Transportation Planning and Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/gtpt20

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TRANSPORTATION PLANNING AND TECHNOLOGY
2020, VOL. 43, NO. 5, 443–462
https://doi.org/10.1080/03081060.2020.1763645

Active school travel: homogeneity or heterogeneity? That is the question

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ABSTRACT

To explain and predict active school travel (AST), most studies have not investigated to what extent considering taste heterogeneity is an important influence on AST share. The main aim of the present study was to evaluate whether considering unobserved taste heterogeneity through mixed logit models – including random coefficient and random coefficient analysis (RCA) – materially improves/influences the AST prediction compared to a simpler model – the multinomial logit (MNL) model. The database comprises 735 valid observations. The results show that, with a 10% increase in perceived walking time to school, the MNL model predicts that the AST share would decrease by 7.8% (from 18.9% to 17.4%) while the RCA model predicts that it would decrease by 8.5% (from 18.9% to 17.3%). Thus, the expected share of AST is overestimated by MNL by one-tenth of a percentage point. Although there might be random taste variations around perceived distance to school, it seems the other important policy-sensitive variables, such as safety perception, homogeneously impacts on the AST share across households with different socioeconomic and built environment characteristics. Our empirical assessment suggests that considering taste heterogeneity does not necessarily improve the accuracy of analysis for the aggregate share of the AST concerning policy-sensitive variables.

KEYWORDS

Active school travel; policy-sensitive variables; taste heterogeneity; random taste variation; mode choice; mixed logit models; homogeneity or heterogeneity

1. Introduction

Promoting pupils' active travel (e.g. walking, cycling) to and from school promises numerous societal benefits. For example, many studies have shown that the low share of active school travel (AST) and physical activity might increase children's health risk factors such as obesity (Chung et al. 2012; Hedley et al. 2004), cardiovascular issues and bone health problems (Boreham and Riddoch 2001; Larouche et al. 2014). Furthermore, AST could improve children's mental health and cognitive and psychological functioning (Biddle and Asare 2011; Fyhri and Hjorthol 2009), and their independent mobility in the future (Carver, Timperio, and Crawford 2013). Active transport modes might reduce

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motorized-mode use (e.g. car use), traffic congestion near schools and the subsequent emissions of greenhouse gases (GHG) such as CO_2 (Wilson, Wilson, and Krizek 2007).

Despite the importance, however, to explain and predict AST, most studies have either relied on some types of analysis which do not reflect unobserved taste heterogeneity of various factors at the individual level or have not investigated to what extent considering taste heterogeneity is an important element on the AST share. Several studies have found simple logistic regression or multinomial logit models to be inadequate and have instead used more complex forms such as nested or cross-nested logit. Yet it is unlikely that the effect of a given variable would be fixed across decision makers – i.e. the parents who choose their children's travel mode to/from school. For example, for some parents' safety considerations may be paramount, whereas others are less concerned about safety (since the walk is relatively safe) than about the fact that the school is just too far away. For some, vehicle ownership may be important because it could reduce mode choice flexibility, while for others it is unimportant because it is not a constraint. A parent's desire that the child have enough physical activity may be more important to school mode choice when the child has little other physical activity than when she is already playing soccer or taking dancing lessons outside of school. These different influences of various factors would reflect unobserved taste heterogeneity or random taste variation at the individual level (Kim and Mokhtarian 2018). To date, although a few studies have incorporated taste heterogeneity on the analysis of mode choice in school trips (Ulfarsson and Shankar 2008; Khan, Choudhury, and Wang 2011; Noland et al. 2014; Forsey et al. 2013; Mehdizadeh, Nordfjaern, and Mamdoohi 2018) we are not aware of any studies that investigated to what extent considering unobserved taste heterogeneity is an important element on the share of different travel modes such as the AST in school trips.

In theory, by virtue of relaxing some restrictive assumptions (such as, in this case, that 'one coefficient fits all'), a more complex model can more faithfully represent, and therefore predict, reality – certainly a desirable trait for informing public policy. On the other hand, the fact that complexity is doubtless present in reality does not mean it is strong enough to justify the greater elaborateness of the model – which entails some assumptions of its own and contravenes the scientific goal of parsimony in explanation. With these complementary perspectives in mind, the two related aims of the present study are: (1) to identify any heterogeneity or random taste variation among decision makers, and speculate on its possible source, and (2) to evaluate whether considering unobserved taste heterogeneity through a more complex model materially improves/influences the AST prediction compared to a simpler model.

The remaining sections are organized as follows. Section 2 reviews and discusses the relevant literature. Section 3 represents the methodology including the modeling framework and the data used in this study. Section 4 reports model specification and results. Section 5 provides an in-depth discussion over the results of sensitivity analysis. Section 6 concludes the study with summarizing the key findings.

2. Review and discussion of relevant literature

A number of different variables have been found to influence AST and school travel mode choice: socioeconomic and household factors (e.g. income, car ownership, parental job and educational status, household size), demographic variables (e.g. age, gender), built-environmental variables (e.g. distance, accessibility, and land-use patterns), parental perception about traffic and AST facility safety, and some other psychological factors (e.g. attitudes, worry) (see Mitra 2013 or Mehdizadeh, Mamdoohi, and Nordfjaern 2017a for reviews of these factors).

Among the variables identified as important, distance (including travel time or physical distance from home to school), some socio-economic factors (e.g. car ownership) and safety perception were among the most policy sensitive. Some important strategies such as safe route to school (SRTS), walking school bus (WSB), community schools and optimal school siting are directly derived from these policy-sensitive variables. Travel time (e.g. by walk or auto) or physical distance from home to school were the most significant barriers in the school travel mode use studies. An increase in physical distance or walk travel time could increase the probability of choosing motorized modes or reduce the probability of AST use (e.g. see Sener, Lee, and Sidharthan 2018; Mehdizadeh, Mamdoohi, and Nordfjaern 2017a; Mehdizadeh et al. 2017b; Ermagun and Samimi 2017; Curtis, Babb, and Olaru 2015; Easton and Ferrari 2015; Ermagun and Levinson 2016, 2017; McDonald 2008; Mitra and Buliung 2015; Ermagun and Levinson 2016; Elias and Katoshevski-Cavari 2014).

