Transport Policy 37 (2015) 203–211

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Promoting active transportation modes in school trips

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ARTICLE INFO

Article history:
Received 13 March 2014
Received in revised form
22 September 2014
Accepted 30 October 2014
Available online 25 November 2014

Keywords:
School trip
Mode choice
Policy
Three level nested logit
Tehran

ABSTRACT

Urban and transportation planners have put a special focus on students' health and fitness in the past decade, however they struggle to find effective policies to promote walking and biking for school trips. Commuting to school is an opportunity to embed a regular physical activity in students' daily routines and prevent many health issues that are stimulated by physical inactivity during childhood. A three level nested logit model is introduced to explain the motives behind school trip modal selection. Four choice situations, namely walking, driving, school busing, and taking public transit are considered. This study, particularly, underscored the significance of model misspecification in terms of policy outcomes, since multinomial logit models are typically adopted in the literature and have strong and, in many cases, unrealistic assumptions. Elasticity analysis of the MNL model showed an indirect elasticity of vehicle ownership of −0.13 for non-automobile modes, while NL model provides different elasticities of −0.12, −0.20 and −0.08, respectively for public, school bus, and walk modes. This misspecification results in over estimating the reduction in the share of students who walk to school when vehicle ownership increases. Moreover, a wide range of policy-sensitive variables along with their effect magnitude was discussed and compared with the previous studies. The results showed that one percent increase in the probability of walking to school is expected for every 0.04 percent increase in auto travel time, 0.07 percent increase in the normalized-to-income cost of driving, 0.08 percent decrease in vehicle ownership, 0.03 percent increase in distance to public transit, or 2.37 percent decrease in commute distance. Safety was also found to be very influential on active commuting, such that addressing the safety concern of parents is expected to increase propensity of active commuting to school by around 60 percent.

1. Introduction

A global increase in the children obesity rate has triggered policy-makers to promote a more active lifestyle among students. Many studies have shown that cardiovascular diseases along with several other health issues in adulthood are rooted in a lack of physical activity during childhood and adolescence (Andersen et al., 2003, 2006). Since walking is the most common form of physical activity for all ages (Saelens et al., 2003), transportation and urban planners struggle to find policies that promote active modes of transportation (AMT). This is, particularly, deemed as an opportunity for children to perform regular physical activity and diminish several diseases throughout their life (Cavill et al., 2008; Tudor-Locke et al., 2002). AMT is also a prospect for city officials to decrease congestion levels in the morning peak hours and thereby mitigate externalities of the transportation system (Rabl and Nazelle, 2012; Pedestrian and Bicycle Information Center, 2008). Parents, on the other hand, have understandable reservations that have led to a significant decline in the share of active modes.

It is essential to study the motives behind the mode choice decisions in school trips, and implement effective policies to promote AMT. Students' mode choice have received a growing attention since 1994, when Towner conducted a descriptive analysis on students' modal selection behaviors in England and measured exposure to injury risk in school trips (Towner et al., 1994). Since then a wide range of factors are found to influence students' active travel to school that includes 1) household demographic and socio-economic factors, 2) students' characteristics, 3) built-environment variables, and 4) socio-economics of the residential neighborhood. Table 1 provides a summary of explanatory variables, alternative modes of school travel, and data analysis methods that are applied in some previous studies. According to this table, very few studies (Larsen et al., 2009; McDonald and Aalborg, 2009; Yarlagadda and Srinivasan, 2008) had a complete coverage on the alternative modes, while the rest focused on a subset of alternatives. Moreover, an overview of the explanatory variables reveals that commute distance to school,

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http://dx.doi.org/10.1016/j.tranpol.2014.10.013
0967-070X/

Table 1
Summary of school trips studies.

