Effects of Mode Shares on Mode Choice

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December 12, 2011

Abstract

This study considers the influence of the knowledge of existing mode shares on travelers mode choice. This contrasts with traditional mode choice models, where the main objective is to predict the overall mode shares as the aggregate of individual mode choices according to variables encompassing attributes of the modes, and characteristics of the travelers. In this study, a computer-administered adaptive stated preference survey is developed and applied to a sample of subjects selected from the University of Minnesota. The results indicate that the presence of mode shares in the mode choice model does influence the decision of travelers.

Keywords: *mode choice, mode shares, mixed logit, stated preference.*

Word Count: *5,197*
Word Count incl. figures and tables: *6,697*

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1 Introduction

In principle, mode shares are the outcome of the choices of individual travelers. These decisions are based on several groups of relevant factors including characteristics of the travelers (e.g. auto availability/ownership, driving license, income), characteristics of their environment (residential density), characteristics of the journey (trip purpose, time of day), and characteristics of the facilities (travel time, monetary costs, parking services, quality of service).

Traditionally, the main purpose of developing mode-choice models has been to predict mode shares. This statement is true for both aggregate and disaggregate modeling efforts. Aggregate models consider average characteristics of travelers (and/or the journey and facilities) based on intra- and inter-zonal information, and thus are hard to justify behaviorally as they are based on the representative agent assumption. This ignores important factors such as the heterogeneous behavior of travelers. Disaggregate models have their roots in consumer behavior, and are based on micro data (observed choices of individual units, household units, and other similar agents). Typically, these models allow for a more realistic representation by using utility functions including several key variables such as the attributes of the modes (e.g. travel time, travel costs) and the characteristics (e.g. income, gender) of the travelers (26).

In this study, the mode shares play a different role. Instead of looking at the effects of micro behaviors on macro outcomes, here we look at the feedback from macro-outcomes to the micro-behavior. The main objective is on exploring the effect of the aggregate mode share on travelers individual mode choice decisions. In addition, other questions are also explored such as whether a dominant mode (i.e. a mode with highest share) is likely to exert a pull (attraction) on travelers. In other words, the study explores the persuasion of mode shares as a source of information for travelers to base their choices. It should be noted that the interpretation travelers may give to mode shares may be different across them. For example one hypothesis for the increase in bicycling is simply the increase in bicycling, i.e. it is more socially acceptable to bike if more people do it. This has several possible mechanisms, one is simple copying behavior, if instead of gathering their own data, people rely (at least in part) on information collected and processed into decisions by others when making decisions, they are in part deciding based on copying. We might suppose copying is proportional to observations, such that the amount of copying increases with the number of originals. Second is a substantive change in the environment, cities with more bicyclists are safer to bicycle in (in terms of crash-rate), perhaps because car drivers have more experience safely interacting in an environment with bicycles. Cities with more bicyclists will also have more demand for bicycle facilities, which in a virtuous cycle, reduces travel time, making it easier and more attractive to bike, which encourages more riders. The same kinds of mechanisms apply to other modes (transit, automobile).

High mode shares may be interpreted by travelers as a higher level of service and/or more widespread availability of a mode' facilities. It may also serve as a signal of what others find acceptable. The exploratory analysis presented here is based on stated preference data. The main reason is because mode shares are outcomes of individual mode choices, and thus once the choices of the aggregate of travelers are made, it is difficult to offer alternative choice situations to subjects or at least alternative choice situations with significant variation. This is discussed further in the subsequent sections.

In contrast, high mode share may be taken as a crowding effect, low auto mode share indicates less congestion, high transit mode share indicates crowding. Some people may choose to be contrarian to avoid the crowd.

The remainder of the study is organized as follows: Section 2 presents a literature review briefly covering the principal areas of research in travelers' mode choice. Section 3 presents the data collection effort, descriptive statistics of the data and the econometric model used in the analysis. That is followed in Sections 4 and 5 with a discussion of the results and concluding remarks respectively.

