the Southern California Association of Governments (NuStats 2003), the Metropolitan Transportation Commission (MORPACE 2002a, 2002b), and the San Diego Association of Governments (SANDAG 2008). The database has travel survey records of households from different regions of California with different zonal, demographic, and land use characteristics. The refined database consists of travel records for 37,145 households and includes the following trip modes: single-occupancy vehicles (SOVs), high-occupancy vehicles with two occupants (HOV2), high-occupancy vehicles with three or more occupants (HOV3+), school busses, drive-access transit, walk-access transit, cycling, and walking. Under a tour-based modeling framework, the database classifies the above trip modes into tour modes, where a tour mode is defined based on the following assumptions:

- Single Occupancy Vehicle: tours that consist of trips primarily made by the solitary driver of an automobile. If any trip on a tour is made by a SOV, then the tour mode is coded as SOV.
- High-Occupancy Vehicle with two occupants: tours that consist of at least one trip made by an automobile with two occupants, and no other trips are made by SOV.
- High-Occupancy Vehicle with three or more occupants (HOV3+): tours that consist of at least one trip made by an automobile with three or more occupants, and no trips are made by SOV or HOV2.
- School bus: tours that consist of trips made by school busses or combinations of school bus and walking.
- Drive-access transit: tours that consist of trips on transit where the access mode or egress mode is an automobile or a combination of drive access, walk access, and auto passenger.
- Walk-access transit: tours that consist of trips made on transit or combinations of transit and walk or bike.
- Bike: tours that consist of trips made by bike or combinations of walking and cycling.
- Walk: tours where all trips are made by walking only.

It is observed in the data-set that the total number of observations of drive-access transit is significantly less than that of walk-access transit for school tours. Therefore these two tour modes are combined for analytical purposes and referred to as the transit tour mode. In the case of grade school tours, the study considers seven types of tour mode: SOV, HOV2, HOV3+, school bus, transit, bike, and walk. The SOV tour mode is considered only for those students who are 16 years of age or above and have a driving license. In the case of college-university school tours, six types of tour mode are considered: SOV, HOV2, HOV3+, transit, bike, and walk.

5. Model development

Previous empirical studies on school travel mode choice modeling have identified a number of influential attributes including inter alia: characteristics of students and their parents; household characteristics; spatial separation between home and school; built environment; socioeconomic characteristics of the residential neighborhood, etc. A systematic review of relevant attributes may be found in Yarlagada and Srinivasan (2008) and Pont et al. (2009). The present study considers travel skim characteristics such as travel time and direct travel cost as independent attributes in the utility model specification to represent the spatial separation between home and school. Under the tour-based modeling framework, the travel skim is calculated for both the outbound leg and the return leg of the school tour. The utility function also represents specific socio-demographic characteristics of students and their household characteristics (Yarlagada and Srinivasan 2008; McMillan 2007) for some specific tour modes. During model development, travel-time and travel-cost values are entered in cardinal linear form;

whereas mode-specific socio-demographic and household characteristics are coded using a dummy variable that takes on values either of 0 or 1. In addition, the utility function has a set of mode-specific constants. A total of 1740 and 5445 school tour observations are used for grade school and college-university tour mode choice models, respectively. Initially, the MNL model is estimated as the base model. Then NL is estimated in order to identify whether the set of alternative tour modes faced by a student can be partitioned into various groups with similarities, called nests. Thereafter, the tour mode choice model is developed using an RPL model. In the RPL model, the coefficient of travel-time attribute is split into two components: a fixed component, which remains the same across the sampled students, and a random component, which accounts for the taste variation (through random taste heterogeneity) across the sampled students. In the present study, the direct travel-cost attribute is considered to have a fixed component. For the dummy attributes, a uniform distribution is assumed. The RPL models are then estimated using a simulated log-likelihood estimator.

6. Results and discussion

Table 1 reports the coefficient estimates for grade school and college-university school tour mode choice models using the MNL model. The signs of the coefficients are found to be consistent with expectations and in agreement with the actual conditions of the study area. The negative sign of the coefficients indicates that utility decreases with an increase in the magnitude of the associated attribute and vice versa. The goodness-of-fit of the estimated model is expressed using ρ^2 values.