Author/Year	**Country**	**Age**	**Mode**				**AMT (%)**	**Indicated Parameters**									**Analysis Method**
			Active (walk / bike)	*Automobile*	*Public Transit*	*School Bus*		*Gender*	*Age*	*Income*	*Vehicle ownership*	*Safety*	*Comfort*	*Distance*	*Travel time/cost*	*Transit Specs.*	
Ermagun et al., 2014	Iran	12-17	×	×	×	×	49	×	×	×	×	×	×	×	×	×	Copula-based Joint Approach
D'Haese et al., 2011	Belgium	11-12	×	×			59	×			×	×		×			Two level Bivariate Regression
Johansson et al., 2011	Sweden	11-15	×	×	×		63	×	×		×						Descriptive
Alemu and Tsutsumi, 2011	Japan	15-18	×	×	×		29		×		×			×	×	×	Multinomial Logit
Leslie et al., 2010	Australia	10-14	×	×	×		56	×									Binary Logistic Regression
Wilson et al., 2010	U.S.	7-12	×	×	×		24		×	×				×			Multinomial Logit
Dyck et al., 2010	Belgian	17-18	×	×	×		58	×				×					Logistic Multi Level
Mitra et al., 2010	Canada	11-13	×	×			70	×	×	×	×			×			Binomial Logit
Larsen et al., 2009	Canada	11-13	×	×	×	×	62	×		×				×			Logistic Regression
McDonald and Aalborg, 2009	U.S.	10-14	×	×	×	×	30	×	×	×		×	×	×			Descriptive
Rodriguez and Vogt, 2009	U.S.	9-11	×	×		×	12		×		×	×		×			Logistic Regression
Nelson et al., 2008	Ireland	15-17	×	×	×		37	×						×			Logistic Regression
Yarlagadda and Srinivasan, 2008	U.S.	< 18	×	×	×	×	15	×	×		×			×			Multinomial Logit
Wen et al., 2008	Australia	9-11	×	×	×		32	×	×		×	×	×	×			Logistic Regression
McDonald, 2008a	U.S.	7-14	×	×	×		12	×	×	×	×			×	×		Multinomial Logit
McMillan, 2007	U.S.	9-11	×	×			22			×	×	×	×	×			Binomial Logit
Martin et al., 2007	U.S.	9-15	×				48	×	×	×				×			Logistic Regression
Mota et al., 2007	Portugal	12-16	×	×	×		52							×		×	Logistic Regression
Kerr et al., 2007	U.S.	5-18	×				14	×		×	×						Logistic Regression
Kerr et al., 2006	U.S.	5-18	×				25				×	×					Logistic Regression
Merom et al., 2006	Australia	5-12	×	×	×		30	×	×		×	×		×			Logistic Regression
Timperio et al., 2006	Australia	5-6 / 10-12	×				33		×			×		×		×	Logistic regression
Schlossberg et al., 2006	U.S.	12-15	×	×	×		25					×		×			Logistic regression
deBruijn et al., 2005	The Netherlands	12-18	×				79	×	×								Three Step Linear Regression
Schlossberg et al., 2005	U.S.	12-14	×	×	×		26					×	×	×			Descriptive
Ewing et al., 2004	U.S.	7-18	×	×		×	8				×			×	×		Multinomial Logit
Evenson et al.,2003	U.S.	12-15	×				10	×	×								Logistic Regression

students' gender, age, and vehicle ownership have been widely used, while other important variables such as travel time, cost, comfort, and specifications of the transit system have received a limited attention. There are comprehensive reviews (Panter et al., 2008; Pont et al., 2009; Ding et al., 2011; Wong et al., 2011) of the past studies that compared influential factors of active school travel. Furthermore, a review of the analysis method shows that descriptive analysis and binary logit models are predominantly used to explain school travel modes, while very few studies have implemented multinomial logit (MNL) models to explain this behavior. We found very occasional attempts (Ewing et al., 2004) that tried to develop more advanced econometric models (e.g. a nested logit specification), but the outputs was unsuccessful in practice.

The current literature has certain gaps that have motivated this research. First, many previous studies (Mitra et al., 2010; McMillan, 2007) distinguishes between only two alternatives with binary choice models. Although this approach simplifies the modeling methodology, the results provide a vivid picture of school travel modal split that limits applicability of the findings. Second, a few studies (Ewing et al., 2004; McDonald, 2008a) that distinguishes between multiple travel modes, have potential model misspecification issues. This is because IIA (independence of irrelevant alternatives) property of MNL is not intuitively acceptable in school mode choice decisions, unless a very wide range of explanatory variables reduces the effect of correlated unobserved factors. IIA property implies that characteristics of a third alternative (say school busing) do not change the relative odds between the two alternatives (say walking and driving). This is an inappropriate assumption, since IIA of the MNL model indicates that likelihood of taking a school bus and having the kid walk alone would increase proportionally, if the parents cannot drive their kids to school. This is, intuitively, not true, as parents who take a school bus and those who ride their kids to school could have similar safety reservations and therefore, taking a school bus seems more probable when they cannot drive the kids to school. Lastly, parents have reservations about their kids' travel method, including safety, comfort, and reliability, that are expected to influence students' mode choice decisions. These variables have received very limited attention in previous models that leads to a form of missing variable model misspecification.

The rest of the paper is structured as follows. First, the modeling methodology is briefly reviewed, followed by a description of the empirical data that is collected for this purpose. The estimation results of a three level nested logit (NL) model is, then, presented and analyzed from a policy perspective. Finally, the paper concludes with a summary and recommendations for future research.

2. Method

A multinomial logit model has a closed form formula and a straightforward estimation method. However, assumption of IID (independently and identically distributed) extreme value error terms induces certain limitations that are discussed in details by Train (2009). IIA property of MNL is the primary consequence of IID assumption, which is intuitively unacceptable in many cases; unless all the unobserved factors that make the error terms dependent, explicitly enter the model (Train, 2009). The NL model specification, an extension of MNL, was introduced by Ben-Akiva and Lerman (1985) to capture correlation among alternatives to some extents. Although IIA is maintained within each nest, it is relaxed to IIN (independence of irrelevant nests) for alternatives in different nests. This allows variance of errors to differ across the nests, and yet the choice probabilities have a closed-form formula.

