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A STRUCTURAL EQUATIONS ANALYSIS OF REVEALED AND STATED TRAVEL MODE AND ACTIVITY CHOICES

RYOICHI SAKANO[1] AND JULIAN M. BENJAMIN[2]

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This study extends the structural equations model to incorporate both revealed and stated preference data to analyze activity-based travel behavior. The model is applied to examine the relationship between activities and mode choice on the data from the first wave of the panel study conducted for the Puget Sound Regional Council. It is found that the attitude toward comfort of travel, car requirement for job, and travel time are significant predictors for the mode choice decision. Comparing alternative decision processes, the data support that the mode choice and activity choice decisions are affected by unobserved common factors, and the mode choice and the activity choice decisions are made independently. There is some evidence that the stated-preference model has the same model structure as the revealed-preference model, and the stated-preference data help improve the fit of the entire model.

KEYWORDS: Structural equations model, revealed-stated preference

1. INTRODUCTION

Among the issues of urban transportation, the journey to work by urban commuters has historically received the most attention; almost half of all travel in an urban area is from home to work and back again. The journey to work inherently involves the complex decision process of choice of mode and activities along the route.

The problems of the journey to work have been studied extensively in the past three decades. The decision process of mode choice typically has been analyzed by means of a single equation model, in particular a logit equation, in which the activities along the route are considered as exogenous. Thus, the single stage model implicitly assumes that the activity decision has been made prior to mode choice, that factors which affected the activity decision are different from determinants of mode choice, and that a decision-maker will not change his activity decision along the route. Although there has been a debate over these assumptions, the single stage model is unable to examine these assumptions.

Many studies have focused on the interaction between activities and travel behavior, and analyzed the interaction by various methods based on logit models. Alternatively, the structural equations model can be used to analyze a complex decision-making process involving interactions among decisions. The structural equations model provides a number of advantages. It can explicitly specify an unobserved utility which derives a mode or activity decision as a function of its determinants, and estimate it as a latent variable. The decision-making process and interactions among decisions can be expressed as linear relations among utilities in equations. The relations among utilities can be tested statistically to compare alternative decision-making processes. Thus, structural equations analysis helps us better to understand the decision-making process of travel mode and activity choices and to model their relationship correctly, both of which are fundamental for a statistically valid model estimate and accurate prediction of

[1] Department of Economics and Transportation/Logistics, North Carolina A&T State University, Greensboro, NC 27411, USA. Corresponding author (E-mail: sakanor@ncat.edu).
[2] Department of Economics and Transportation/Logistics, North Carolina A&T State University, Greensboro, NC 27411, USA.

travel behavior. In addition, by applying confirmatory factor analysis as a part of the structural equations model, individual attitude and perception toward travel and activity can be extracted from important rating and agreement questions (e.g. How important is it to be on time? Do you agree that riding a bus is safe?). These unobservable determinants of mode and activity choices can improve its prediction ability.

The interaction between activities and travel behavior can be analyzed more effectively by using both revealed and stated preference data. Revealed preference data reflect the full interaction between activities and travel behavior, but are limited to observed choice sets. On the other hand, stated preference data allow an analysis of a wide variety of conditions and choice sets. It is plausible to observe changes in individual mode and activity choices under hypothetical conditions which may not be present in repeated observations of the same individual. The interaction between activities and travel behavior may be observed more clearly under a wider range of characteristics and responses obtained by the stated preference than what is actually observed in the revealed preference.

The objectives of this study are (1) to propose a structural equations model to analyze the complex decision-making process which involves an interaction between mode and activity choices and (2) to illustrate its estimation using combined revealed preference and stated preference data. This study develops the structural equations model which incorporates both revealed and stated preference data. The model is applied to the first wave of a panel survey which was conducted by the Puget Sound Regional Council. Then, the empirical model is used to compare and examine alternative decision-making processes of mode and activity choices. The paper will contribute to the existing literature on travel behavior in advancing the methodology of structural equations analysis with combined RP-SP data, and by examining various interaction structures between mode choice and activity choice which are often assumed in other empirical works.