In the case of the grade school tour mode choice model, the travel-time coefficient for SOV/HOV2/HOV3+ tour modes is estimated together using a single coefficient, whereas the travel-time coefficient of all other modes is estimated separately. But a single direct travel-cost coefficient is estimated for SOV/HOV2/HOV3+ and transit modes. As shown in Table 1, household annual income has an effect on choosing an auto mode such as SOV/HOV2/HOV3+ for grade school students. Students from households where household annual income is more than or equal to US$75,000 prefer the SOV tour mode. This observation is consistent with the findings observed by DiGuiseppi, Roberts, and Li (1998) and Vovsha and Petersen (2005).

A similar type of observation is found for HOV2 and HOV3+ tour modes, if household annual income is more than or equal to US$35,000. Table 1 also shows that the propensity of using HOV2 and HOV3+ tour modes can increase if the total number of automobiles in a household is less than the total number of licensed drivers. Table 1 also indicates that grade school students prefer to go school by school bus, if the household does not have access to an automobile or has less automobiles than the total number of licensed drivers. The propensity of choosing the school bus also increases if the school tour starts between 6:00 am and 10:00 am (i.e. morning peak hours). Table 1 also indicates that grade school students aged 9–14 years prefer the school bus more than students aged 9 or younger. A similar type of observation was found by McDonald (2005). Grade school students also prefer to choose transit, bike, or walk modes if the household is without an automobile. It is interesting to note that male students are fond of cycling (McMillan et al. 2006) for their school tours.

In the college-university tour mode choice model (as reported in Table 1), the travel-time coefficient of HOV2 and HOV3+ modes is estimated together using a single coefficient whereas the travel-time coefficient of all other modes is estimated separately.

Table 1. School tour mode choice models using MNL.

Attributes	Grade school tour Coefficient	Grade school tour t-statistics	College-university tour Coefficient	College-university tour t-statistics
Travel time by mode				
SOV			−0.1657	−2.18395
SOV, HOV2, and HOV3+	−0.01578	−2.03048		
HOV2 and HOV3+			−0.01518	−1.87292
Transit	−0.00546	−4.70654	−0.00488	−3.81174
School bus	−0.01824	−2.52316		
Bike	−0.01785	−5.62678		
Bike time ≤70 minutes			−0.03821	−4.21706
Additional bike time >70 minutes			−0.02764	−1.80293
Walk	−0.00569	−11.9469		
Walk time ≤20 minutes			−0.10131	−2.15094
Additional walk time if walk time >20 minutes and walk time ≤70 minutes			−0.05388	−7.66137
Additional walk time, if walk time >70 minutes			−0.00389	−4.73562
Direct travel cost by mode				
SOV, HOV2, HOV3+, and transit	−0.11804	−3.93828		
SOV and transit mode			−0.08874	−2.72885
HOV2 and HOV3+			−0.14471	−2.20638
Mode-specific dummy variable: 1 if yes and 0 otherwise				
SOV: whether total number of house-hold (HH) vehicle ≥ total number of HH license	−0.44442	−1.94059	0.95679	6.15982
SOV: whether annual HH income is ≥US$75,000	1.40546	8.87935	1.36565	5.59138
SOV, HOV2, and HOV3+: whether full-time student			−0.28376	−1.57185
HOV2 and HOV3+: whether total number of HH vehicle < total number of HH license	0.21935	0.91795		
HOV2 and HOV3+: whether the annual HH income is ≥US$35,000	0.81536	6.73972		
HOV2 and HOV3+: whether the annual HH income is ≥US$75,000			0.94689	2.40295
HOV2 and HOV3+: whether the HH is without vehicle			1.20979	2.04657
HOV3+: whether total number of HH vehicle < total number of HH License			1.76143	2.41144
School bus: whether school tour starts between 6:00 am and 10:00 am.	1.09861	4.85096		
School bus: whether the HH is without vehicle	2.03443	8.78262		
School bus: whether total number of HH vehicle < total number of HH license	−0.1608	−1.51827		
School bus: whether the students' age ≤9	0.17289	1.74438		
School bus: whether the students' age >9 and ≤14	0.26204	2.79687		
Transit: whether the HH is without vehicle	3.15719	12.3928	2.87518	8.13865

Table 1 (*continued*)