The utility that student j perceives from travel mode i is the sum of a systematic utility (V_{ji}) and an error term. The probability of choosing each mode is given by Eq. (1) (Coldren and Koppelman, 2005), assuming a linear-in-parameter function of explanatory variables for the systematic utility and maximizing the likelihood of occurrence for the sampled observations. In this equation, subscript n is omitted for ease of representation, P_m is the probability of choosing an upper-level nest (limb), $P_{n|m}$ is the conditional probability of choosing a lower-level nest (branch) given a limb, $P_{i|n}$ and is the conditional probability of choosing an alternative given a branch. μ is the inverse logsum parameter, also known as the coefficient of inclusive value (IV). τ_n and τ_m are, respectively, given by $\tau_n = \ln(\sum_{i`\in N_j} \exp(\mu_n V_{i`}))$ and $\tau_m = \ln(\sum_{i`\in N_m} \exp(\frac{\mu_m}{\mu_{n`}}\tau_{n`}))$.

$$P_i = P_m \times P_{n|m} \times P_{i|n} = \frac{\exp(\frac{1}{\mu_m}\tau_m)}{\sum_{m`\in M}\exp(\frac{1}{\mu_{m`}}\tau_{m`})} \times \frac{\exp(\frac{\mu_m}{\mu_n}\tau_n)}{\sum_{n`\in N}\exp(\frac{\mu_m}{\mu_{n`}}\tau_{n`})} \times \frac{\exp(\mu_n V_i)}{\sum_{i`\in n}\exp(\mu_n V_{i`})} \quad (1)$$

NL models may be estimated either sequentially or simultaneously. The first estimation method is termed limited information maximum likelihood (LIML), and the latter is known as full information maximum likelihood (FIML) estimation. Although FIML estimation is more challenging and one may encounter convergence problems, Hensher (1986) showed that LIML provides statistically inefficient estimates for a NL model. Therefore, a FIML estimation method is adopted to obtain consistent, asymptotically normal, and efficient estimates.

3. Data

To study school trip mode choice decisions, three folds of data were obtained: students' travel information, household demographics, and transportation and built-environment characteristics. The data was obtained for Tehran, with an area of 700 km^2, a population of 7.5 million, and 620 traffic analysis zones. Around 15 million daily trips are made in Tehran, 27 percent of which are educational (Municipality of Tehran, 2006). There were 5352 schools and 1,119,571 registered k-12 students in Tehran in 2010 (Statistics of Minister of Education, 2012). Public schools have a dominant share and are mainly funded by the government. Therefore, the administrations are relatively more under the influence of the government. Private schools, on the other hand, have a higher academic quality and very costly in some cases. Public schools, as opposed to private schools, are "zoned schools" meaning that only those who live in a designated area could be registered. We observed a range of 60 m to just about 10 km for the commute distance to school in Tehran.

A paper-based survey was conducted in May 2011, targeting 4900 middle-school and high-school students throughout Tehran. Primary school students were not covered, as the literature (Panter et al., 2008; McMillan, 2005) suggests a relatively different mode choice decision making process for them. A stratified random sample was taken based on gender and level of education, since schools are gender-segregated in Iran. Further, parents were asked to fill out the questionnaires, because they have more precise information about household demographics and influence on students' choice of travel mode (McMillan, 2005). The survey had a response rate of 72 percent, and collected information on five folds: 1) household socio demographics (e.g. household size, income, education, vehicle ownership, working status of parents), 2) student characteristics (e.g. age, gender, grade), 3) built-environment attributes (e.g. walk time to school, access to public transit, commuting to or from a restricted traffic zone), 4) school trip

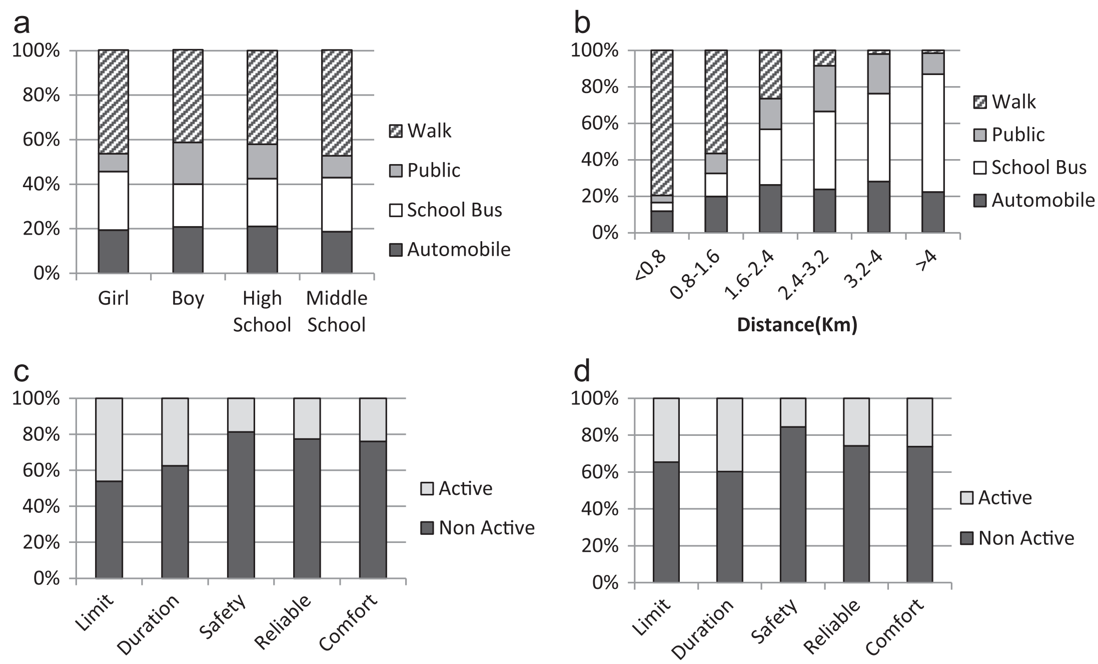

Fig. 1. Children's mode choice descriptive.

behaviors (e.g. escort pattern, primary mode of travel, travel cost, and trip chain), and 5) parental reservations about school trips (e.g. safety, reliability, duration, and comfort).