2 Literature Review

The mode choice of travelers have been extensively studied in the transportation research literature. Initially through the development of the so-called aggregate models to predict mode shares. These models consider the mode choices made by representative individuals with the average characteristics of travelers in geographic zones. However, these models fell out of favor for the (behavioral based) disaggregate models described in detail in Domencich and McFadden (14). The disaggregate models of mode choice are mostly based on *Random Utility Theory*. The main idea is that individuals are rational, and thus select their optimal choice (i.e. the choice with the highest utility) from a set of alternatives according to the utility associated with each alternative. The utility (associated with each mode) is represented as a mathematical function of attributes (e.g. travel time, travel costs) specific to each mode of travel, and the characteristics (e.g. income, gender) of the travelers. Furthermore, the optimization process of travelers is considered inaccurate due to perception error, and computational issues, as well as the inability of the analyst to measure all relevant attributes. Therefore, utility functions are assumed to have a deterministic component (i.e. systematic utility), and a stochastic component (i.e. unsystematic utility or error term). The systematic utility includes the attributes the analyst considers relevant, and the mathematical relationship he presumes they share. On the other hand, the unsystematic utility allows for different substitution patterns that may be adequate depending on the data, and the choices involved (i.e. distributional function assumptions, correlation among alternatives, heteroskedasticity, and others; see (24), Chp. 3).

There are several aspects that researchers have investigated with respect to mode-choice models to date. Among these are: trip purpose (e.g. commute, leisure); mode types (e.g. bike, walking); mode attributes (e.g. travel time); travelers characteristics (e.g. income), features of the built environment; and data type/sources (3).

Trip purpose refers to the travelers' intentions with regards to their prospective destinations and activities. Generally, mode choice models has been developed for commute trips. This may be because of data availability. The general idea is that travelers will evaluate their mode choices differently depending on their trip purpose (13).

Travel time and out of pocket travel costs (e.g. fares, tolls) constitute the main relevant factors in explaining mode choice decisions. Travelers have a fixed amount of time to allocate to different activities as well as a fixed amount of wealth (i.e. income) to allocate to distinct consumption activities. Increased expenditure in either of these therefore translates into disutilities to travelers. Disutilities attached to travel time could further be divided into other components. For example, travelers may incur higher disutility for time spent waiting in comparison to the time spent traveling inside their vehicles (4, 28).The marginal rate of substitution between travel time and monetary cost variables serves to estimate the valuation of travel time savings in disaggregate models (18). Recently, travel time reliability measures have also been incorporated into mode-choice models, and a marginal rate of substitution (the value of travel time reliability) between an attribute measuring reliability (e.g. standard deviation) and travel cost has been estimated (see Carrion and Levinson (10) for a review.) In addition, unobserved heterogeneity among travelers especially with regards to travel time variable in mode-choice models has become increasingly important (e.g. (15)). Other attributes of importance include comfort, convenience, and safety. However, these attributes are attitudinal, and hard to accurately ascertain in contrast to attributes such as travel time though Recker and Golob (30) provides an example where a mode choice model specified only with attitudinal attributes performs as well as a mode choice model with only time and costs attributes.

Travelers' characteristics have been incorporated in mode choice models in order to control for (observed) heterogeneity. The evaluation of attributes may also differ across travelers, and thus the inclusion of travelers' characteristics allows for market segmentation. Several studies have shown the importance of income, gender, auto ownership, age, occupation, number of licensed drivers in the household, and others (22).

The importance of the built environment in the travelers' decision-making process continues to be a topic of debate and polar disagreement. One line of research asserts the existence of a strong relationship between the built environment and travel behavior (e.g. (11, 21)). Another line argues that if such a relationship exists at all, its impact is minimal (e.g. (12), (9)). Furthermore, others (e.g. (19, 25)) also argue that sociodemographic variables have a greater significant influence over built environment variables. Efforts of researchers to study the effects of the built environment on travelers mode choice and other choice dimensions continues (see Parthasarathi (27) for a comprehensive review).

Several mode types can be considered as part of the choice set of travelers in mode choice analysis. The inclusion of modes in the travelers' choice set when using revealed data depends on the existence of the mode in the market. These choices can be limited to the automobile and transit or may include carpools and non-motorized alternatives. There are also cases where researchers desire to ascertain the possible demand for modes entering the current market (see for example (8)). Situations where the choices of interest are not yet part of the market can be handled by the collection of stated preference (SP) data. Stated preference experiments put decision makers in a simulated (or fictional) market while revealed preference (RP) refers to observed behavior in an actual market (23).

It has been well known that SP experiments may differ in results from RP. One of the main reasons is the difference behind what individuals say and what they actually do. This difference may be to a myriad of reasons that may be related to how the stated preference experiments resemble reality or emulates the situation the individual will confront in a real market. Unfortunately, it is typically hard to obtain revealed preference data. In some cases, the variables exhibit high levels of multicollinearity as there is not sufficient variation of values of the variables in the real market, and thus stated preference experiments may help. In other cases, real market situations (e.g. a new mode) may yet not exist, and thus revealed preference data cannot be collected. The validity of the preferences collected from SP data may be affected by the lack of realism, and the subject's understanding of the abstract situations. Thus, the subject's mode preferences may not be similar to the ones during their actual trips (16, 23). However, new modeling techniques have been developed to combine RP and SP data, and to correct for the scale issues of one over the other (23). The idea behind these techniques is to ground stated choices to real choices, and to use SP data to stabilize RP data allowing more precise estimates.