Attributes	Grade school tour: Coefficient	Grade school tour: *t*-statistics	College-university tour: Coefficient	College-university tour: *t*-statistics
Transit: natural logarithmic of total number of stops in a tour			−1.59434	−7.06377
Walk and bike: whether the HH is without vehicle	2.32325	10.6509	1.92965	5.13464
Walk and bike: whether full-time student			0.55601	1.47054
Bike: whether the biker is male	1.30517	6.69283	0.57119	1.86548
Alternative specific constant by tour mode				
HOV2	1.77667	8.07886	−1.47508	−6.35049
HOV3+	1.47154	6.21329	−4.39399	−7.20697
School bus	−0.57441	−1.78622		
Transit	0.19986	0.65264	−0.74675	−2.20199
Walk	1.78177	7.93651	2.41776	2.65053
Bike	−1.65132	−5.71447	−1.82595	−3.73657
Final log likelihood	−6967.842		−1232.8115	
Rho-squared w.r.t zero	0.2577		0.5692	
Rho-squared w.r.t constants	0.103		0.2237	
Number of observations	5445		1740	

The coefficient of walking time is estimated separately for three different segments of walk time: less than or equal to 20 minutes, greater than 20 minutes but less than or equal to 70 minutes, and greater than 70 minutes. A similar type of approach is also undertaken to estimate the coefficients of bike ride time for two different segments: less than or equal to 70 minutes and greater than 70 minutes. This approach of estimating time coefficients is adopted to examine the nonlinearity effect in the perception of different length of travel time. The direct travel-cost coefficient for SOV and transit tour modes is expressed together using a single coefficient whereas that for HOV2 and HOV3+ tour modes is expressed together using another coefficient. It is observed from Table 1 that college-university students are more likely to take auto modes such as SOV, HOV2, and HOV3+, if their household annual income is more than US$75,000. Additionally, the propensity of using SOV increases if the number of vehicles are more than or equal to the number of licensed drivers within a household. Full-time college-university students are less likely to take SOV, HOV2, or HOV3+ modes for their school tour. Like grade school students, college-university students are more likely to take HOV2, HOV3+, or transit, if the household is without automobiles or has fewer automobiles than licensed drivers. It is also found that college-university students are less likely to take transit, if the total number of stops (modeled as the logarithmic of the number of stops) in a tour increases.

In order to identify possible nesting structures, a number of NL models are attempted with a combination of various nesting structures of alternative tour modes. However, only the nesting structures shown in Figures 2 and 3 are reported here for the grade school and college-university school tour mode choice model, respectively.

Table 2 reports the coefficient estimates for the grade school and college-university school tour mode choice models using the NL model. In both choice models, the nesting coefficient is not found significantly different from unity at the 95% confidence level. This finding indicates the possible collapsing of the NL model into an MNL model for

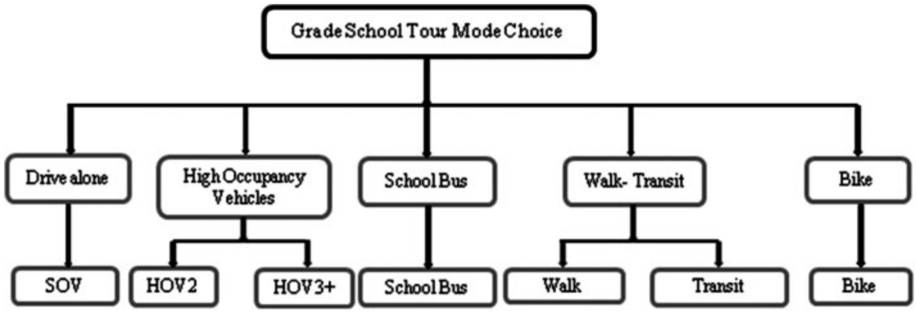

Figure 2. Nesting structure of NL-mode choice model for grade school tours.

the underlying data-set. It implies that all tour mode alternatives are observed by students to be dissimilar to each other. Therefore, in the present study, the value of travel time calculated from the NL model estimate is not considered. The interpretation of the travel-time and travel-cost coefficients in Table 1 does not convey much information except for sign and significance. Therefore, the value of travel time is quantified by the marginal rate of substitution between the travel-time and travel-cost attributes. In this study, the value of travel time is expressed in US dollars per hour, which implies an individual's willingness to pay the monetary amount to save one hour of time spent on traveling or the amount that an individual would accept as compensation for one hour lost time during their travel.