Four modes of travel are considered in this study: walk, auto drive, school bus, and public transportation. Travel time and cost of auto and transit is essential for a mode choice study and was obtained from Tehran Comprehensive Transportation and Traffic Studies Company (TCTTS) (2012). TCTTS estimated travel cost and time from an EMME2 model that was recalibrated in 2010. Travel time of the walking mode, on the other hand, was asked in the survey and double checked with the commute distance. Bike mode was not considered, since less than 1 percent of students reported to use bicycles for school trips. Share of each mode, classified by gender, school level, and commute distance is illustrated in Fig. 1. This figure also illustrates the relationship between parental concerns and share of active modes among genders. Fig. 1(a) shows that girls are more inclined, in general, toward walking to school. However, as per Fig. 1(b), commute distance is negatively correlated with walking. Further, Fig. 1(c) and (d), respectively, shows the share of active travel modes for girls and boys. A descriptive analysis of parental reservations reveals that 85 percent of parents whose kids avoid active modes of travel are primarily concerned travel safety.

4. Model

A three level NL model was developed in this study to explain choice of school travel mode among walk, automobile, school bus, and public transportation. Explanatory variables that are used to model the choice situation are defined in Table 2 and estimation results for MNL and NL models are reported in Table 3. The tree of the NL model is structured in a way that the upper level has two limbs that cleave into *active* and *non-active* limbs and the lower level of the *non-active* limb divides into *public* and *private* branches (Fig. 2). The *active* limb and *public* branch have one

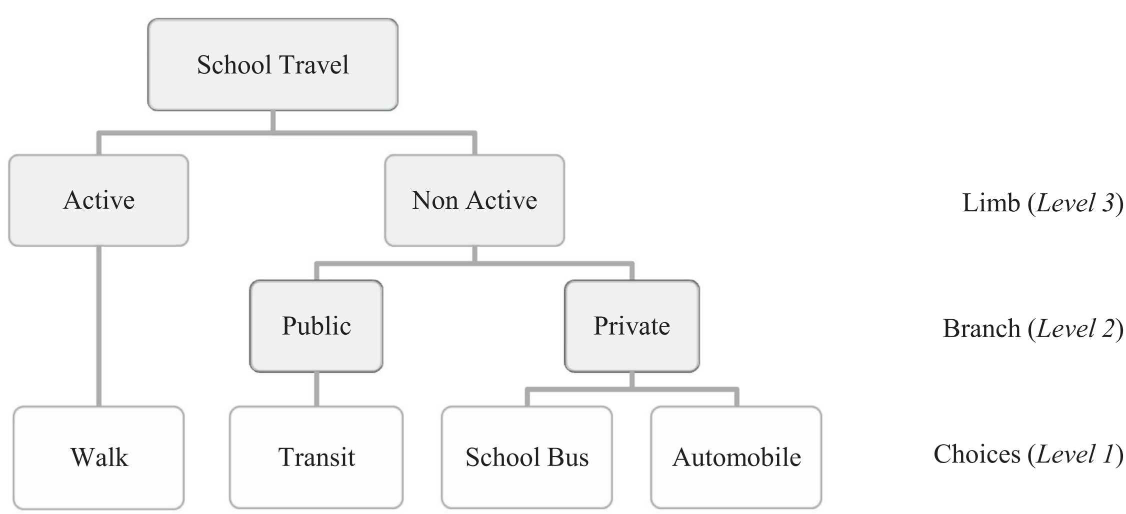

Fig. 2. Tree structure for the nested logit model.

alternative in their lower levels, and thus, the IV parameters are fixed to one. The remaining IV parameters, however, are estimated. IV parameters have to meet certain conditions in order for a nested logit model to be consistent with the global utility maximization theory. In a two level NL, the IV parameters should be positive and less than one, while in a three level NL, the IV parameter of a lower nest has to be less than that of the upper nest, as well. The IV parameters of the *non-active* limb and the *private* branch are, respectively, 0.79 and 0.74, and both are statistically positive and less than one, according to a Wald test. This implies that the MNL logit has misspecification issue and, therefore, NL estimates should be employed for policy assessment. School bus is classified under the private branch, given the characteristics of school bus system in Tehran. School administrations, usually, sign an agreement with private taxi service agencies to employ registered drivers for this purpose. Parents pay the entire cost, directly to the taxi company. Recently, the municipality required a short training course for school taxi drivers in Tehran. This travel mode is considered private, because a taxi or van drops off 4 to 10 students to school.

Student's *t*-test is conducted to show a statistically significant effect of each explanatory variable in Table 3. All the variables are of the right sign and significant at a 99 percent confidence interval in both MNL and NL models, except for school bus travel time (*SBUS_TIME*), income (*INCOME*), and population density (*POPDENS*). Although the latter two variables are significant at 99 percent confidence interval in the NL model, they have a 95 percent confidence interval in the MNL model. Likelihood ratio test is also conducted to measure the overall goodness of fit of the models. The NL model has a McFadden pseudo-rho-squared (likelihood ratio index) of 38 percent which is slightly higher than 32 percent likelihood ratio index of the MNL model. The NL model has a better explanatory power and the significant IV parameters convey a misspecification bias in the MNL model. This would results in incorrect interpretations of the results and eventually leads to misdirecting policy assessments. Significance of model specification is further elaborated in the next section along with an in-depth analysis of the models.