2. LITERATURE REVIEW

Travel is a secondary demand where urban travel decisions are made to participate in activities (Hanson, 1986) and urban travelers decide to make trips based on the type of desired activity and time and space constraints (Pas, 1986). Several different approaches have been used to analyze the relationship between activity types, locations and network characteristics in trip chaining where travel decisions are analyzed one by one (e.g. Kitamura and Kermanstrah, 1983; Kitamura, 1983, 1984; Adler and Ben-Akiva, 1979; Damm, 1982). These approaches model either the travel choice to each activity sequentially or several travel choices simultaneously. Recent work on activity analysis of urban travel behavior has extended into more elaborating decision-making processes, and further refinement and complexity of activities in decision-making process. Many studies continue to illustrate the relationship between activities and mode choice (e.g. de Lapperent, 2006; Arentae et al., 2006).

Golob (1996), Golob and McNally (1997), and Lu and Pas (1999) use a structural equations model to analyze activities. One aspect of activity choice in these studies is the mode used to attend the activity. Their models of activity choice include consumer background, the interaction of different activities during the day, the characteristics of modes, and urban geography. Recently, Cao et al. (2007) addressed the questions of whether people move to where activities are accessible by various modes and how people participate in accessible activities, in studies of the built environment. Using a structural equations approach, they conclude that travel attitudes toward modal characteristics affect the residential choice, thus accessibility to activities, and travel behavior.

Other studies model a decision process by using individual attitudes and perceptions along with individual, mode, and activity information to analyze mode choice (Koppelman and Pas, 1980; Benjamin and Sen, 1982). Ben-Akiva et al. (1999) discuss the role of psychological elements in the decision-making process and outline the analytical framework to incorporate unobservable factors (e.g. perception, attitude, preference) in choice model. This framework was applied to model the complex decision-making process of mode and activity choices and their interaction in simultaneous equations (Ben-Akiva et al., 1996; Benjamin et al., 1999). Morikawa et al. (2002) and Johansson et al. (2006) include latent variables representing various personal attitudes and preferences in an analysis of mode choice. In particular, Johansson et al. conclude "our 'latent variable enriched' choice model outperforms a traditional choice model and provides insights into the importance of unobservable variables in mode choice." This framework was extended by Walker (2001) and Ben-Akiva et al. (2002a,b) to combine the structural equations model and the logit model in one analysis.

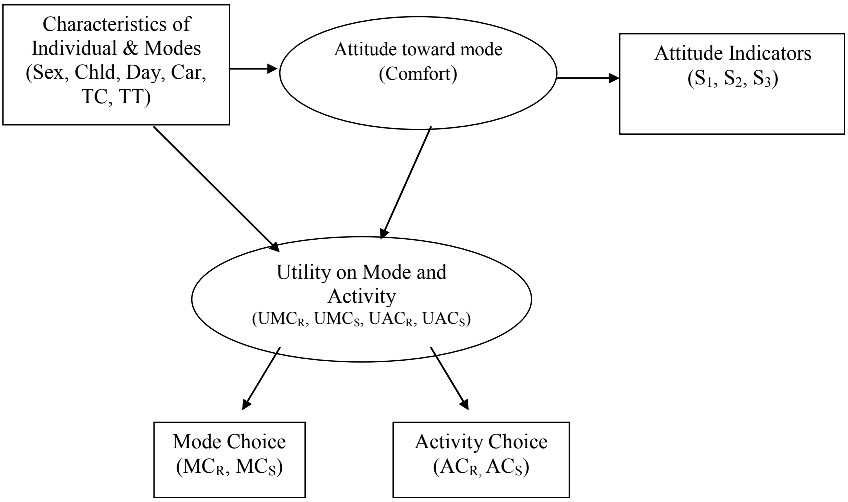
Although there are many shortcomings in stated preference (SP) data, SP data can provide information not available in actual observations. To overcome some of its shortcomings, many researchers developed joint models of RP and SP data to obtain benefits of both types of data where RP data are used to constrain more plausible estimates. Almost all RP-SP combined models in transportation literature are based on conjoint analysis, in particular the nested logit model (Ben-Akiva and Morikawa, 1991; Ben-Akiva et al., 1994) or the random effects heteroscedastic extreme value model (Bhat, 1995). Recently, Brownstone et al. (2000) extended the mixed logit model to jointly model SP and RP data, and Bhat and Castelar (2002) proposed a unified RP-SP framework along this line. However, no study has yet developed the structural equations model in the RP-SP framework.