Table 3 shows the quantified average value of travel time for the sampled grade school and college-university student population emanating from the MNL model.

As shown in Table 3, for a particular category of school tour, the value of travel time differs among tour modes. Grade school students' perceived value of travel time for auto tour modes, such as SOV/HOV2/HOV3+, is around 1.9 times higher than that of the transit tour mode; whereas the college-university students' perceived values of travel time for SOV and HOV2/HOV3+ tour modes are respectively 2.88 and 2.33 times higher than that of the transit tour mode. In comparison to grade school students, college-university students pay a premium of about 26% in their value of travel time for the SOV tour mode. The values of travel time obtained in the present study are consistent with the findings of Bradley and Bowman (2010) for the Sacramento Region of California.

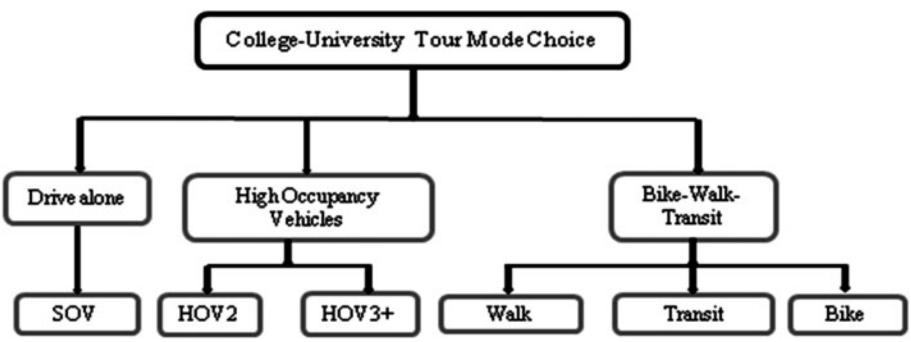

Figure 3. Nesting structure of NL-mode choice model for college-university tours.

Table 2. School tour mode choice models using NL.

Attributes	Grade school tour		College-university tour	
	Coefficient	*t*-statistics	Coefficient	*t*-statistics
Travel time by mode				
SOV			−0.01655	−1.91954
SOV, HOV2, and HOV3+	−0.01120	−1.16219		
HOV2 and HOV3+			−0.01668	−1.80666
Transit	−0.00546	−11.1456	−0.00575	−3.47858
School bus	−0.00830	−0.75926		
Bike	−0.01814	−4.87573		
Bike time ≤70 minutes			−0.04088	−4.20193
Additional bike time >70 minutes			−0.03015	−2.01777
Walk	−0.00589	−4.72931		
Walk time ≤20 minutes			−0.12903	−2.08353
Additional walk time if walk time >20 minutes and walk time ≤70 minutes			−0.05614	−7.18732
Additional walk time, if walk time >70 minutes			−0.00457	−4.0805
Direct travel cost by mode				
SOV, HOV2, HOV3+, and transit	−0.09178	−2.49252		
SOV and transit mode			−0.10735	−2.50169
HOV2 and HOV3+			−0.13368	−1.81581
Mode-specific dummy variable: 1 if yes and 0 otherwise				
SOV: whether total number of HH vehicle ≥ total number of HH license	−0.53414	−1.90988	1.14247	4.28363
SOV: whether annual HH income is ≥US$75,000	1.67011	6.62219	1.60899	4.25497
SOV, HOV2, and HOV3+: whether full-time student			−0.2627	−1.32652
HOV2 and HOV3+: whether total number of HH vehicle < total number of HH license	0.36731	1.29445		
HOV2 and HOV3+: whether the annual HH income is ≥US$35,000	0.99765	5.79451		
HOV2 and HOV3+: whether the annual HH income is ≥US$75,000			1.08307	2.35343
HOV2 and HOV3+: whether the HH is without vehicle			1.34030	1.94081
HOV3+: whether total number of HH vehicle < total number of HH license			1.87499	2.47633
School bus: whether school tour starts between 6:00 am and 10:00 am.	1.31332	4.32649		
School bus: whether the HH is without car	2.43161	6.48049		
School bus: whether total number of HH vehicle < total number of HH license	−0.19202	−1.49537		
School bus: whether the students' age ≤9	0.21218	1.74845		
School bus: whether the students' age >9 and ≤14	0.31787	2.69912		
Transit: whether the HH is without car	3.65520	8.46233	3.31411	5.42755
Transit: natural logarithmic of total number of stops in a tour			−1.87181	−4.7827