5. Analysis of results

Influential factors on school trip mode choice decisions are reported in Table 3. Further, elasticities of some explanatory variables are estimated through sample enumeration (Table 4). An elasticity value shows the percentage of change in the choice probability as a result of one percent increase in the explanatory variable. Estimated elasticities are compared with the findings of McDonald (2008a) and Ewing et al. (2004) in Table 5. One needs to consider differences in demographics, socio-economics, culture, built-environment, and analysis method, when comparing the outputs. Influence of age and gender of the students are discussed, followed by some household demographics such as income, education, and vehicle ownership on the children tendency to walk to school. Then, parental concerns are discussed that include safety, comfort, reliability, and duration of trip.

We found a positive relationship between students' age and their tendency to walk or take transit to school. On the contrary, the use of school bus decreased with an increase in age. This could be attributed to the fact that when children get older they seek a more independent lifestyle (Fyhri and Randi, 2009). In fact, high-school students are 11 percent more likely to walk compared to middle-schoolers. Contrary findings about the effect of student's gender on AMT utilization are reported in the literature. Although some studies (McMillan et al., 2006) found a higher propensity for boys to use AMT, others (Panter et al., 2010) found the opposite.

Dissimilarities in culture, demographics, built-environmental factors, and analysis methods are possible reasons for these contradictory findings. A study (Leslie et al., 2010) in Australia, for instance, targeted 2961 10 to 14 years old students and argued that gender of the kids affect their tendency to walk and bike. Although they found girls to be more willing to walk (44.3 percent versus 37.4 percent), boys were more likely to bike to school (22.4 percent versus 8.3 percent). We also found boys more reluctant to walk. This could be due to some female students' willingness to take after school time as an opportunity to socialize with friends and be less constrained for a short while (Samimi and Ermagun, 2012a).

Income, car ownership, and parental education are also recognized in school trip AMT utilization. A negative relationship that income and vehicle ownership have with AMT propensity is widely recognized (McMillan, 2007; McMillan et al., 2006,

Table 2
Description of explanatory variables used in the model.

Variable	*Description*	*Average*	*Std. Dev.*
WALKSCH	1: less than 10/2: 10–20/3: 20–30/4: 30–40/5: 40–50/6:more than 50 min walk time to school	2.6392	1.5442
GENDER	1:Male/0:Female	0.3908	0.4879
AGE	Age of children between 12–17 years old	14.1064	1.6103
AUTO	Number of cars in a household	0.9984	0.6828
NON_AUTO	1: Households with no car/0: Otherwise	0.2077	0.4057
INCOME	1: less than 5/2: 5–10/3: 10–15/4: 15–20/5: 20–25/6: more than 25 million Iranian Rials[a] household income	2.0988	1.2159
SAFETY	1: If parents are primarily concerned about their children travel safety/0: Otherwise	0.3165	0.4651
RELIABLE	1: If parents are primarily concerned about their children travel reliability/0: Otherwise	0.1817	0.3856
COMFORT	1: If parents are primarily concerned about their children travel comfort/0: Otherwise	0.1818	0.3857
DURATION	1: If parents are primarily concerned about their children travel time/0: Otherwise	0.2347	0.4238
TRF_LIMIT	1: Students that live or study in a limited traffic zone/0: Otherwise	0.1124	0.3159
AUTO_TIME	Automobile travel time to school (min)	9.9057	8.7472
SBUS_TIME	School bus travel time to school (min)	13.2309	11.2344
EDUCATION	Educational level of parents 1: less than a high school diploma/2: high school diploma/3: bachelor of science/4: master of science or equivalent/5: higher degrees	2.0295	0.9735
WALKTRNT	Distance between home and the nearest bus station (m)	571.2101	449.7286
POPDENS	Population density in each zone (person per m^2)	0.0258	0.0128
ESCORT	1: If parents accompany their kid to school/0: Otherwise	0.3597	0.4799
NORM_COST	Out-of-pocket automobile travel cost (10 Rials) divide by INCOME	212.0423	118.8475

[a] 11800 Iranian Rails was equivalent to 1 USD in May 2011.

Table 3
Mode choice models.