3 Data and Methodology

3.1 Recruitment

Subjects were randomly selected from a University of Minnesota staff list excluding students and faculty. Subject recruitment was done through announcements sent through email in the Summer of 2004. Furthermore, subjects had to fulfill the following requirements for their participation:

1. Legal driver,
2. Full-time job and follow a "regular" work schedule
3. The main mode of travel is in the study's choice set (automobile, bike/walking, and transit).

A total of 91 subjects were recruited for the study. Only 76 subjects were left after dropping subjects that did not answer most of the survey questions, and the travel diary.

3.2 Survey Design

The survey is computer administered. It consists of three components: an adaptive stated preference set of questions for the mode shares; a set of questions about sociodemographics and mode preferences (e.g. auto/bike ownership, biking frequency) of the subjects; and a travel diary section for the day of the survey.

In the first component, subjects are given hypothetical situations in which the existing mode shares of the Twin Cities are altered and they are asked which mode they would use under each scenario. The questions start from a mode share distribution that is 85% auto, 10% transit and 5% bike/walk and respondents are asked to select the mode they would use under the given conditions. The mode use distribution is represented using a pie chart, and numerical values. After a selection is made the survey instrument redistributes the mode share so that the value of the share of the selected mode is decreased and that of the other modes is increased. Each subject faces choices under four alternative distributions. An example of the survey presentation is shown in Figure 1.

In the second component, the survey asks the subjects to report their current mode, and other demographic variables that may be important indicators of choice behavior. For example, questions about subjects' age, income, auto/bike ownership are included as well as questions about frequency of biking/walking, and preferred mode for distinct situations such as mode used today, used on summer, and others.

In the third component, a short travel diary (a paper form) has been completed by the subjects prior to taking the SP survey. It retrieves further information with regards to the subjects' chosen mode used to arrive at the University for the survey, number of stops during their trip, travel time and travel distance of the trip (stated according to their perception).

3.3 Estimation of Travel Time

Though each subject reported their travel time to work using a travel diary, this only provided the travel time for their chosen mode. Since travel time by alternative modes from the subject's home to work may influence their choices, estimated travel time for transit, automobile, and bicyclists