Several studies have identified a distance threshold for AST through descriptive statistical analysis. Schlossberg et al. (2005) showed that the 52% of pupils who live within a mile of their schools have a higher probability of AST than the 48% of pupils who live farther away. Two studies, in China (Li and Zhao 2015) and the Netherlands (Van Goeverden and De Boer 2013), have shown that when home-to-school travel distance is longer than 3 km, the share of AST will dramatically decline, while Timperio et al. (2006) reported that 800 meters might be a cut-off for children's AST in Australia. Curtis, Babb, and Olaru (2015), applying a cluster analysis, found a five-to-10 minutes threshold for home-to-school walk travel time.

A number of other studies employed discrete choice modeling to evaluate the impact of distance. Nelson et al. (2008) used a binomial logistic regression model and found that a 1-mile increase in home-to-school distance reduced the odds of AST by around 71%. McMillan (2007) estimated a binomial logit model and found that the odds of walking/cycling to school are three times higher for pupils who live less than a mile away from their schools than for others. McDonald (2008) estimated a multinomial logit (MNL) model and found that a 10 percent increase in self-reported walk travel time reduces pupils' AST share by about 7.5%. Also using an MNL model, Ewing, Schroeer, and Greene (2004) found that a 1% increase in walking time decreased the probability of walking by around 0.67%. Ermagun and Samimi (2015) found the MNL model to be a misspecification, and they improved the formulation to the nested logit (NL). A 1% increase in walking time decreases the probability of choosing AST by 2.44% and 2.37% in the MNL and the NL model, respectively (Ermagun and Samimi 2015). Ermagun and Levinson (2017) further advanced the mode choice model to a cross-nested logit (CNL) formulation, using a similar database. They found that a 1% increase in walk travel time to school decreases the probability of choosing walking by around 3.51%. They pointed out that the simpler mathematical forms of previous analyses, including the independence from irrelevant alternatives (IIA) property of MNL, might produce inaccurate elasticities and other results, which could subsequently affect important policies (Ermagun and Levinson 2017).

Furthermore, a 1% increase in the child's age, household income, or car ownership reduced the share of AST by 0.82%, 0.26%, and 0.15%, respectively (McDonald 2008). One percent increases in income, car ownership, and average sidewalk coverage decreased the probability of AST by around 0.84%, and 1.16%, and increased it by 0.42%, respectively (Ewing, Schroeer, and Greene 2004). On the other hand, 1% increases in parental educational background, car ownership, and income reduced the probability of AST by 0.36%, 0.08%, and 0.03% in a NL model, respectively (Ermagun and Samimi 2015). By contrast, the direct elasticities of income and parental educational status with respect to the probability of AST were −0.10% and −0.55% in a CNL model (Ermagun and Levinson 2017). Further, a 100% increase in parental worries about safety reduced the probability of AST by 60% (Ermagun and Samimi 2015), and a one unit increase in the caregiver's perceived lack of safety in the neighborhood (measured on a 5-point scale) reduced the odds of AST by around 13% (McMillan 2007).

In most countries, school travel alternatives are household private cars, walking, public transport, cycling, school service modes (e.g. school bus, carpooling) and other modes. However, many previous studies have examined children's mode choice in a binary situation (e.g. AST versus other modes; walking vs motorized modes) with binomial logit or logistic regression model, and other statistical analysis. Although this manner simplifies model's structure, the finding has policy limitation for each alternative. Hence, several studies tried to estimate multinomial logit (MNL) model to consider all alternatives.

In MNL models, there are two assumptions (or restrictions): independently and identically distributed (IID) error terms in the utilities of each alternative, and the behaviorally comparable assumption of independence of irrelevant alternatives (IIA) (Hensher, Rose, and Greene 2005; Ortuzar and Willumsen 2011). Although these assumptions provide a closed-form solution and ease the estimation of the model, they also have their violations and errors. To partially relax the IID and IIA assumptions of the MNL model, the model structure was advanced to NL. Although the NL model partially relaxes these assumptions through variance components of the model together with some correlation within subsets of alternatives, it also has a closed-form solution. For instance, Ermagun and Samimi (2015) tried to estimate a three level NL model for school travel (12–17 years old) mode choice (see also Lin and Chang 2010). They almost were the first that introduced a slightly advanced model (NL model) to the literature of school travel mode choice. Meanwhile, Ewing, Schroeer, and Greene (2004) further aimed to relax IIA property (potential misspecification issues in MNL model) with a NL model. But their results showed that the MNL model has a decent structure. More recently, Ermagun and Levinson (2017) have developed a cross-nested logit (CNL) model to overcome some issues in previous analyses, even the NL model. Moreover, some recent studies have recommended accounting more realistic analysis to consider heterogeneity (Ermagun and Samimi 2015; Ewing, Schroeer, and Greene 2004; Mehdizadeh, Nordfjaern, and Mamdoohi 2018).

To summarize, in all mentioned methods including utility-based models (i.e. binary, MNL, NL, CNL) and other statistical analysis, the effects of variables are considered fixed across the population (parents or students). In other words, these analyses are not able to identify any heterogeneity or random taste variation among observations. In addition, although a few studies have accommodated taste heterogeneity on mode choice decision in school trips (e.g. Noland et al. 2014; Forsey et al. 2013; Mehdizadeh, Nordfjaern, and Mamdoohi 2018), no study has investigated how important is taste heterogeneity of various factors at the individual level on modal share in school trips, especially on the AST share. Knowing such information could give new insights into planners' viewpoints to make sure how policies associated with active school travel should be implemented. The answer to such a research question can help policymakers to better understand which segments of parents/households have a specific concern towards their children's active school travel.

3. Methodology

3.1. Model structures

The current research aims to estimate several more behaviorally realistic mode choice models and compare them to each other and to simpler ones. In the following sub-sections, the MNL, MXL random coefficient (RC), and random coefficient analysis (RCA) structures are explained. The NL structure and its specification process is addressed in the model specification section (Section 4).