3. METHODOLOGY

3.1 A conceptual model of commuters' choices

In this study, it is assumed that mode choice (car or bus) is a function of modal characteristics (i.e., bus fare and the price of gasoline), descriptions of the respondent (i.e., age and income), and the additional activities that the respondent will take part in after traveling (i.e., shopping and banking). It is hypothesized that the individual simultaneously decides on his activities leading to the number of stops, and on his mode of transportation to achieve these chosen activities. Various alternative decision processes (i.e., an order of decisions on activity and mode choices) are formally tested through nested model comparisons.

The general conceptual model of consumer choice is presented in Figure 1. The model contains elements of both the transport consumer behavior models proposed by Ben-Akiva et al. (1999, 2002a,b) and the activity structural models proposed by Golob (1996), Golob and McNally (1997), and Lu and Pas (1999). Overall, the model indicates that personal background (e.g. gender and number of children) and transportation systems constraints (e.g. travel cost and time) lead to attitudes and perceptions that result in preferences and utilities to participate in activities and to travel to chosen activities by a set means. These preferences and utilities are reflected in observed decisions (i.e., a particular choice of mode and activities). The decision process is therefore divided into observable (manifest) variables and unobservable (latent) variables. The observable measures are indicated by rectangles and the latent variables by ovals in Figure 1.



Note: Variables in [box] are observable, while variables in [oval] are not observable (latent). Subscript R and S indicate revealed preference variables and stated preference variables, respectively.

FIGURE 1: Basic scheme of decision making of mode and activity choices

3.2. Structural equations model

The analytical procedure is based on a structural equations model using LISREL. This procedure allows specification of variables as latent or manifest, and multiple-equations models where the functional forms among endogenous and exogenous variables are assumed to be linear.

The proposed model is expressed in two equations. The first equation specifies the structure among latent variables such as utilities for modes of transportation and attitude and perception factors, and individual-specific and mode-specific exogenous variables, and is given by a structural equation (1). These latent processes are related to respondents' observed opinions, and mode and activity choices by the measurement equation (2):

Structural equation: $$\eta = \mathbf{B}\eta + \Gamma\mathbf{X} + \zeta, \tag{1}$$

Measurement equation: $$\mathbf{Y} = \Lambda\eta + \varepsilon, \tag{2}$$

where η is a vector of latent variables such as utility of mode and activities and individual attitude toward mode and activities, $\mathbf{X}$ is the vector of observed exogenous variables describing characteristics of individual and mode, $\mathbf{Y}$ is the vector of observed endogenous variables such as opinions and statements, and mode and activity choices measured with errors, ζ is the vector of other exogenous random error variables affecting utility and attitude, but not included in the model, and ε is the vector of measurement errors. Both ζ and ε are assumed to follow i.i.d. across observations, but are allowed to correlate to each other. This model assumes that some determinants of mode and activity choices, which are commonly treated as exogenous variables in the conjoint RP-SP models, are measured with measurement errors. Endogenous latent variables (η), endogenous observed variables (**Y**), exogenous observed variables (**X**), exogenous unaccounted latent variables (ζ), and exogenous measurement errors (ε) in equations (1) and (2) are defined in this study as follows:

$$\eta = \begin{bmatrix} \text{Comfort} \\ \text{UMC} \\ \text{UAC} \end{bmatrix}, \quad \mathbf{Y} = \begin{bmatrix} S_1 \\ S_2 \\ S_3 \\ \text{MC} \\ \text{AC} \end{bmatrix}, \quad \mathbf{X} = \begin{bmatrix} \text{Sex} \\ \text{Chld} \\ \text{Day} \\ \text{Car} \\ \text{TC} \\ \text{TT} \end{bmatrix}, \quad \zeta = \begin{bmatrix} \zeta_{\text{Comfort}} \\ \zeta_{\text{MC}} \\ \zeta_{\text{AC}} \end{bmatrix}, \quad \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_{S1} \\ \varepsilon_{S2} \\ \varepsilon_{S3} \\ \varepsilon_{MC} \\ \varepsilon_{AC} \end{bmatrix},$$

where Comfort is the unobserved endogenous attitude variable, UMC is the unobserved endogenous mode choice utility variable, UAC is the unobserved endogenous activity choice utility variable, S_1, S_2, S_3 are the observed endogenous attitude indicator variables (statements), MC is the observed endogenous mode choice variable, AC is the observed endogenous activity choice variable, Sex, Chld, Day, Car are the observed exogenous individual characteristic variables without measurement errors, and TC, TT are the observed exogenous mode characteristic variables without measurement errors.

All variables and their measurements are defined in Appendix 1. Then, equations (1) and (2) and coefficient matrices (**B**, Γ, and Λ) are expressed in linear equations as follows:

$$\text{Comfort} = \gamma_C \text{ Sex} + \zeta_{\text{Comfort}}, \tag{3a}$$

$$\text{UMC} = \beta_C \text{ Comfort} + \beta_M \text{ UAC} + \gamma_{M1} \text{ Car} + \gamma_{M2} \text{ TC} + \gamma_{M3} \text{ TT} + \zeta_{MC}, \tag{3b}$$

$$\text{UAC} = \beta_A \text{ UMC} + \gamma_{A1} \text{ Sex} + \gamma_{A2} \text{ Chld} + \gamma_{A3} \text{ Day} + \gamma_{A4} \text{ Car} + \zeta_{MC}, \tag{3c}$$

and

$$S_1 = \lambda_{S1} \text{ Comfort} + \varepsilon_{S1}, \tag{4a}$$

$$S_2 = \lambda_{S2} \text{ Comfort} + \varepsilon_{S2}, \tag{4b}$$

$$S_3 = \lambda_{S3} \text{ Comfort} + \varepsilon_{S3}, \tag{4c}$$

$$\text{MC} = \lambda_{MC} \text{ UMC} + \varepsilon_{MC}, \tag{4d}$$

$$\text{AC} = \lambda_{AC} \text{ UAC} + \varepsilon_{AC}. \tag{4e}$$

The structural equations (3a) through (3c) and measurement equations (4a) through (4e) above reflect causal relationships among the variables described in Figure 1. The structural equation (3a) and measurement equations (4a) through (4c) show how the latent attitude variable (comfort of travel mode) is affected by gender among other individual characteristic variables considered and is observed by three indicators (S_1, S_2, and S_3). The structural equation (3b) shows the utility of mode choice (UMC) to be determined by the latent attitude (comfort of travel mode), the utility of activity choice (UAC), the need for a car at work (Car) among other individual characteristics considered, and the travel cost and travel time (TC and TT), among other mode characteristics considered. The utility of activity choice (UAC), shown in the structural equation (3c), is determined by the utility of mode choice (UMC) and four individual characteristics (gender, number of children, number of days at work per week, and need for a car at work).

If there is no causal relationship between two variables, a zero coefficient in $\mathbf{B}$, $\mathbf{\Gamma}$, or $\mathbf{\Lambda}$ is expected and variables are absent in equations. Interaction between mode choice decision and activity choice decision is reflected in non-zero parameters (β_M and β_A) in the structural equations (3b) and (3c). However, the base mode assumes no interaction, so β_M and β_A are both assumed to be zero. This assumption will be formally tested by a t-test on β_M and β_A as well as by likelihood ratio tests. Thus, this model is flexible enough to explicitly model an interaction between decision elements; the decision to use a mode may be affected by the decision to participate in activities (i.e. non-zero β_M) and the decision to participate in activities may be affected by the chosen mode of transportation (i.e. non-zero β_A). The model can test the interaction between decision elements and examine a decision-making process of activities and mode choice.