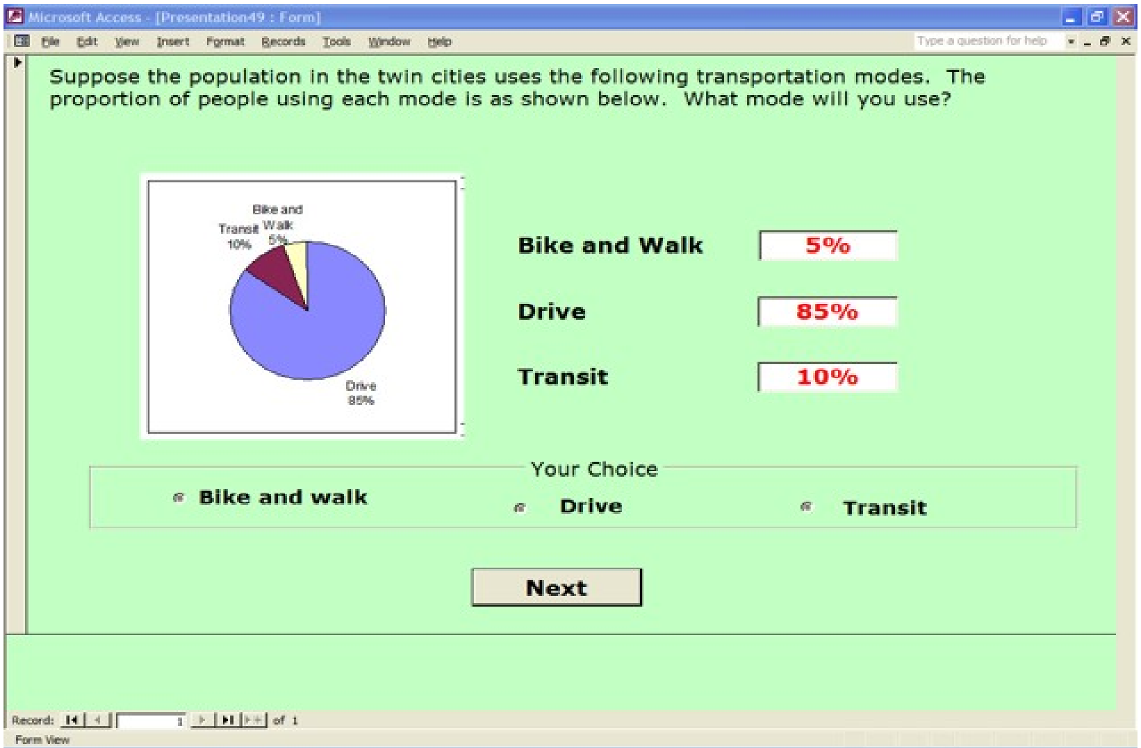

Figure 1: Sample screenshot of survey questions.

for each respondent was used to supplement the data. These estimates were calculated using the Access to Destinations Map which allows users to select two points in the Twin Cities region and produce a travel time estimate for different modes. In this study, the closest time period for the sample is 2005. This map is part of the Access to Destinations Study. In cases where the map could not produce transit travel time estimates, the study uses travel time estimates available at Metro Transit of Twin Cities, the main transit operator in the Twin Cities area.

The travel time estimates (for each mode for each subject) are compared to the travel times reported by the subjects for their chosen mode to arrive to the University. These travel times are divided by mode, and regressions are performed to ascertain their similarity statistically. It is expected that the R-squared for each regression comparing the reported travel times to the map's travel times (referred here as model travel times) should be as close as possible to 1. The regressions are shown in Figure 2 for the three modes of interest.

The regression results indicate that the estimated travel times are reasonable although not terribly accurate. Typically, it is not expected that the R-squared will be too close to 1 as there are many possible discrepancies including variation across routes between home and work locations, seasonal variation, heterogeneity in driver's behavior, special traffic conditions due to incidents, and others. In addition. the small number of observations for Bike and Transit may be a concern. At the moment, these are the only estimates available to the study, and thus are used in the econometric model. The inclusion of the estimates is to ascertain whether the subjects considered travel time differences of the modes during the stated choice phase of the survey (i.e. mode shares' redistribution according to the subjects' choices). The linear regressions are done in the R Statistical Package. Procedures and examples can be found in (20) Chp. 3.