Table 2 (*continued*)

Attributes	Grade school tour Coefficient	Grade school tour *t*-statistics	College-university tour Coefficient	College-university tour *t*-statistics
Walk and bike: whether the HH is without car	2.81943	6.87829	2.36284	3.79687
Walk and bike: whether full-time student			0.65026	1.59108
Bike: whether the biker is male	1.56419	5.47436	0.55745	1.77801
Alternative specific constant by tour mode				
HOV2	2.12881	6.14826	−1.7364	−4.58288
HOV3 +	1.87245	4.97499	−4.69787	−6.65043
School bus	−0.69383	−1.76884		
Transit	0.58994	1.39983	−0.60935	−1.51923
Walk	2.15195	6.01838	3.0013	2.45884
Bike	−1.96326	−4.93483	−1.85166	−3.51814
Nesting parameter	0.83488	9.52530	0.84501	6.21279
Final log likelihood	−6966.204		−1232.24	
Rho-squared w.r.t zero	0.2579		0.5694	
Rho-squared w.r.t constants	0.1032		0.2241	
Number of observations	5445		1740	

In order to investigate the random taste heterogeneity in the value of travel time across the student population, a set of RPL models was estimated. In the RPL model, random taste heterogeneity is expressed using spread or standard deviation estimates of the travel-time attribute. In this study, two types of tent-shaped distributional assumptions – triangular and normal – are considered for the random component of the travel-time attribute, whereas a uniform distribution is assumed for dummy variables. In the case of triangular and uniform distributions, the spread of the random component is estimated, whereas for the normal distribution the standard deviation of the random component is estimated. The RPL models are estimated using a simulated log-likelihood estimator.

Tables 4 and 5 show the coefficient estimates of the RPL mode choice models for grade school and college-university tours, respectively. Table 4 shows that the spread and standard deviation of travel-time attribute for the SOV/HOV2/HOV3+ mode and transit mode are estimated with significant *t*-statistics. On the other hand, Table 5 shows a similar type of observation for the SOV and HOV2/HOV3+ tour mode. But in the case of

Table 3. Value of travel time for home-based school tours from MNL model estimate.

Tour mode	Value of travel time
Grade school tours	
SOV, HOV2, and HOV3 +	US$ 8.02/hour
Transit	US$ 2.77/hour
College-university tours	
SOV	US$ 11.2/hour
HOV2 and HOV3 +	US$ 6.29/hour
Transit	US$ 3.29/hour

Table 4. Grade school tour mode choice model using RPL model.