3.1.1. MNL model

In a discrete choice model such as MNL, an individual n is assumed to obtain some utility from choosing an option i in his (or her) choice set. This utility is decomposed into an observed, or systematic, portion (which is usually specified to be linear in parameters) and an unobserved, random portion:

$$U_{ni} = \beta' X_{ni} + \varepsilon_{ni} \quad i = 1, 2, \ \ldots, J, \tag{1}$$

where the first term ($\beta' X_{ni}$) is the observed portion; X_{ni} is a vector of observed variables relating to individual n and alternative i, β' is a vector of coefficients to be estimated (which is constant across observations in the MNL model), and J is the number of available options. The ε_{ni} is the error (or random) term, representing the effect of unobserved variables on utility, and which, in the MNL model, is assumed to be IID extreme value. In the MNL model, the probability of choosing alternative i for individual n is a closed form:

$$P_{ni} = \frac{\exp(\beta' X_{ni})}{\sum_j \exp(\beta' X_{nj})}. \tag{2}$$

The method of maximum likelihood is used to estimate the parameters of the MNL model (Ortuzar and Willumsen 2011).

3.1.2. MXL random coefficient (RC) model

MXL models relax the IID assumption by allowing the coefficients to vary over decision-makers in the population with a density of $f(\beta)$ rather than being fixed as in MNL. In the RC model the individual-specific β associated with the k^{th} attribute is:

$$\beta_{nk} = \beta_k + \eta_{nk}, \tag{3}$$

where η_{nk} is a random term whose distribution over individuals depends in general on underlying parameters, and can take on different distributional forms such as normal, lognormal, uniform, or triangular. η_n denotes a vector of K random components in the set of utility functions in addition to the J random elements in ε_n. The unconditional probability of choosing alternative i for individual n is:

$$P_{ni} = \int \left(\frac{\exp(\beta' X_{ni})}{\sum_j \exp(\beta' X_{nj})}\right) f(\beta|\theta) d\beta, \tag{4}$$

Where θ is the vector of underlying parameters of the distributions of the β's, for instance the means and covariances of the β's in the population.

3.1.3. MXL random coefficient analysis (RCA) model (decomposition of heterogeneity around the mean)

To reveal the absence or presence of preference heterogeneity around the mean coefficient of a given variable, we can interact each random coefficient with other attributes or variables (by incorporating $\delta'_k z_n$ into β_{nk}) that one supposes might be possible sources of preference heterogeneity (Hensher, Rose, and Greene 2005). In the RCA model β_{nk} is:

$$\beta_{nk} = \beta_k + \eta_{nk} + \delta'_k z_n, \tag{5}$$

where Z_n is a vector of observed variables specific to the individual, such as socio-economic and demographic characteristics. Hence, the probability function in the RCA model is the same as that for the MXL model, the only difference being that β_{nk} obeys eq. (5) rather than eq. (3), and thus that for each random coefficient there is an additional vector δ of parameters to estimate:

$$P_{ni} = \int \left(\frac{\exp(\beta' X_{ni})}{\sum_j \exp(\beta' X_{nj})}\right) f(\beta|\theta, \delta) d\beta, \tag{6}$$

The integral is approximated via simulation (this process is repeated for many draws), and the method of maximum simulated likelihood is used to estimate the parameters of MXL models (Hensher, Rose, and Greene 2005; Train 2009).

3.2. Data

The study area consists of the city of Rasht, a rather large municipality in northern Iran with a population of almost 64,000 in the 2011 census. The city has a radial urban form with a rather dense built environment, residential areas and narrow roads. Car use has dramatically increased in recent years. Therefore, high levels of traffic congestion are expected, particularly during peak hours. Public transport includes some urban buses and taxis (carpooling). The number of urban buses and their time scheduling cannot adequately support passengers in certain areas of the city. Hence, the study area has rather weak public transport facilities compared to Western countries. There are no metro systems, urban rail or other advanced transport systems as of January 2014.

Active travel in the city is walking and bicycle use is very low among both the general population and children. The city has a poor dedicated bicycling infrastructure. In addition, there are some safety and security concerns for females bicycling. Hence, active school travel (AST) is associated with walking in this study and we have ignored bicycling. The study area does not apply specific rules for public schools that are commonly found in Europe. In Rasht public schools are mostly located in centers of communities, whereas private schools tend to be geographically spread around the city. School locations therefore do not follow any specific pattern or criteria in the study area. Some parents may choose a school that is allocated far from their residence because the school may have a good educational program or well-educated teachers. Private schools usually have a better educational quality compared to public schools in Iran. Some schools may not have transport services. School services (such as carpooling) have not been restricted to a specific distance. Pupils who live in the same neighborhood usually use the same services to minimize distance and costs of travel. The number of services is dependent upon their demand. Services usually pick up pupils about half an hour before the start of the first class of the day. School services are also not free of charge in Iran. Of note, in the city of Rasht, available modes for school trips are a variety of school service modes (school bus or minibus or carpooling where school officials are responsible for managing both cars and chauffeurs), household private cars, walking, public transportation (e.g. urban bus), and motorcycle.

The present study uses a school trips database gathered in January 2014 by a cross-sectional questionnaire survey among pupils (7-9 years old). Since this research has assumed that parents make the final mode use decision for their children, the respondents were parents. A combined random clustered and stratified sampling was the sampling method deployed. The urban area of Rasht had two educational districts in 2014. The two clusters of the sample were therefore based on these two educational districts. Nine schools were randomly selected based on two criteria: pupil's gender (schools are either exclusively for girls or boys) and school type (public and private). All pupils in the randomly selected classes (first to third grade classes) of these nine schools were given the questionnaire to take home. A total of 1,078 questionnaires were distributed, where the pupils were asked to take the questionnaires home for their parents to complete and return two days later (return rate = 80 percent, $n = 858$). The school trip database (based on these completed questionnaires) included several sections: household and socio-economic characteristics, demographic factors, some built-environment factors, parental perceptions about safety, and parental mode choice for their children.