In addition, the error term in the mode-choice equation is allowed to correlate with the error term in the activity-choice equation (i.e. ζ_{MC} and ζ_{AC}). The correlation between error terms of mode choice and activity choice may be due to the fact that some important individual, mode, and activity characteristics not included in the empirical model may affect both mode choice and activity choice, as Bhat (1997) suggested. Like the seemingly unrelated regression method used by Bhat, this model, which allows a correlation between error terms, can extract a part of the missing effects and, in turn, will lead to more efficient estimates and better prediction.

In order to combine SP and RP data, the model is estimated with two sets of structural equations of mode and activity choices and their measurement equations (i.e., equations (3b), (3c), (4d) and (4e)), one set of equations for the SP data and the other set of equations for the RP data where each model has the same structure expressed in Figure 1. Following the standard assumption of an RP-SP nested-logit model (Ben-Akiva and Morikawa, 1991), the combined model imposes an equality restriction on the parameters between the RP equations and the SP equations (i.e. β_c, β_M, β_A, γ_{M1}, γ_{M2}, γ_{M3}, γ_{A1}, γ_{A2}, γ_{A3}, and γ_{A4}) but allows different variances between the RP structural equations and the SP structural equations; that is, ζ_{RMC} and ζ_{SMC} (ζ_{MC} errors for revealed and stated preference equation, respectively) can be different, and ζ_{RAC} and ζ_{SAC} (ζ_{AC} errors for revealed and stated preference equation, respectively) can be different. This reflects the assumption that RP and SP data have different noise levels. In the framework of the nested-logit model their error variances are related by a scale parameter (μ) where $\mathrm{Var}(\zeta_{RMC}) = \mu_M^2 \mathrm{Var}(\zeta_{SMC})$, $\mathrm{Var}(\zeta_{RAC}) = \mu_A^2 \mathrm{Var}(\zeta_{SAC})$, and $0 \le \mu_M, \mu_A \le 1$ (Ben-Akiva and Morikawa, 1991). In LISREL two sets of equations (3b), (3c), (4d) and (4e) are estimated as a separate group (i.e., RP data as one group and SP data as another group) with an equality constraint on all coefficients and error variances (except for error variances on mode and activity choice equations) between the two groups. Estimated error variances (ζ_{RMC}, ζ_{SMC}, ζ_{RAC} and ζ_{SAC}) are then used to compute scale factors (μ_M and μ_A).

3.3. Estimation method of structural equations model

In the structural equations model shown in equations (3b), (3c), (4d), and (4e) the binary choice variables (MC, AC) are specified as linear functions of explanatory variables (e.g. Sex, Chld, Day, Car, TC, TT) through the utility variables (UMC, UAC). Unlike the regression analysis which focuses on the mean prediction of each observation by minimizing the sum of squared errors or maximizing a likelihood function of errors, the structural equations analysis focuses on predicting the variance-covariance matrix of observed endogenous and exogenous variables of the overall observations, so no distributional assumption is made on an error of individual observation. Therefore, the structural equations analysis does not require a special distributional assumption underlying the logit and probit models used in the regression analysis, but only assumes a linear functional form (Kelloway, 1998, pp. 9-10). Like the classical linear regression analysis, the structural equations analysis assumes all observations to be i.i.d., all error variables ($\boldsymbol{\zeta}$ and $\boldsymbol{\varepsilon}$) to be uncorrelated with exogenous variables ($\mathbf{X}$), and homoscedastic and non-autocorrelated variables to have unbiased and consistent estimates. In addition, the maximum likelihood estimate of the structural equations model assumes all observed variables ($\mathbf{X}$ and $\mathbf{Y}$) to be independently sampled from a multi-normal distribution. The consistency of the estimators from the maximum likelihood method does not depend on the multi-normality of $\mathbf{X}$, but the validity of significance tests (Bollen, 1989, pp. 126). This is problematic for the model with discrete variables. In this study, instead, the weighted least squares (WLS) estimator is applied for all model estimations. The WLS estimator allows for non-normality, is asymptotically efficient, and provides an unbiased and consistent asymptotic covariance matrix of the estimated coefficients, and chi-square test statistics even with discrete variables (Bollen, 1989, pp. 432).