	Triangular distribution		Normal distribution	
Attributes	Coefficient	*t*-statistics	Coefficient	*t*-statistics
Travel time by mode				
SOV, HOV2, and HOV3+	−0.00655	−1.82585	−0.00595	−1.6636
Transit	−0.00930	−3.48623	−0.01735	−4.4509
School bus	−0.006229	−1.47934	−0.00712	−1.4977
Bike	−0.01539	−5.46667	−0.01539	−5.4311
Walk	−0.00509	−15.0867	−0.00507	−14.4998
Direct travel cost by mode				
SOV, HOV2, HOV3+, and walk transit	−0.14835	−4.80513	−0.13664	−4.11846
Mode-specific dummy variable: 1 if yes and 0 otherwise				
SOV: whether total number of HH vehicle ≥ total number of HH license	−0.429450	−1.86531	−0.43639	−1.88692
SOV: whether annual HH Income is ≥US$75,000	1.40837	8.82521	1.38958	8.66678
HOV2 and HOV3+: whether total number of HH vehicle <total number of HH license	0.24797	0.96885	0.25355	0.98317
HOV2 and HOV3+: whether the annual HH income is ≥ US$35,000	2.38647	1.97061	−0.29855	−0.26388
School bus: whether school tour starts between 6:00 am and 10:00 am.	1.12886	4.87213	1.13195	4.83140
School bus: whether the HH is without car	2.13595	8.51721	2.24163	8.27415
School bus: whether total number of HH vehicle < total number of HH license	−0.16294	−1.51861	−0.15315	−1.41570
School bus: whether the students' age ≤9	0.19795	1.94577	0.18764	1.80729
School bus: whether the students' age >9 and ≤14	0.27811	2.890	0.27244	2.77482
Transit: whether the HH is without car	3.42225	11.54694	3.72016	10.96415
Walk and bike: whether the HH is without car	2.43584	10.27149	2.53660	9.92506
Bike: whether the biker is male	1.30399	6.68410	1.30419	6.68312
Alternative specific constant by mode				
HOV2	1.64435	7.1496	1.64549	7.11937
HOV3+	1.325371	5.38075	1.34582	5.4191
School bus	−0.75937	−2.28146	−0.73652	−2.18496
Transit	0.51056	1.32873	1.20015	2.77814
Walk	1.67631	7.17511	1.68854	7.16187
Bike	−1.75214	−5.92	−1.73875	−5.84187
Estimate of spread for triangular distribution and standard deviation for normal distribution				
SOV, HOV2, and HOV3+: travel time	0.04940	2.1829	0.03384	2.90216
Transit: travel time	0.01083	2.96	0.00815	4.54332
Estimate of spread for uniform distribution				
HOV2 and HOV3+: whether annual HH income is ≥US$35,000	2.79255	1.30051	2.61032	1.02546
Final log likelihood	−6962.0472		−6948.5139	
Rho-squared w.r.t zero	0.2583		0.2598	
Rho-squared w.r.t constants	0.1037		0.1054	
Number of observations	5445		5445	

Table 5. College-university tour mode choice model using RPL model.

	Triangular distribution		Normal distribution	
Attributes	Coefficient	*t*-statistics	Coefficient	*t*-statistics
Travel time by mode				
SOV	−0.01619	−2.09615	−0.01720	−2.24686
HOV2 and HOV3 +	−0.01578	−1.90180	−0.01624	−1.97589
Transit	−0.00484	−3.76859	−0.00496	−3.85270
Walk time ≤20 minutes	−0.10112	−2.14802	−0.10172	−2.15979
Additional walk time if walk time >20 minutes and walk time ≤70 minutes	−0.05882	−8.0125	−0.05395	−7.67136
Additional walk time if walk time >70 minutes	−0.00388	−4.70561	−0.00393	−4.75815
Bike time ≤70 minutes	−0.03815	−4.20547	−0.03844	−4.23805
Additional bike time, if bike time >70 minutes	−0.02765	−1.79446	−0.02777	−1.80403
Direct travel cost by mode				
SOV and transit mode	−0.08744	−2.68036	−0.08577	−2.63436
HOV2 and HOV3 +	−0.13276	−1.877	−0.14234	−2.16782
Mode-specific dummy variable: 1 if yes otherwise 0				
SOV: whether total number of HH vehicle ≥ total number of HH license	0.95107	6.10452	0.95439	6.14152
SOV: whether the annual HH income is ≥ US$75,000	1.37631	5.62518	1.358713	5.56317
SOV, HOV2, and HOV3+: whether full-time student	−0.28898	−1.59143	−0.27456	−1.51515
HOV2 and HOV3+: whether the annual HH Income is ≥US$75,000	0.78401	1.91312	0.893138	2.24210
HOV2 and HOV3+: whether the HH is without vehicle	1.23534	2.09884	1.20406	2.03788
HOV3+: whether total number of HH Vehicle < total number of HH license	1.77349	2.42775	1.76551	2.41088
Transit: whether the HH is without vehicle	2.89446	8.15734	2.89130	8.16118
Transit: logarithmic of total number of stops in a tour	−1.58747	−7.03721	−1.59141	−7.05294
Walk and bike: whether the HH is without vehicle	1.94341	5.15489	1.94195	5.15657
Walk and bike: whether full-time student	0.55355	1.46321	0.56486	1.49374
Bike: whether the biker is male	0.57369	1.87366	0.57178	1.86730
Alternative specific constant by mode				
HOV2	−1.42926	−6.15222	−1.45535	−6.26484
HOV3 +	−4.37125	−7.15143	−4.37553	−7.15715
Transit	−0.75451	−2.22333	−0.73318	−2.15983
Walk	2.41486	2.64826	2.42773	2.66167
Bike	−1.82589	−3.73497	−1.82295	−3.72987
Estimate of spread for t*-distribution and standard deviation for normal distribution*				
Transit	0.01847	4.0489	–	–
SOV: travel time	0.07931	3.6858	0.001918	0.9364
HOV2 and HOV3+: travel time	0.06270	2.9035	0.006039	1.8412
Final log likelihood	−1212.7286		−1230.9713	
Rho-squared w.r.t zero	0.5762		0.5699	
Rho-squared w.r.t constants	0.2364		0.2249	
Number of observations	1740		1740	