The explanatory variables are: pupils' grade (7–9 years old), gender, household characteristics (such as fathers and mothers driving license status, their educational background, job status, household income level), household car ownership, parental physical activity in a week, parental age and some built-environmental factors (including walking travel time from home to school, accessibility to public transport along the home-to-school route), parental worries about walking facility safety, and school service status. The dependent variable is pupils' mode use in school trips. Parental dominant mode choice was assumed as children mode in school travel.

3.3. Data analysis

Descriptive statistical analysis of data from the questionnaires that had been adequately completed ($n = 735$) show that nearly 56 percent of parents chose the school service, nearly 22 percent chose the car, nearly 19% allowed children to walk, and the other three percent chose other modes like public transport and motorcycle (see Figure 1).

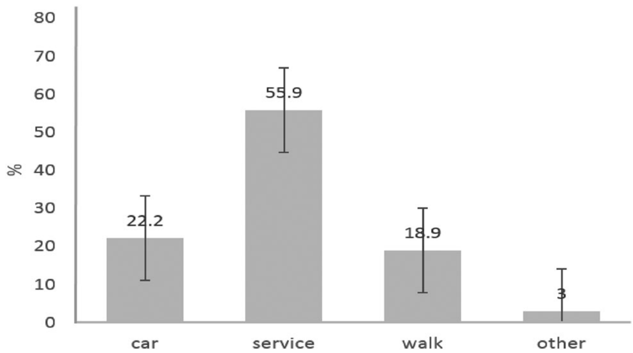


Figure 1. School travel mode share (%).

Parents who allowed their children to use AST (i.e. walking) reported less perceived walking time from home to school (as a measure of active travel distance) (Figure 2).

The Pearson's and Spearman's correlation coefficients results showed (Table 1) that pupils who traveled by household car, their parents reported higher car ownership. They were also likely to have a higher income. Parents who permitted their children to walk to school were more likely to perceive less walking time from home to school. They also reported fewer owned cars. Parents who reported higher walking times were more likely to have higher worries about AST safety. Parents who had reported more physical activity (e.g. the amount of exercise in a week) had less propensity to choose AST (i.e. walking) for their children. Parents who had reported a higher educational background were less likely to choose AST, and more likely to choose car travel. Mothers who had a full-time job were more likely to use their car on school travel.

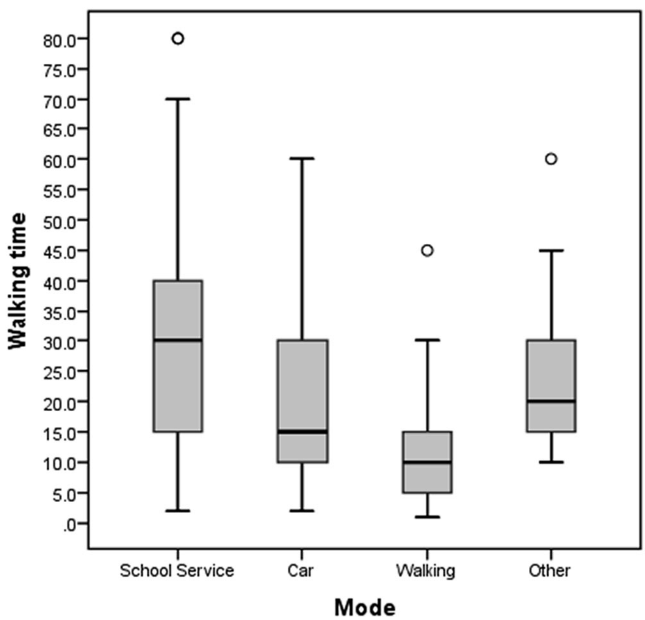


Figure 2. Parents' mode choice and their relevant perceived walking time.

Table 1. Correlations among selected study variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1-Pupils grade	1	−0.04	0.06	.08*	.11**	−.12**	−0.02	0.06	−0.06	−.22**	−0.01	−0.01	0.03
2-Car ownership		1	0.01	−.10**	−.15**	.27**	.38**	0.06	−0.03	0.03	−.07*	.27**	−.16**
3-Father job status			1	.14**	−.14**	−.15**	−.15**	0.01	0.04	−0.01	0.01	−0.01	0.02
4-Mother job status				1	−.27**	−.37**	−.21**	0.04	0.06	−0.01	0.04	−.10**	0.02
5-Father education					1	.59**	.31**	.11**	−.07*	0.05	−0.03	.11**	−.07*
6-Mother education						1	.32**	0.06	−0.03	0.06	−0.05	.15**	−.09**
7-Income							1	.16**	−.07*	−0.01	−0.06	.13**	−0.03
8-Parents exercise								1	−0.01	−.08*	0.03	−0.11*	0.03
9-Walking time									1	.13**	.34**	.09	−.33**
10-Worry about safety										1	.10	0.04	−.17**
11-Service use											1	−.59**	−.54**
12-Car use												1	−.258**
13-Walking													1

Note: **, * = Significance at 1%, 5% level.

Table 2. Definition and descriptive statistics for variables appearing in the models.

Variable type	Variable definition	Symbol	Average	Std. Dev.
Dummy	Father's driver license status (yes = 1, no = 0)	F_LIC	0.93	0.24
	Mother's driver license status (yes = 1, no = 0)	M_LIC	0.67	0.46
	Type of school (public = 1, private = 0)	TYPE	0.79	0.40
	Accessibility to public transportation in home to school path (yes = 1, no = 0)	PUB_ACC	0.52	0.49
	School service status (school has a service = 1, not = 0)	H_SERV	0.90	0.29
	Parental physical activity in a week (Less than 2 hours = 1, otherwise = 0)	L_EXER	0.79	04.0
	Having more than one owned car (more than one car = 1, otherwise = 0)	CAR++	0.10	0.30
Continuous	Walking time from home to school (minutes)	PWTS	25.08	20.72
Ordinal	Mother's educational level (Illiterate = 0, Under diploma = 1, High school = 2, B.s & higher = 3)	M_EDU	2.09	0.64
	Parental worry about safety of walking facility (very low = 1, low = 2, average = 3, high = 4, very high = 5)	SAFETY	2.24	0.95
Count	Number of cars owned by household	N_CAR	0.89	0.58

4. Model specification and results

School service, private car and AST (i.e. walking) are considered as modes for school travel. These three modes constitute a multinomial logit modeling (MNL) problem. Explanatory variables used in the models are shown in Table 2.