Variables	Alternatives	Multinomial logit		Nested logit	
		Coefficient	t-statistic	Coefficient	t-statistic
Constant	Automobile	−4.91***	−15.10	−7.60***	−5.09
COMFORT		0.47***	2.88	0.83***	2.65
DURATION		1.11***	9.33	1.28***	8.62
AUTO_TIME		−0.03***	−4.16	−0.038***	−4.16
NORM_COST		−0.002***	−4.36	−0.003***	−4.87
AUTO		0.49***	5.01	0.57***	5.10
Constant	School Bus	−4.44***	−7.82	−7.27***	−4.48
COMFORT		0.78***	4.79	1.16***	3.50
RELIABLE		0.82***	6.35	0.90***	5.87
SBUS_TIME		−0.003	−0.63	−0.01	−1.32
TRF_LIMIT		0.78***	3.22	0.80***	3.12
AGE		−0.114***	−3.21	−0.118***	−2.86
INCOME		0.38***	7.29	0.46***	6.74
Constant	Public	−5.42***	−7.98	−6.54***	−5.13
TRAFIC_LIMIT		2.15***	8.28	2.06***	8.23
AGE		0.11***	2.66	0.12***	2.87
NON_AUTO		1.21***	6.26	1.28***	6.23
EDUCATION		−0.52***	−5.42	−0.54***	−5.70
WALKTRNT		−0.0006***	−4.16	−0.0006***	−3.73
INCOME		−0.23**	−2.49	−0.28***	−2.62
SAFETY		−0.59***	−4.01	−0.59***	−3.82
EDUCATION	Active	−0.28***	−3.90	−0.28***	−3.71
SAFETY		−1.72***	−12.08	−1.68***	−11.45
POPDENS		12.10**	2.54	12.69***	2.68
NON_AUTO		0.95***	5.13	0.94***	4.88
ESCORT		−1.82***	−13.04	−1.82***	−12.12
GENDER		−0.51***	−4.08	−0.53***	−4.20
WALKSCH		−1.27***	−19.04	−1.24***	−16.52
TRAFIC_LIMIT		1.48***	5.51	1.12***	3.96
Inclusive value parameters:					
Non-active				0.78862***	4.95
Active				1.0(fixed)	
Private				0.74299***	4.97
Public				1.0(fixed)	
Log-likelihood at zero:		−3404.45		−3404.45	
Log-likelihood at convergence:		−2280.40		−2110.75	
McFadden Pseudo-R-squared:		0.33		0.38	
Bayesian information criterion:		4789.41		4465.85	
Sample size:		2653		2653	

Note: ***, **, * means significance at 1 percent, 5 percent, 10 percent level.

McDonald, 2008b), although the effect magnitudes are different. Moreover, a dummy variable (*NON_AUTO*) for households with no private car indicates students from such families are, understandably, more likely to walk or take transit to school. Table 4 indicates that one percent increase in the family income reduces likelihood of public transit use by 0.46 percent, and increase chance of driving, walking, and riding on school bus, respectively, by 0.06, 0.03, and 0.06 percent. In accordance with Martin et al. (2007), however, a negative association between parental education level and tendency to use AMT and public transportation was found. This could be attributed either to the positive correlation between income and education, or to the fact that educated parents are more aware of potential risks that exist in walking and taking transit.

Safety, comfort, reliability, and duration of the school trip, along with the school or home being located in a limited traffic zone were found to influence students' modal decisions. The first two factors had been explored in previous studies (McDonald and Aalborg, 2009; McMillan, 2007), while the rest have received very little (Samimi and Ermagun, 2012b; Ermagun et al., 2014), if any, attention. According to Table 3, parents who are concerned about their children's safety are more reluctant to have their kids walk or take transit. Further, parents who are primarily worried about the comfort of their kids are more willing to use the school bus or personal vehicle. School bus is more appealing to those who seek a reliable mode, and traffic restrictions incline students toward public transportation, walking, and school bus. As expected, parents who are concerned about the duration of their kid's travel are more willing to use a personal car.

6. Policy implementation

There are some policy sensitive variables in the model that allows the city officials to understand possible ways of promoting active school trips. These variables that include travel time, cost, vehicle ownership, access to public transit, commute distance to school, and students' safety are discussed in the following.

Auto travel time has a direct elasticity of −0.27, according to Table 4. This indicates one percent increase in auto travel time discourages parents from driving their kids to school by a probability of 0.27 percent. Further, this would result in a marginal increase in the share of other modes. Probability of walking, riding a school bus, and public transit, respectively, increases by 0.04, 0.1, and 0.06 percent. A higher sensitivity of automobile mode to the travel time that is arguably relative to congestion level is

Table 4
Elasticities for multinomial logit (MNL) and nested logit (NL) models.

Attribute	Primary alternative	Public		Automobile		School Bus		Active	
		MNL	NL	MNL	NL	MNL	NL	MNL	NL
AUTO_TIME	Automobile	0.06	0.06	−0.25	−0.27	0.06	0.10	0.06	0.04
		0.08	*0.07*	*0.24*	*0.28*	*0.08*	*0.10*	*0.08*	*0.05*
AUTO	Automobile	−0.13	−0.12	0.36	0.36	−0.13	−0.20	−0.13	−0.08
		0.15	*0.13*	*0.24*	*0.25*	*0.15*	*0.19*	*0.15*	*0.10*
NORM_COST	Automobile	0.10	0.10	−0.41	−0.46	0.10	0.19	0.10	0.07
		0.10	*0.09*	*0.25*	*0.31*	*0.10*	*0.13*	*0.10*	*0.07*
SBUS_TIME	School Bus	0.01	0.03	0.01	0.05	−0.03	−0.08	0.01	0.02
		0.02	*0.05*	*0.02*	*0.07*	*0.02*	*0.07*	*0.02*	*0.04*
AGE	Public	1.39	1.52	−0.19	−0.28	−0.19	−0.28	−0.19	−0.17
		0.25	*0.29*	*0.23*	*0.28*	*0.23*	*0.28*	*0.23*	*0.21*
	School Bus	0.37	0.31	0.37	0.52	−1.23	−1.14	0.37	0.22
		0.36	*0.27*	*0.36*	*0.33*	*0.40*	*0.37*	*0.36*	*0.22*
INCOME	Public	−0.44	−0.46	0.04	0.06	0.04	0.06	0.04	0.03
		0.28	*0.31*	*0.05*	*0.05*	*0.05*	*0.05*	*0.05*	*0.04*
	School Bus	−0.25	−0.24	−0.25	−0.37	0.56	0.60	−0.25	−0.17
		0.37	*0.34*	*0.37*	*0.45*	*0.27*	*0.30*	*0.37*	*0.27*
EDUCATION	Public	−0.97	−0.97	0.11	0.14	0.11	0.14	0.11	0.09
		0.52	*0.55*	*0.13*	*0.14*	*0.13*	*0.14*	*0.13*	*0.10*
	Active	0.21	0.21	0.21	0.21	0.21	0.21	−0.36	−0.36
		0.20	*0.20*	*0.20*	*0.20*	*0.20*	*0.20*	*0.32*	*0.32*
WALKTRNT	Public	−0.34	−0.32	0.04	0.05	0.04	0.05	0.04	0.03
		0.28	*0.27*	*0.06*	*0.07*	*0.06*	*0.07*	*0.06*	*0.05*
POPDENS	Active	−0.14	−0.15	−0.14	−0.15	−0.14	−0.15	0.15	0.15
		0.14	*0.15*	*0.14*	*0.15*	*0.14*	*0.15*	*0.12*	*0.12*
WALKSCH	Active	0.94	0.91	0.94	0.91	0.94	0.91	−2.44	−2.37
		0.74	*0.71*	*0.74*	*0.71*	*0.74*	*0.71*	*2.45*	*2.37*