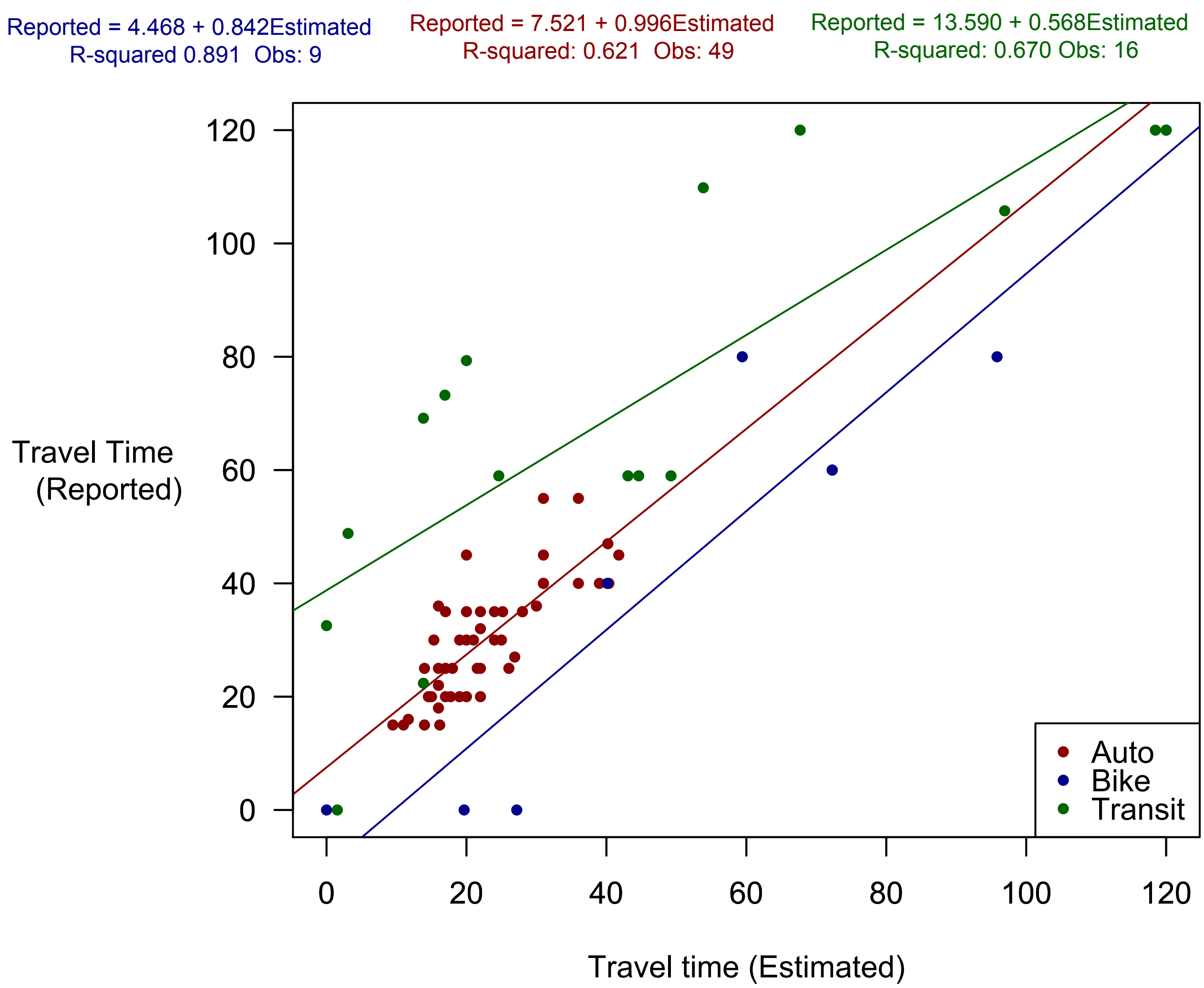

Figure 2: Regression Plot of Reported vs. Estimated Travel Times.

3.4 Descriptive Statistics

Table 1, summarizes socio-demographic information of the subjects. Main difference of the sample vs. the population of the Twin Cities include: higher proportion of females; and subjects are on average older, more educated, and have higher income. Table 2 presents the subjects' mode choices in the following order: (stated) mode chosen at the time of the survey; mode usually preferred; mode preferred during summer; and mode chosen according to travel diary. The subjects favor the automobile in all four situations as their preferred mode. Transit and Biking/Walking compete for the second and third position with regards to subjects' preferences. Subjects seem to prefer alternative modes to the automobile especially during the summer. In addition, it is interesting that there's a difference between the mode shares for the mode chosen at the time of filling the survey, and the mode chosen as indicated in the travel diary. Both choices were indicated at while completing the survey. Table 3 presents the subjects' frequency for biking and walking in the following order: biking for work, biking to any destination, and walking to work. The table indicates that most subjects do not prefer to either walk or bike to work, but more subjects are more willing to bike to work in comparison to walk to work. On the other hand, some subjects do prefer to bike to other destinations.

Table 1: Socio-Demographics attributes of the sample

Number of Subjects		76	
		Sample	Twin Cities
Sex	Male	32.58%	49.40%
	Female	68.42%	50.60%
Age (Mean, Std. Deviation)		(44.03, 10.49)	(34.47, 20.9)
Education	11th grade or less	0.00%	9.40%
	High School	2.63%	49.60%
	Associate	13.16%	7.70%
	Bachelors	50.00%	23.20%
	Graduate or Professional	34.21%	10.10%
Household Income	$49,999 or less	32.89%	45.20%
	$50,000 to $74,999	27.63%	23.30%
	$75,000 to $99,999	17.11%	14.60%
	$100,000 to $149,999	17.11%	11.00%
	$150,000 or more	5.26%	5.90%

The Twin Cities population statistics are obtained from the 2006-2008 American Community Survey (1)

3.5 Econometric Model: Specification and Estimation

The administered survey is analyzed through a random utility model (5). Three systematic utility functions are specified for each alternative in the choice set. The alternatives considered are obtained directly from the survey design, and these are: Bike and Walk, Drive (or automobile), and Transit. Furthermore, a linear in parameters functional form is used for the systematic utility functions. The main reason is because of the exploratory nature of the study. It is unknown at the

Table 2: Modal distribution of Subjects

Number of Subjects	76			
Modes	Today	Usual	Summer	Travel Diary
Automobile	63.16%	61.84%	55.26%	64.47%
Transit	21.05%	27.63%	21.05%	21.05%
Bike	13.16%	9.21%	21.05%	11.85%
Walking	2.63%	1.32%	2.63%	2.63%

Table 3: Cumulative Frequency of Biking and Walking

Number of Subjects	76		
Frequency	Biking to Work	Biking	Walking to Work
Bikes	34.22%	76.32%	18.41%
Everyday	10.53%	11.84%	5.26%
In the last month	21.06%	48.68%	10.52%
In the last three months	21.06%	52.63%	13.15%
In the last twelve months	34.22%	76.32%	18.41%
Never Bikes	65.78%	23.68%	81.59%

moment to the authors what type of nonlinearities will be present, and the main purpose is set on identifying whether the mode shares have any influence on the mode choice process of the travelers.