the transit mode, the spread of travel-time attribute is found to be estimated with significant *t*-statistics when a triangular distribution is assumed, the standard deviation is found to be estimated with nonsignificant *t*-statistics when the normal distribution is assumed. Therefore, the RPL model is reestimated assuming the transit travel time without a random component. The estimated absolute values of coefficients are different from those of the MNL model, but the signs of the coefficients remain the same. Therefore, the qualitative interpretation of the attributes of the RPL model estimates remains the same as that of the MNL model.

In this work, the unconditional simulated value of travel time (expressed in US dollars per hour) is calculated at the student population level as per Equation (9). Figures 4 and 5 show the variation of the values of travel time from minimum to maximum. The variation in the value of travel time is due to the taste heterogeneity in the perception of the travel-time attribute across the student population.

Figures 4 and 5 also show the possibility of obtaining negative values for travel time. The negative values of travel time suggest that individuals require payment to save an hour of travel time as opposed to their being willing to pay to save time spent on traveling. These values of travel time are behaviorally unrealistic. Therefore, in this study, the behaviorally implausible values of travel time are not considered for comparison.

A comparative analysis between the values of travel time emanating from the MNL and RPL models is carried out. The overall comparison shows that a percentage of the student population is likely to pay a higher value of travel time when the RPL model is employed over the MNL model. Here, there may be some unobserved effects a student considers and correlates with noncost travel attributes (Jara-Diaz 2000). This kind of gain in the value of travel time emanating from the RPL model has also been reported by other researchers (Basu and Maitra 2010; Basu and Hunt 2012; Hensher 2001b; Rubite and Muromachi 2008). Figure 4 indicates that a percentage of the grade school student population is willing to pay even a higher value for the travel-time attribute of the SOV/HOV2/HOV3+ tour mode, when a normal distribution is employed over a triangular

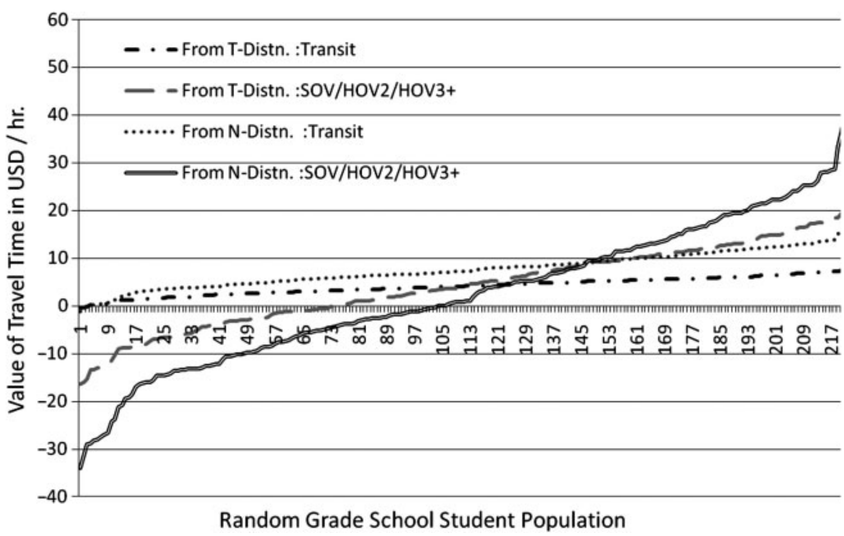

Figure 4. Variation of the value of travel time: grade school tour.