Note I: standard deviation for each elasticity is reported in the *Italic* format.

Table 5
A comparison of elasticities.

Variable	Walk			Automobile	
	Ewing	McDonald	Current study	McDonald	Current study
Walk time	−0.66	−0.748	−2.372	0.104	0.918
Auto time	–	0.010	0.046	−0.078	−0.277
Income	−0.84	−0.255	0.03/−0.17	0.211	0.06/−0.37
Age	–	0.820	−0.17/0.22	−0.577	−0.28/0.52
Population density	–	0.116	0.158	−0.017	−0.153
Vehicle ownership	−1.16	–	−0.088	–	0.369

understandable, as many parents (10 percent) drive their kids to school on their way to work. Travel time of the school bus, on the other hand, has a direct elasticity of −0.08 in the NL models, while this number is about −0.03 in MNL model. This is a direct consequence of model misspecification that leads to an underestimation of automobile use when school bus becomes less appealing. The results indicate that school bus is a likely replacement for private cars, mainly due to the safety and reliability of service. Therefore, it could be considered as a potential alternative for parents who drive their kids to school.

Cost of travel is normalized to household income to consider a systematic taste variation among families. This makes the model outputs more realistic, since low-income and high-income families have different reactions to one dollar increase in their kid's travel cost. In our study, one percent increase in the normalized auto cost decreases the likelihood of driving by 0.46 percent and 0.23 percent, respectively, for low and high income households. This distinction is essential for assessing policies that aim at reducing auto driving through different pricing scenarios. Furthermore, a direct elasticity of −0.46 for the normalized auto travel cost, and indirect elasticities of 0.10, 0.19, and 0.07, respectively, for public, school bus, and walk modes are reported in Table 4. Consequences of model misspecification is evident in this table, as indirect elasticities of public, school bus, and walk modes are all equal to 0.10 in the MNL model. Therefore, expected share of students who walk to school will be over-estimated; if a taxation policy on automobile usage is assessed by a MNL model.

Vehicle ownership has a direct elasticity of 0.36 in the automobile mode. This, arguably, indicates that acquiring a second car in families with one vehicle, increases propensity of automobile use in school trips by 36 percent. As a result, the probabilities of walking and using public transportation decrease by almost 8 and 12 percent, respectively. This estimate should only be considered as an approximation, because partial derivatives that are used to calculate elasticities are valid in a small vicinity of the observation point. Expecting a growing trend in vehicle possession, city planners should be alerted of a potential increase in the use of private cars and reducing the share of active transportation modes. An interesting observation in Table 4 that underscores the consequences on model misspecification is that indirect elasticities of vehicle ownership (*AUTO*) is −0.13 in the MNL model, while NL model provides different elasticities of −0.12, −0.20, and −0.08, respectively for public, school bus, and walk modes. This misspecification results in overestimating the reduction in the share of students who walk to school, when vehicle ownership increases.

Access to public transit is a key variable that is recommended in many previous studies to be accounted for in school trip mode choice studies. Distance to the nearest bus station that is located on the way of each student to school was obtained and turned out to have a significant negative effect on public transit usage. Table 4 shows that one percent increase in the distance to the nearest bus station decreases the likelihood of transit usage by 0.32 percent. This would also increase probabilities of auto, school bus, and walk, respectively, by 0.05, 0.05, and 0.03 percent. Again, the MNL model predicts a similar indirect elasticity of 0.04 for all the non-transit modes. Therefore, a misspecification bias slightly over predicts share of students who walk to school instead of taking transit, when access to the public transit system is decreased.