The explanatory variables considered in the study relate to those discussed previously in the literature review and that are available in the collected data. In addition, the mode shares distributions presented to each traveler for exactly four choice situation are included.

The final selection of the explanatory variables and their specification as either generic or alternative-specific variables was done based on the goodness of fit of the discrete choice model with and without the variables (nested models). Ultimately, the variables selected will be discussed in the subsequent sections along with possible explanations about why other variables were not selected. Moreover, the analysis of panel data such as this one (repeated observations per subject) requires a model that handles explicitly the individual-specific variation (or heterogeneity). Both (2) and (17) discuss and recommend several parametric approaches to model the heterogeneity. In this study, a parametric method of random effects is adopted. The assumption is that the observations for each subject represent a cluster with its own variation (within subject variation), but also variation across clusters may be present (between subject variation).

The random effects specification can be formulated in a mixed multinomial logit model (31). Assume that the utility function a decision-maker k in the set of decision-makers $\mathcal{N}$ associates with alternative j in the set of choices $\mathcal{C}$ for a given choice situation t in the set of choice situations $\mathcal{T}$ is given by:

$$\mathbf{U^k_{jt}} = \mathbf{V^k_{jt}} + \xi^\mathbf{k}_\mathbf{jt} \tag{1}$$

$$\mathbf{U^k_{jt}} = \mathbf{V^k_{jt}} + [\eta^\mathbf{k} + \epsilon^\mathbf{k}_\mathbf{jt}] \tag{2}$$

In the equation (1), $\mathbf{V^k_{jt}}$ is the systematic utility, and $\xi^{\mathbf{k}}_{\mathbf{jt}}$ is the unsystematic utility (or error term). This is the standard functional form for any random utility model. For this case of mixed logit model, the functional form is given by equation (2). The random term is partitioned into two additive parts: The first (η^k) is an individual-specific random vector distributed as a bivariate normal density function (with zero mean vector) as is typically done for random intercept logits (2), and the second (ϵ^k_{jt}) is a random vector identically and independently distributed (i.i.d.) over alternatives and decision-makers following a extreme value type 1 (or Gumbel) distribution.

The likelihood for this mixed logit model is given by:

$$\mathbf{LL} = \mathbf{\Pi}_{\forall \mathbf{k} \in \mathcal{N}} \int_{-\infty}^{\infty} \mathbf{\Pi}_{\forall \mathbf{t} \in \mathcal{T}} \mathbf{\Pi}_{\forall \mathbf{j} \in \mathcal{J}} \left(\frac{\mathbf{exp(V^k_j)}}{\sum_{\mathbf{j=1}}^{\mathbf{J}} \mathbf{exp(V^k_j)}} \right)^{\gamma_{\mathbf{kjt}}} \mathbf{f}(\eta^{\mathbf{k}} | \mathbf{0}, \mathbf{\Sigma}) \mathbf{d}\eta^{\mathbf{k}} \tag{3}$$

Where the γ_{kjt} variable is one for the chosen j alternative of the k decision-maker for choice situation t, and zero otherwise. The function $f(\eta^k|0, \Sigma)$ represents the bivariate normal density with zero mean vector (the mean is estimated by the alternative specific constants of the alternatives), and a zero off diagonal for the covariance matrix (the covariance is assumed to be zero between alternatives). Furthermore, the estimation of the parameters (for a linear in parameters specification, $V^k_j = \beta^T x^k_j$), where β is the coefficient vector, and x^k_j are the vectors of explanatory variables in the regressors matrix) in this model is done using a free software called BIOGEME (6, 7).

3.5.1 Systematic Utility for the models

The additive linear in parameters systematic utility for the alternatives is:

$$\mathbf{U^k_j} = \mathbf{f(S, J, M, C, A)} \tag{4}$$

where

- S: SP Mode Shares variables
- J: Attributes of the Trip
- M: Travelers' Original Mode Preference
- C: Characteristics of the Travelers
- A: Alternative specific constants (ASC)

3.5.2 SP Mode Shares

Two variables are considered to capture the effects of the SP mode shares: ratio of Bike/Walking share to Auto share; and ratio of Transit share to Auto share. The value of these variables will vary from values close to 0 to values close to 1 as the redistribution of mode shares never reduces the auto share below the other two shares. Higher values of the ratios means that the Bike/Walking and Transit shares are closer to the auto share. Furthermore, mode shares are the only set of variables that are specific to the choice situation and are dimensionless. The rest of the variables are specific to the subjects. These variables are alternative specific to the Bike/Walking and Transit alternatives.