To check some potential misspecifications related to the independence of irrelevant alternatives (IIA) in the MNL model (Figure 3(a)), two nested logit (NL) models were estimated (Figure 3(b and c)). The structure in (b) had an upper level nest with AST (walking) and motorized modes, and the lower level nest with car and school service as available choices, conditioned on a motorized modes choice occurring at the higher level. The structure in (c) had an upper level nest with non-sustainable (car) and sustainable modes, and the lower level nest with AST (walking) and school service as available choices, conditional on a sustainable transport choice occurring at the higher level. The results of the NL models showed that the inclusive value (IV) parameters for all nested structures were not statistically equal to 1 but were statistically greater than 1, which is theoretically impermissible and indirectly argues for the MNL structure. Hence, the MNL was accepted as the base structure for estimating a more complex model – a mixed logit (MXL) model. Then a random coefficient (RC) model (to explore heterogeneity) was estimated together with a random coefficient

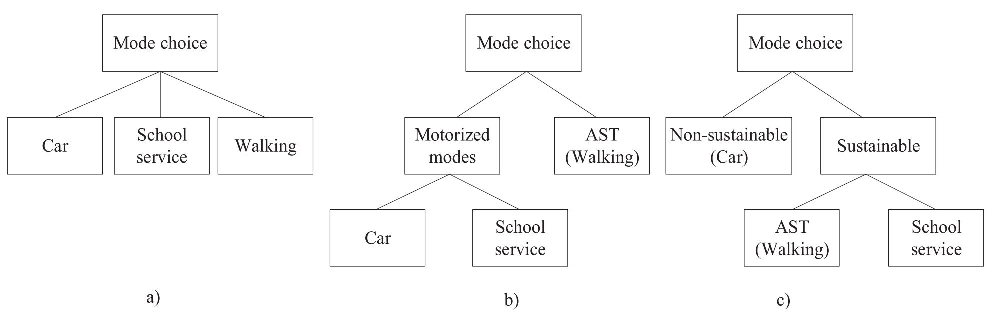


Figure 3. (a) MNL and (b and c) NL model structures.

analysis (RCA) model (to identify possible sources of heterogeneity). The three models (i.e. MNL, RC and RCA) are reported in Table 3.

Of note, in the RC model all coefficients hypothesized to be random were tested with respect to four prospective distributions (normal, lognormal, triangular and uniform). Only coefficients statistically significant at the 10% level or better have been retained in the models. All explanatory variables in the final models had the expected signs according to the literature and common sense. Also, the signs of the coefficients are the same across all three models, with only slightly different values.

A likelihood ratio test with chi-squared statistics was applied to measure any significant improvement in the overall goodness of fit of the three models (Table 3). Results show that the overall goodness of fit of both the RCA and RC models were higher than the MNL model with 99 percent confidence. In addition, the RCA overall goodness of fit was higher than that of the RC model, at 99 percent confidence. In addition, the observable part of the utility function for modes in the three models are shown in Table 4.

The results (Table 3) show that some socio-economic and household factors (i.e. car ownership status, mother's and father's driving license status, mother's educational background), some built-environmental characteristics (walk travel time and accessibility to public transport in home to school path), school related factors (service situation and public vs private schools), and parental worries about the safety of AST facilities were significant variables in the models. Furthermore, consistent with Mitra and Buliung (2015) and Mehdizadeh, Mamdoohi, and Nordfjaern (2017a), we did not find any significant relationship between children's gender and mode use. Although income had a positive and significant relationship with car use in the correlation coefficients analysis (Table 1), it was not found to be statistically significant in the models.

Mothers who had a driving license and lower physical activity level were more likely to choose a private car than other modes. Attending a public school may reduce the probability of choosing car travel. Accessibility to public transport, the higher education degree of mothers, father's driving license status and parental worries about safety had negative effects on the probability of AST use. School service status had a positive effect on the probability of service mode.

There was heterogeneity in the estimated coefficient over the sampled population around the mean coefficient estimate. There was found to be significant heterogeneity around the mean of perceived walking time to school (*PWTS*) in the AST and the school service utilities and also car ownership (*N_CAR*) in car utility in the RC model. This shows that different parents possess parent-specific coefficient estimates that may be different from the sample population mean coefficient estimate. A likelihood ratio test showed that among different hypothesized distributions, the normal distribution had a slightly better goodness of fit compared to other statistical distributions. Therefore, a normal distribution was considered for the random coefficients.

The RCA model showed that some elements of heterogeneity around the mean of random coefficients may be the result of a dummy variable (CAR^{++} – household owned more than one car = 1, otherwise=0). Households that own more than one car have a greater sensitivity towards perception of walk travel time from home to school. A negative sign (−0.35 for CAR^{++}) for the random coefficient (*PWTS* in walking utility) indicates that this dummy variable (CAR^{++}) will reduce the probability of choosing AST.

Table 3. Results from the three models: MNL, RC and RCA.