Furthermore, some variables are discrete or dichotomous in the model (i.e. MC, AC, Sex, Chld, Day, Car, S_1, S_2, and S_3). PRELIS software is used to transform these variables to better approximate multi-normality by estimating category thresholds (threshold model). The resulting transformed variables (e.g. MC^*, AC^*) are latent continuous indicators. The relationship between the observed discrete variable and the latent continuous indicator is analogous to the relationship between an observed choice and the underlying utility used in logit models based on the random utility theory. The latent continuous variables (e.g. MC^*, AC^*) are used in place of observed discrete variables (e.g. MC, AC) in equations (3a) through (3c) and (4a) through (4e). Since the structural equations analysis is based on a correlation matrix of observed variables, an asymptotic covariance matrix based on polychoric, polyserial, and tetrachoric correlations rather than the Pearson correlation is estimated along with the respective correlation matrices to reflect this transformation.[3]

In the structural equations analysis, latent factors are estimated in measurement equations by confirmatory factor analysis. Although there is no definite minimum number of indicators required for each latent factor, Bollen (1989, pp. 244) suggests three-indicator rules and two-indicator rules as sufficient conditions to identify latent factors in the measurement model. Empirically, three or more indicators are commonly used for multifactor models in literature. Bollen also states “With more than three indicators, the unifactor model is over-identified.” Following these, the latent attitude variable (comfort of travel mode) is measured by three observed indicators (S_1, S_2, S_3). Since a latent variable is unit free, a coefficient of one indicator is usually assumed to be one to scale the latent variable (i.e. S_1 in this study). On the other hand, in this study both

[3] Econometricians may perceive that the linear model specifications of equation (3b) with (4d) and (3c) with (4e) indicate a limited dependent variable problem. However, the use of polychoric, polyserial, and tetrachoric correlations rather than Pearson correlations transforms discrete variables into continuous variables, and estimates thresholds under an assumption of normal distribution. This is similar to the logit transformation in a linear regression model and analogous to the use of the probit model. The transformation in the structural equations model is superior to a logit transformation, because it estimates threshold points rather than simply converting to a continuous variable. In this sense, it is more like a probit model, but the transformation and estimates of threshold points are made before estimation of coefficients in the structural equations model, rather than jointly with coefficient estimates. This may result in less efficient estimates of the structural equations model than the probit model.

mode utility and activity utility (latent) variables associate only with one observed variable (MC and AC, respectively); it is assumed that both λ_{MC} and λ_{AC} are one and both error variances (ε_{MC} and ε_{AC}) are zero. This means that observed variables and latent variables are identical (i.e. UMC = MC and UAC = AC), so that there will be no identification problem for these variables (UMC and UAC). Therefore, the latent utility variables are not directly estimated in this model as in logit models. This may be considered a limitation of this study due to limited observations (indicators) on mode and activity choices, and the model does not fully take its methodological advantage of treatment of measurement errors from these variables. Note that Bollen (1989, Chapter 5) presents several studies and examples of a single indicator model like the latent mode and activity variables in this study.

The structural equations analysis proposed in this study has a number of methodological advantages over the nested-logit models. First, the structural equations model can explicitly include latent variables such as individual attitude toward travel and individual utilities of mode and activity. Second, the model can use qualitative information such as respondents' perception and attitude statements on the mode of transportation and activities to examine how respondents' perceptions and attitudes affect their mode and activity choices. Although previous studies using structural equation analysis have applied some of these advantages, none of the previous structural equation models incorporate both the revealed and stated preference data in the same manner as the nested-logit models.