3.5.3 Attributes of the Trip

The variable travel time which is a generic is included. The variable's name is self explanatory, and the quantity is obtained according to the section 3.3. It is measured in minutes.

3.5.4 Travelers' Usual Mode Preference

During the survey, travelers were asked to provide their usual mode choices. This variable represents dummy choices where subjects indicate whether they chose drive, transit or biking/walking as their usual mode choice. The variable is specified as an alternative-specific variable. In this way, for each subject there is an additional coefficient added to the alternative recognized as their usual mode. It is specified only in the Bike/Walking and Transit alternatives.

3.5.5 Characteristics of the Travelers

Three characteristics are considered: travelers preference with regards to biking (a dummy variable indicates whether travelers have biked or not to work before; Never Biked); and travelers' telecommuting habits (a dummy variable indicating whether travelers telecommute or not; Telecommute); and travelers' education background (a dummy variable indicating whether the traveler received a Bachelor's or greater degree; BachEduc)

3.5.6 Alternative specific constants

These variables are specified to each alternative. For identification purposes, the alternative specific constant of the auto is set to 0. In addition, the variance of the auto must be set to zero as only two variances can be estimated (see (32)). Furthermore, the random effect can be understood as a random intercept (or alternative specific constants) model. Thus, alternative specific constants represent mean values, and the variances are the random effects deviations.

4 Results and Discussion

Table 4 presents the estimates of the mixed logit model. The goodness of fit statistics (especially the likelihood ratio index, and its adjusted version) indicate that the variables perform significantly better than an empty model (or a model with no parameters), even if the number of variables is taken into account. Furthermore, the standard deviations of the subjects random effects are statistically significant at the 1% level. This indicates that individual-specific effects (unobserved heterogeneity) are present in the data, and thus supports the use of the mixed multinomial logit model as the independence assumption for the error term will be inadequate. In addition, most of the specified variables are found statistically significant, except for the alternative specific constant for Bike/Walking, travel time variable, and the telecommuting variable.

The statistical significance of the travelers' original mode of preference variables (i.e. Bike to work and Transit to work) indicate that the subjects are likely to favor their original mode choices. For example, subjects who arrived at the university by transit will favor the transit alternative, if all else is equal. Likewise, subjects who arrived at the university by bike will favor the the biking/walking alternative, if all else is equal. This is expected as subjects are likely to keep in mind their chosen mode while answering the questions of the survey. In addition, subjects that always choose the same mode to work for a large period of time are likely to remember it as well. In Table 2, it can be seen that the modal distribution across subjects for their modes are very similar for mode chosen today, mode chosen according to travel diary, and their usual choice of mode to work.

In terms of travelers' characteristics, subjects with college degrees of at least Bachelor's were found to favor Bike/Walking, and Transit relative to the auto. This is puzzling as other variables such as income, auto ownership, bike ownership... were found statistically not significant. In addition, it is clear from Table 1 that although most of the subjects (about 65) fall into this category, there are still 11 subjects who do not gain the additional utility. The statistical significance may be due to the characteristics of the jobs of the subjects, or perhaps any bike or transit programs available. For example, the University of Minnesota has MetroPass programs for their employees. Furthermore, subjects that indicated that they have never biked to work were founded to be less likely to favor the Bike/Walking alternative, and subjects that telecommute were found to favor the Bike/Walking or Transit alternatives over auto. It should be noted that only Biking preference (i.e. subjects who have never biked to work) and subjects with college education of at least Bachelor's were the variables statistically significant. Telecommute was close, but it was not found statistically significant even at a 10%.

The estimated travel time variable did not have any statistical significant impact. The reason for this could be due to the survey design. Initially, subjects are asked to choose modes by focusing on the mode shares rather than other attributes. Subjects are only asked to report their travel times for the current mode they chose to arrive to the University. However, subjects may not know the travel times or travel distances of biking and/or transit close to their home locations. Thus, subjects may be familiar with the alternatives they have, but may not be experienced enough to consider them in the presented choices. This is especially likely as some subjects indicated in the survey that they have never biked to work (one of the alternatives).