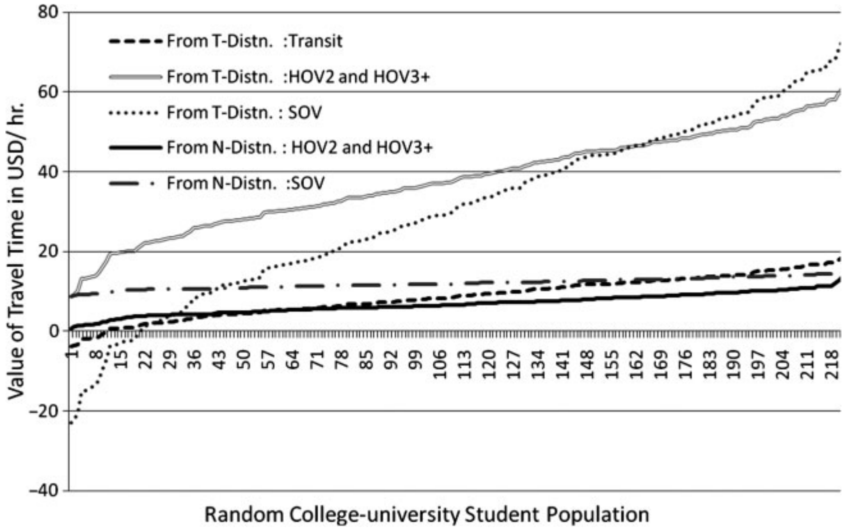

Figure 5. Variation of the value of travel time: college-university tour.

distribution for the random component of the travel-time attribute with the RPL model estimate. A similar type of observation is also indicated for the transit tour mode. In Figure 5, a similar trend of observation is found for the college-university student population taking SOV as the school tour mode. But in the case of the HOV2/HOV3+ tour mode, a percentage of the total population of college-university students is found willing to pay a higher value for the travel-time attribute, when a triangular distribution is employed over a normal distribution for the random component of the travel-time attribute with the RPL model estimate. As much as 89% of the college-student population is found to be willing to pay a higher value of travel time for the transit tour mode when a triangular distribution is employed. Therefore, it becomes evident from the above findings that the distributional assumption for the random component of the travel-time attribute also plays a vital role in the calculated value of travel time.

A comparison among the values of travel time obtained from different model estimates indicates the importance of alternative logit model specifications. However, it is difficult to judge which logit model specification is the best for quantification of the value of travel time. From an analytical point of view, an estimation technique that imposes a less restrictive structure on the error term holds more appeal. In this regard, the RPL model may be preferred over the fixed coefficient logit model as the former relaxes the restrictions of taste variation imposed by the latter. The less restrictive RPL model reveals more behavioral information of the underlying data-set.

7. Conclusions

This paper has presented new evidence and contributes to the limited literature on the behavioral value of travel time in the context of the home-based school tour. The value of travel time has been quantified for two types of school tour: grade school and college-university. The findings of the present study found that mode choice pertaining to school travel depends not only on the characteristics of students and household socioeconomic characteristics but also on their interaction. The results of the current study can provide necessary inputs for evaluating alternative transportation facility or service improvement projects for school travel in California.

The study explored the role of logit model specification in the calculation of the value of travel time. It highlighted how the RPL model may be employed to overcome the limitations of the fixed coefficient class of logit model in accounting for taste heterogeneity across tour makers. This is a crucial factor in terms of estimating user-benefit analysis more accurately across individuals based on savings in time spent on traveling. The work identified the importance of the distributional assumption on the random component of the travel-time attribute for the quantification of the value of travel time.

Though the present study has demonstrated experience in accounting for random taste heterogeneity by assuming triangular and normal distributions for the random component of the travel-time attribute, the role of the constrained version of distributional assumption should also be explored as a part of future work in order to obtain plausible values of travel time with appropriate signs (Basu and Maitra 2010; Basu and Hunt 2012). In this study, the value of travel time has been quantified assuming the coefficient of travel-cost attribute as a nonrandom parameter. The quantification of the value of travel time considering the travel-cost coefficient as a random parameter can also be attempted in a future study. In addition, further investigation needs to be carried out to quantify the value of travel time at an individual level (Sillano and Ortuzar 2005).

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