Alternative	Variable	MNL Coefficient	MNL *t*-value		RC Coefficient	RC *t*-value		RCA Coefficient	RCA *t*-value		Source	*t*-value
Car	Constant	0.70*	1.91	F	1.24*	1.94	F	1.43*	1.95	F		
Car	N_CAR	1.01***	5.01	F	Mean = 1.70***	2.64	R, Normal	Mean=2.50***	2.70	R, Normal	CAR++	
					Std. Dev. = 3.67***	2.74		Std. Dev. = 2.91***	1.95		−1.62*	−1.74
Car	M_LIC	0.58**	2.30	F	1.56**	2.15	F	1.39**	1.96	F		
Car	L_EXER	0.49**	2.27	F	1.52**	2.17	F	1.32**	2.13	F		
Car	TYPE	−0.43**	−2.31	F	−1.21**	−2.11	F	−1.17**	−2.17	F		
AST	Constant	7.70***	8.21	F	13.07***	6.28	F	13.07***	5.78	F		
AST	PUB_ACC	−1.02***	−4.06	F	−1.51***	−3.76	F	−1.57***	−3.78	F		
AST	PWTS	−0.12***	−7.32	F	Mean = −0.22***	−4.45	R, Normal	Mean = −0.22***	−4.16	R,	CAR++	
					Std. Dev. = 0.10***	3.98		Std. Dev. = 0.10***	3.82	Normal	−0.35**	−2.43
AST	M_EDU	−0.53***	−2.80	F	−0.80***	−2.73	F	−0.64**	−2.15	F		
AST	F_LIC	−1.34***	−2.96	F	−1.88***	−2.48	F	−1.73**	−2.27	F		
AST	SAFETY	−0.23**	−2.16	F	−0.26**	−2.31	F	−0.31**	−2.38	F		
Service	H_SERV	2.67***	6.02	F	5.06***	4.66	F	5.15***	4.29	F		
Service	PWTS	0.02***	4.10	F	Mean = 0.09***	3.27	R, Normal	Mean = 0.10***	3.14	R,	CAR++	
					Std. Dev. = 0.07***	3.12		Std. Dev. = 0.07***	2.94	Normal	−0.05	−0.94
		LL(0):−781.11			*LL(0)*:−781.11			*LL(0)*:−781.11				
		LL(β):−503.08			*LL(β)*:−479.50			*LL(β)*:−468.32				
		LL(C):−692.19			*LL(C)*:−692.19			*LL(C)*:−692.19				
		$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} = 0.35$			$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} = 0.38$			$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} = 0.40$				
		$\rho_C^2 = 1 - \frac{LL(\beta)}{LL(C)} = 0.27$			$\rho_C^2 = 1 - \frac{LL(\beta)}{LL(C)} = 0.30$			$\rho_C^2 = 1 - \frac{LL(\beta)}{LL(C)} = 0.32$				
		Sample size: 711			Sample size: 711			Sample size: 711				

Where *LL(0)*: Log-likelihood at zero; *LL(β)*: Log-likelihood at convergence; *LL(C)*: Log-likelihood at market shares; R: Random coefficient; F: Fixed coefficient.
Note: ***,**,* = Significance at 1%, 5%, 10% levels.

Table 4. Utility functions of car, AST and school service in the three models.

Alternative	Model	Observable part of utility function
Car	MNL	$0.70 + 1.01 \times N\_CAR + 0.58 \times M\_LIC + 0.49 \times L\_EXER - 043 \times TYPE$
	RC	$1.24 + [1.70 + 3.67 \times n^*] \times N\_CAR + 1.56 \times M\_LIC + 1.52 \times L\_EXER - 1.21 \times TYPE$
	RCA	$1.43 + [2.50 - 1.62 \times (CAR^{++}) + 2.91 \times n^*] \times N\_CAR + 1.39 \times M\_LIC + 1.32 \times L\_EXER - 1.17 \times TYPE$
AST	MNL	$7.70 - 1.02 \times PUB\_ACC - 0.12 \times PWTS - 0.53 \times M\_EDU - 1.34 \times F\_LIC - 0.23 \times SAFETY$
	RC	$13.07 - 1.51 \times PUB\_ACC - [-0.22 + 0.10 \times n^*] \times PWTS - 0.80 \times M\_EDU - 1.88 \times F\_LIC - 0.26 \times SAFETY$
	RCA	$13.07 - 1.57 \times PUB\_ACC - [-0.22 - 0.35 \times (CAR^{++}) + 0.10 \times n^*] \times PWTS - 0.64 \times M\_EDU - 1.73 \times F\_LIC - 0.31 \times SAFETY$
Service	MNL	$2.67 \times H\_SERV + 0.02 \times PWTS$
	RC	$5.06 \times H\_SERV + [0.09 + 0.07 \times n^*] \times PWTS$
	RCA	$5.15 \times H\_SERV + [0.10 - 0.05 \times (CAR^{++}) + 0.07 \times n^*] \times PWTS$

n^*: Normal standard distribution.

5. Sensitivity analysis and discussion

In terms of the behavioral implications of the models, such as the aggregate elasticities (direct and cross) and marginal effects of the key policy-sensitive variables (Greene and Hensher 2010), our evidence shows no distinguishable differences between the advanced model and the simpler one. Aggregate elasticities and marginal effects (both direct and cross) of the three models are shown in Table 5.

Car ownership (*N_CAR*) has an aggregate direct elasticity of 1.10 in the RCA model. Therefore, a one percent increase in household car ownership increases the share of choosing the car by around 1.10%. Also, this variable has cross elasticities on the share of the AST and the service mode by about −0.28%, and −0.34%, respectively, *ceteris paribus*. Car ownership had a different aggregate direct elasticity of 0.70% and cross elasticities of −0.20% for the AST and the service mode in the MNL model (see Figure 4(a) for more detail). With a 10% increase in car ownership the MNL model would estimate that the AST share would decrease by 2% (from 18.9% to 18.52%) while the RCA model estimates that it decreases by 2.8% (from 18.9% to 18.37%). Thus, the expected share of AST is underestimated in the MNL model by 0.15 of a percentage point. Several studies have reported the negative effect of car ownership on the share of AST use (cf. McDonald 2008). For example, Ermagun and Samimi (2015) showed that with a 10% increase in car ownership the MNL model would estimate that the AST probability would decrease by 1.30% while the NL model would estimate that it decreases by 0.80%.