The SP mode shares variables (i.e. Ratio - Bike to Auto share; and Ratio - Transit to Auto share) are statistically significant at 5% level. This confirms the original hypothesis of mode shares influencing the mode choice of travelers. The sign of the variables is positive. This indicates that the subjects are more attracted to favor the Bike/Walking and/or Transit alternatives as their mode shares increase. Thus, the sign of the variables indicate that subjects (especially those with original mode preference for the auto) are likely to consider Bike/Walking or Transit alternatives as the mode share for the auto reduces, and the mode share for the other two alternatives increases. This agrees with the hypothesis that higher value of mode shares means an increase in the pull (or attraction) of this share over travelers. There are several possible reasons behind the attraction: copying behavior (subjects may favor the alternative with higher shares because other have explored and found that it is adequate); higher mode share may be correlated with better services, and more facilities.

In addition, mode shares at the census tract level from the (1) were initially included in the mode, but later dropped. The reason is because they did not have any statistically significant impact. This is possible for two main reasons: subjects may perceive, but are likely to not know the mode share for their surrounding areas (except perhaps that auto is the dominant mode, and that facilities for bike or transit may exist); and the mode shares are relatively constant across census tracts (i.e. exhibiting similar features such as auto being the dominant mode).

Table 4: Mixed Logit for Mode Choice

Variables	Description	Estimates (T-Stat) Bike/Walking	Auto	Transit
Ratio - Bike to Auto	Alternative Specific Variable (ASV) It is the ratio of the SP Bike share to the auto share	1.28 (2.15) **		
Ratio - Transit to Auto	ASV; It is the ratio of the SP Transit share to the auto share			2.70 (2.00) **
Travel Time	Generic variable (GV); Estimate of travel time for each alternative, see section 3.3	-1.77 (-1.33)	-1.77 (-1.33)	-1.77 (-1.33)
Bike to Work	ASV; dummy variable indicating the chosen mode of the subject to arrive at work	9.02 (2.47) **		
Transit to Work	ASV; dummy variable indicating the chosen mode of the subject to arrive at work			8.46 (3.30) ***
Biking Preference	ASV; dummy variable indicating whether subjects have never biked to work	-5.79 (-2.77) ***		
Telecommuting	ASV; dummy variable indicating whether subjects telecommute	1.39 (1.28)		1.39 (1.28)
4+ Years Degree	ASV; dummy variable indicating whether subjects hold a Bachelors or graduate degree	2.67 (1.86) *		2.67 (1.86) *
Alternative Specific Constant for Bike/Walking	ASV: Intercept	-0.108 (-0.07)		
Standard Deviation for Bike/Walking	ASV: Random Effect for Bike/Walking	4.21 (3.11) ***		
Alternative Specific Constant for Transit	ASV; Intercept			-5.46 (-2.49) **
Standard Deviation for Transit	ASV; Random Effect for Transit			3.40 (2.76) *
Null Log-Likelihood	ll_0	-333.978		
Final Log-Likelihood	$ll_{\hat{\beta}}$	-180.736		
Likelihood ratio index	ρ^2	0.459		
Adj. Likelihood ratio index	Adj-ρ^2	0.423		
Number of subjects		76		
Observations		304		

* is 10% significance level, ** is 5% significance level, *** is 1% significance level

5 Conclusion

The use of disaggregate mode choice modeling has become standard practice among practitioners and researchers in the travel demand field. In this framework decisions are modeled as individual choices made within the confines of a time and income budget, trip characteristics, mode availability, and household constraints. Each decision maker is considered to be independent. Despite these assumptions, that the choice of others is likely to influence our decisions is intuitive - either directly through copying behavior, or indirectly, through the improvements in service that are likely to accompany the well used alternative. However, these influences are difficult to test using revealed data, and more so for mode choice, which does not change significantly over a short period of time. In this study we use Stated Preference data instead to test the influence of changing mode share on individual decisions. The results corroborate the hypothesis that increased mode share in the alternative modes is associated with a higher probability of choosing them. While one additional traveler's mode choice is not likely to change the magnitude of the mode shares dramatically , larger shifts can have a self propagating quality further pushing their own share illustrating the feedback process of the subjects' choices.

While we do not test for nonlinearities, they may exist. Travelers may be attracted to a mode due to high usage only up to a point; a small change in the mode share may have no impact on copying behavior; a larger change may have even larger impacts. Future research is required to expand on these relationships as well as the following points. First, the magnitude of the influence of mode shares when they are included along with the traditional variables (i.e. travel time) explicitly stated in the survey questions. Second, explore the travelers perception with regards to higher vs. lower mode shares. For example, some travelers might believe that smaller mode shares will allow them to move more freely without too much obstruction. In contrast, some travelers might believe that higher mode shares could be correlated with more developed facilities for modes.

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