4. QUESTIONNAIRE AND SAMPLE

The questions were asked during the first stage of the panel travel study in the Puget Sound area (Puget Sound Regional Council, 1996; Murakami and Ulberg, 1997). Separate questions were asked about family and personal characteristics, travel diaries, and stated preferences (Section E of the original questionnaire) at the same time. The stated preference questions presented details of the attributes of car, carpool and bus under a hypothetical scenario, and were analyzed by Benjamin and Price (1997). The stated preference questions used in the questionnaire are presented in Appendix 2. Transport modes were set to have different levels of factors among respondents, and each factor was arranged in an orthogonal partial-factorial experimental design across respondents. A summary of the factor levels used in the SP questions is also presented in Appendix 2. Only one hypothetical scenario was given to each respondent, and each respondent answered two variables (i.e., mode choice and number of stops).

Of the 5,174 households that participated in the household questionnaire, 645 completed all stated preference questions and lived in an area where both RP and SP data were available for all modes. Of 645 subjects, travel time and travel cost are reasonably estimated for 447 individuals, of which 201 individuals traveled by either driving alone or riding the bus.

Of the 201 subjects, modal preferences were 83.1% driving alone and 16.9% riding the bus, and activity preferences were 50.8% not engaging in an additional activity along the commute route and 49.2% engaging in an additional activity along the commute route. A summary of personal descriptors used in this study is presented in Table 1. Respondents were limited to people who were engaged in work or school trips. The sample data include more males (59%) than females; the vast majority were middle-aged households (92%), the majority without children (65%). About half of households earned around national median incomes (47% between \$30,000 and \$50,000); a relatively large number of respondents were managerial and professional job holders (46%). Workers mostly worked five days a week (79%), and a slight majority of respondents did not require car for their jobs (57%).

TABLE 1: Summary of individual characteristics, mode and activity choices, and importance rating statements

(a) Summary of individual characteristics

Individual characteristics	Category or range	Number of respondents
Gender	Female	83 (41.3%)
	Male	118 (58.7%)
Number of children	None	130 (64.7%)
	1	33 (16.4%)
	2 or more	38 (18.9%)
	Average	0.6
Household Income	\$0 - \$15,000	25 (12.4%)
	\$15,000 - \$30,000	43 (21.4%)
	\$30,000 - \$50,000	95 (47.3%)
	\$50,000 or more	38 (18.9%)
Occupation	Managerial/Professional	93 (46.3%)
	Others	108 (53.7%)
Number of work days per week	1-3	7 (3.5%)
	4	9 (4.5%)
	5	159 (79.1%)
	6	24 (11.9%)
	7	2 (1.0%)
	Average	5.0
Job require car	Yes	87 (43.3%)
	No	114 (56.7%)

(b) Summary of mode and activity choice

Mode	(1) Revealed preference data (extra stops)			(2) Stated preference data (extra stops)		
	No	1 or more	Total	No	1 or more	Total
Car	78	89	167	36	77	113
(SOV)	(38.8%)	(44.3%)	(83.1%)	(17.9%)	(38.3%)	(56.2%)
Bus	24	10	34	66	22	88
	(11.9%)	(5.0%)	(16.9%)	(32.8%)	(11.0%)	(43.8%)
Total	102	99	201	102	99	201
	(50.8%)	(49.3%)	(100%)	(50.8%)	(49.3%)	(100%)

(c) Summary of importance rating statements

Statement	Scale			Average and median
	Not important (1-2)	Important (3-5)	Extremely important (6-7)	
S1. Protection from weather.	24	70	107	5.2
	(11.9%)	(34.9%)	(53.2%)	6
S2. Having a seat.	27	54	120	5.4
	(13.4%)	(27.1%)	(59.7%)	6
S3. Short wait time.	18	43	140	5.6
	(9.0%)	(21.3%)	(69.7%)	6

Along with the household and person surveys, the Puget Sound Transportation Panel Survey included a supplementary attitude survey administered three times over the course of the panel. The perception and needs survey included 91 rating and agreement questions. “Section A: Importance Rating” of the survey included questions, which allowed respondents to rate the importance of seventeen attributes of transportation. All seventeen “Importance Ratings,” along with the questionnaire instruction in the original survey, are presented in Appendix 3.