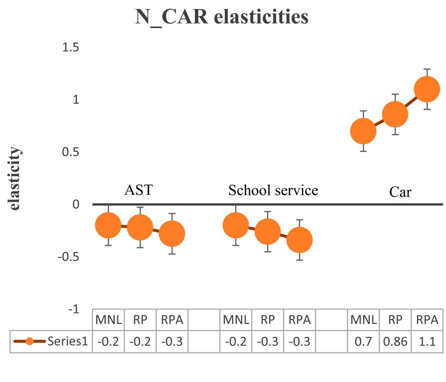
The aggregate direct elasticity of choosing AST, with respect to the perceived walking time to school (PWTS), is −0.78% in the MNL model, −0.84% in the RC model, and −0.85% in the RCA model, while this variable has cross elasticities on the service in the MNL, RC and RCA models of about 0.17%, 0.21%, and 0.21%, respectively. PWTS had cross elasticities on the share of car by around 0.22%, 0.17%, and 0.19% in the MNL, RC, and RCA models, respectively (see also Figure 4(b)). With a 10% increase of the PWTS the MNL model would estimate that the AST share would decrease by 7.8% (from 18.9% to 17.4%) while the RCA model would estimate that it decreases by 8.5% (from 18.9% to 17.3%). Thus, the expected share of AST is overestimated by MNL by one-tenth of a percentage point. Distance (e.g. physical and travel time) was the most reported barrier and policy-sensitive variable for children's active school travel. A 1% increase in distance reduced the probability of AST by 2.44% in the MNL model and 2.37% in a NL model (Ermagun and Samimi 2015).

A 1% increase in mother's educational degree decreases the share of choosing the AST mode by 0.56% in the MNL model, 0.56% in the RC model, and 0.45% in the RCA model (see also Figure 4(c)). Hence, with a 10% increase in the mother's educational degree, the MNL model would estimate that the share of AST would decrease by 5.6% (from 18.9% to 17.84%) while the RCA model would estimate that it decreases by 4.5% (from 18.9% to 18.05%). Thus, the expected share of AST is underestimated by the MNL by one-fifth of a percentage point. Of note, some previous studies have found that mothers with high educational degrees had less tendency to choose AST (e.g. walking, cycling) for their children (cf. McMillan 2007). For instance, a 1 percent increase in parental educational background reduced the probability of AST by around 0.36% in both MNL and NL models (Ermagun and Samimi 2015) for students' (12-17 years old) AST.

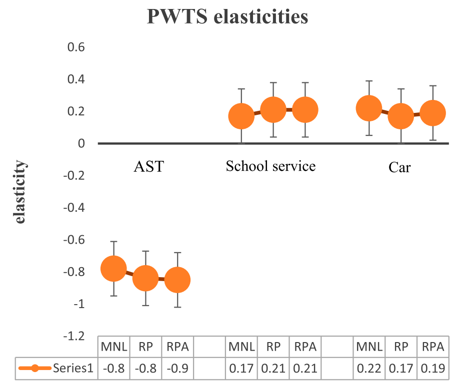
Table 5. Aggregate elasticities (direct and cross) and marginal effects of variables for three models.

Variable		Primary alternative	AST			School service			Car		
			MNL	RC	RCA	MNL	RC	RCA	MNL	RC	RCA
Elasticities	*N_CAR*	Car	−0.20	−0.22	−0.28	−0.20	−0.26	−0.34	0.70	0.86	1.10
			0.26	*0.17*	*0.22*	*0.25*	*0.16*	*0.21*	*0.29*	*0.56*	*0.64*
	PWTS	AST	−0.78	−0.84	−0.85	0.17	0.21	0.21	0.22	0.17	0.19
			0.82	*0.65*	*0.69*	*0.20*	*0.34*	*0.35*	*0.23*	*0.27*	*0.29*
		Service	−0.11	−0.11	−0.28	0.16	0.14	0.15	−0.32	−0.25	−0.28
			0.14	*0.15*	*0.32*	*0.10*	*0.08*	*0.09*	*0.35*	*0.30*	*0.32*
	M_EDU	AST	−0.56	−0.56	−0.45	0.11	0.13	0.10	0.18	0.13	0.11
			0.36	*.043*	*0.34*	*0.17*	*0.25*	*0.20*	*0.21*	*0.19*	*0.17*
	SAFETY	AST	−0.53	−0.38	−0.41	0.11	0.09	0.10	0.16	0.08	0.10
			0.31	*0.26*	*0.29*	*0.16*	*0.16*	*0.17*	*0.19*	*0.12*	*0.14*
Marginal effects	*M_LIC*	Car	−0.04	−0.04	−0.02	−0.06	−0.04	−0.04	0.10	0.09	0.08
			0.31	*0.04*	*0.03*	*0.33*	*0.04*	*0.04*	*0.29*	*0.04*	*0.04*
	L_EXER	Car	−0.03	−0.04	−0.03	−0.05	−0.05	−0.05	0.09	0.08	0.08
			0.02	*0.04*	*0.03*	*0.02*	*0.04*	*0.04*	*0.02*	*0.04*	*0.04*
	TYPE	Car	0.03	0.03	0.03	0.05	0.04	0.06	−0.08	−0.05	−0.07
			0.02	*0.03*	*0.03*	*0.02*	*0.03*	*0.04*	*0.02*	*0.04*	*0.05*
	PUB_ACC	AST	−0.18	−0.04	−0.04	0.05	0.02	0.02	0.05	0.01	0.01
			0.06	*0.08*	*0.09*	*0.06*	*0.04*	*0.04*	*0.05*	*0.02*	*0.03*
	F_LIC	AST	−0.24	−0.18	−0.20	0.06	0.06	0.05	0.06	0.04	0.04
			0.08	*0.11*	*0.12*	*0.07*	*0.07*	*0.07*	*0.07*	*0.04*	*0.05*
	H_SERV	Service	−0.30	−0.37	−0.32	0.45	0.38	0.42	−0.36	−0.21	−0.29
			0.16	*0.29*	*0.24*	*0.17*	*0.22*	*0.21*	*0.16*	*0.12*	*0.17*

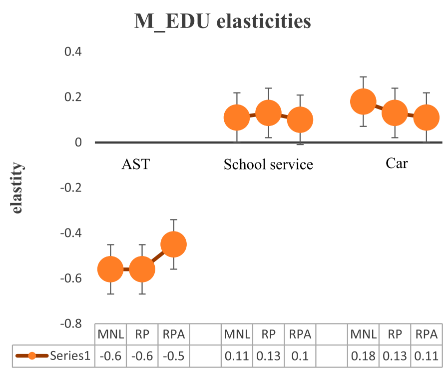
MNL, Multinomial logit model; RC, Random coefficient; RCA, Random coefficient analysis.
Note: Standard deviation for each elasticity and marginal effect are reported in the *Italic* format.