Commute distance to school is, arguably, the most prominent factor that influence walking and biking to school. This parameter has received a central attention in smart development of land-use, and has the highest absolute value of elasticity in our model. Previous studies (Fyhri et al., 2011; Larsen et al., 2009; Ewing et al., 2004; Merom et al., 2006) have unanimously noted a negative correlation between commute distance and use of active modes. We also found a direct elasticity of −2.4 for walk time to school that indicates every one percent increase in the students' commute distance discourages use of active modes by a probability of 2.4 percent. Urban planners argue that "sprawl school siting" can intensify urban challenges and make the land-use patterns inefficient (Cole et al., 2010; Passmore, 2002). Some recent guidelines, on the other hand, in the United States required a minimum of 30 acre plus one acre for every 100 high-school students (Schlossberg et al., 2005). This type of regulation urges developers to build schools in urban fringes, to acquire enough land and minimize their costs. City planners, therefore, need to be aware of the magnitude of such impacts and must have more contemplation on such policies that discourage active modes of commute to school. In Iran, on the other hands, public policies encourage neighborhood schools, although regional private schools are also growing. Results of the model also indicated a direct elasticity of 0.15 for population density in the active mode, and an indirect elasticity of −0.15 in the other modes. MNL and NL models, however, predict fairly similar results for this parameter.

Safety is an important concern of parents that is influential on reducing the use of active travel modes. Our model shows that addressing the safety concerns of parents could increase propensity of active commuting to school by around 60 percent. This increase in the probability of walking is calculated setting the continuous variables at average and discrete variables at their mode. Therefore, planers need to study policies that increase parents' perception about their kids' travel safety to school. Safe Routes to School (McDonald and Aalborg, 2009; Staunton et al., 2003) and Walk School Bus (Collins and Kearns, 2010; Staunton et al., 2003; Engwicht, 1992) are implemented in the United States to address parental safety concerns and improve share of active modes among students.

7. Conclusion

This study was an effort to develop a three level nested logit model to explain the behavioral aspects of school trip modal selection. Understanding the motives behind such behaviors is essential for city planners to promote active commuting to school. This is deemed an opportunity to prevent many health issues that are stimulated by a lack of physical activity during childhood. Further, promoting active modes for school trips is an opportunity to decrease the morning peak congestion and thereby mitigate externalities of the transportation system. This study introduced a three level nested logit, a well-grounded econometric model that deals with strong assumptions of the multinomial logit specification. Although there have been some efforts and recommendations (Ewing et al., 2004) for applying such a model specification, to the best of our knowledge, this is the first model that is introduced to the literature of school trip mode choice. This study looked at a wide range of explanatory variables and conducted an in-depth analysis of the models. Particularly, we underscored the significance of model misspecification in terms of policy outcomes. For instance, elasticity analysis of the MNL model showed an indirect elasticity of vehicle ownership of −0.13 in the MNL model, while NL model provides different elasticities of −0.12, −0.20, and −0.08, respectively for public, school bus, and walk modes. This misspecification results in overestimating the reduction in the share of students who walk to school when vehicle ownership increases. A wide range of policy-sensitive variables along with their effect magnitude was also discussed and compared with the previous studies. Particularly, we found that one percent increase in the probability of walking to school is expected by every 0.04 percent increase in auto travel time, 0.07 percent increase in the normalized-to-income cost of driving, 0.08 percent decrease in vehicle ownership, 0.03 percent increase in distance to public transit, or 2.37 percent decrease in commute distance. Safety was also found to be very influential on active commuting, such that we found addressing the safety concern of parents could increase propensity of active commuting to school by around 60 percent. Yet, this study has the following limitations that could be possible avenues for future research.

- Trips of students who take transit to school should be partially considered as active (Morency et al., 2011), since they need to walk to the nearest bus station. This could be addressed by developing a cross nested logit model, and setting the public transit option in the *active* limb as well as the *non-active* limb.
- Built-environment variables such as density of green space, school, sidewalk and other land-use variables that are expected to promote walking trips were not utilized, due to unavailability of disaggregate data.
- School trips are the focus of this study, although walking could be promoted in other trips such as shopping and recreational trips.
- A systematic taste variation for cost of travel is considered in this study, while a mixed nested logit specification allows for accounting for a random taste variation. This is expected to provide a more realistic analysis of pricing scenarios.
- Evaluating latent variables to investigate travel behavior in school trips is a useful attitude which is not included in the current study. To consider latent variables and parental attitudes for each concern more information is needed which were not included in the dataset.

Acknowledgment

We would like to thank Professor William Greene for the helpful comments. The sole responsibility for the content of this paper, however, lies with the authors. We also wish to express our deep regards to Shahrbanou Khaniki for her kind assistance in data collection.

References

Alemu, D.D., Tsutsumi, J.G., 2011. Determinants and spatial variability of after-school travel by teenagers. J. Transp. Geogr. 19 (4), 876–881.
Andersen, L.B., Wedderkopp, N., Hansen, H.S., Cooper, A.R., Froberg, K., 2003. Biological cardiovascular risk factors cluster in Danish children and adolescents: the European youth heart study. Prev. Med. 37, 363–367.
Andersen, L.B., Harro, M., Sardinha, L.B., Froberg, K., Ekelund, U., Brage, S., Anderssen, S.A., 2006. Physical activity and clustered cardiovascular risk in children: a cross-sectional study (The European Youth Heart Study). Lancet 368, 299–304.
Ben-Akiva, M., Lerman, S., 1985. Discrete Choice Analysis. MIT Press, London.
Cavill, N., Kahlmeier, S., Rutter, H., Racioppi, F., Oja, P., 2008. Economic analyses of transport infrastructure and policies including health effects related to cycling and walking: a systematic review. Transp. Policy 15, 291–304.