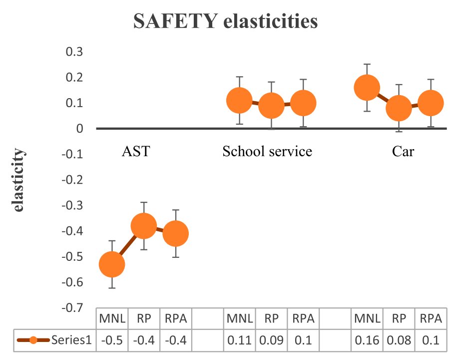
(a) Direct and cross elasticities of car ownership status in MNL, RC, and RCA models.



(b) Direct and cross elasticities of walk travel time to school in MNL, RC, and RCA models.



(c) Direct and cross elasticities of mother's educational background in MNL, RC, and RCA models.



(d) Direct and cross elasticities of parental safety perception in MNL, RC, and RCA models.

Figure 4. Direct and cross elasticities of some variables in MNL, RC, and RCA models. (a) Direct and cross elasticities of car ownership status in MNL, RC and RCA models. (b) Direct and cross elasticities of walk travel time to school in MNL, RC and RCA models. (c) Direct and cross elasticities of mother's educational background in MNL, RC and RCA models. (d) Direct and cross elasticities of parental safety perception in MNL, RC and RCA models.

The aggregate share of choosing AST, with respect to perceptions of safety, is 0.53%, 0.38%, and 0.41% in the MNL, RC and RCA models, respectively (see also Figure 4(d)). With a 1% increase in safety perception, the estimated final share of the AST would be 18.8% (99.47% × 18.9%) in the MNL model, versus 18.82% (99.59% × 18.9%) in the RCA model-essentially indistinguishable. Although this variable is ordinal, it is treated as continuous in the model and can be viewed as representing an underlying continuous safety perception, and thus from that perspective it is appropriate to consider the impact of continuous changes in safety perception.

6. Conclusions

Many studies have shown that the low share of active school travel (AST) and physical activity might increase children's health risks. As a result, a large body of previous studies and projects have recommended a variety of strategies and programs to alleviate the negative effects of policy-sensitive barriers such as home-to-school distance and AST safety problems. However, these studies have neither considered taste heterogeneity at the individual level nor investigated the importance of accommodating unobserved taste heterogeneity. The main aim of the study reported here was to evaluate whether considering taste heterogeneity through advanced models materially influences and/or improves the share of AST compared to a simpler model.

Although our empirical evidence has shown that more complex models (here random coefficient analysis (RCA)) have slightly higher goodness of fits than a multinomial logit (MNL) model, from a behavioral implications perspective (Greene and Hensher 2010), the main policy-sensitive variables had essentially indistinguishable aggregate elasticities in the complex and simpler discrete choice models on the share of AST. The empirical assessment showed that a more complex model may not be of such great empirical consequence in respect of behavioral outputs such as elasticities for policy-sensitive variables. Using a more complex model therefore needs a more considered justification. Based on empirical data obtained for the city of Rasht, the difference between the estimated shares of AST for both the MNL and RCA models was not substantial. With a 1% increase in the perceived walking time to school, the final share of AST was estimated to be 18.75% in the MNL model and 18.74% in the RCA model, a result that is essentially indistinguishable. In addition, with a 1% increase in safety perception, the final share of AST was estimated to be 18.8% in the MNL model and 18.82% in the RCA model, a result that is again essentially indistinguishable.

Although random taste variation might be found around the perceived distance to school, it seems the other important policy-sensitive variable, safety perception, has a homogeneous impact on the AST share across households with different socioeconomic and built environment characteristics. This implies, for example, that planners could meet the safety requirements for all households/neighborhoods in the city in the same way. This may highlight the fact that, regardless of schoolchildren's/households' and neighborhood characteristics, different parents have a similar concern toward their children's active school travel throughout all regions of the study area, which we speculate is due to the lack of integrated and safe pedestrian infrastructures in the city of Rasht.

In general, it is hard to answer the question that considering taste heterogeneity can influence the accuracy of sensitivity analysis. It depends on several things: the aim of the study, the type of database, the 'white noise' issue and/or specifying the remaining unobserved portion of utility functions (Train 2009; Cherchi and de Dios Ortúzar 2008, 2011; Greene and Hensher 2010). Our evidence suggests that the MNL model can be the goal, if by including interaction terms in an MNL model we obtain a specification that does not violate the IIA property (Mokhtarian 2016), then considering taste heterogeneity is not an important element and such a sophisticated model is probably not needed. As a result, when the unobserved portion of utility functions in discrete choice models is 'white noise', an MNL model is, as Train (2009) puts it, the ideal rather than a restriction. For instance, it has been found that some part of taste variation in the perception of walk travel time to school might be a result of household's car ownership status. This may show that the random coefficient analysis (RCA) points to the best variables to interact in an ordinary MNL model.

Finally, our evidence herein is obviously restricted to one dataset. A library of empirical evidence from other data sets is required before we can make any definitive conclusions about the transferability of the evidence and the extent to which analysts should routinely account for taste heterogeneity across individuals.

Acknowledgements

The authors would like to sincerely thank Professor Patricia L. Mokhtarian for her invaluable contribution in revising this manuscript and giving very impressive comments. This is a revised version of a paper presented at the 98th Annual Meeting of the U.S. Transportation Research Board.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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