A choice variable used in the estimation is a binary choice variable between bus and drive-alone as mode choice, and a dichotomous variable between no extra stops and one or more extra stops along the commute route as an activity choice. This measurement of activity is a dichotomous simplification of “number of extra stops” used by Bhat (1997) as a measurement of activity.

5. EMPIRICAL FINDINGS

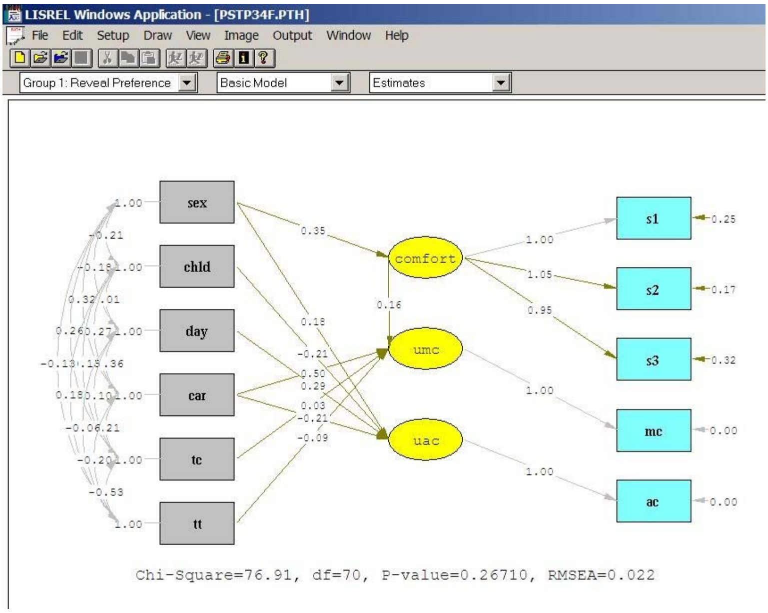
5.1. Model estimation

First, the exploratory factor analysis was performed among seventeen “Importance Rating” questions to identify attitude and preference factors. Five factors were initially identified, and explained twelve “Importance Rating” question results fairly well. Of the five factors, only one was found to be a statistically significant determinant of mode choice later in the structural equations estimation and had more than one indicator. The identified and significant factor is considered to be a “comfort” attitude toward travel mode as observed in the statements. The summary of three “Importance Rating” statements as observed indicators of the “comfort” factor is presented in Table 1c. In all cases, the respondents in each subject considered that these three statements were extremely important.

Including three “Importance Rating” indicators and one factor, the coefficient matrices, $\mathbf{B}$, $\mathbf{\Gamma}$, and $\mathbf{\Lambda}$, of the structural equations models (3a) through (3c) and (4a) through (4e) above were estimated using LISREL. Figure 2 shows the path diagram of the estimated model from LISREL, and Table 2 presents the estimated coefficients and t-statistics of the model. The overall goodness-of-fit statistics indicate a good fit for the model. The chi-square equals 76.91 with 70 degrees of freedom and a p-value equal to 0.27. The goodness-of-fit indices (GFI) are 0.99 for the revealed preference model and 0.99 for the stated preference model. As a whole model system, Bentler and Bonett’s NNFI (Non-Normal Fit Index), which is more relevant to non-normal discrete variables in structural equations models than any other fit indices, is 0.99, indicating that the model is much better fitting to the data than the null model (i.e., the model in which all observed variables are uncorrelated). These summary measures of the overall model indicate that the model fits well to the data.[4]

The estimates of the coefficients of the measurement equations (4a) through (4c) on the confirmatory factor analysis are shown in Table 2a. The variables S1 to S3 are the responses to “Importance Rating” questions regarding comfort of travel mode. As expected, all three indicators are positively significantly related to the underlying “comfort” factor, with R^2 ranging from 0.68 to 0.83. Table 2b presents the estimate for the coefficient of determinant of latent attitude variable on equation (3a). Among seven characteristic variables of a respondent, only gender is a significant predictor of the latent attitude variable “comfort” factor of travel mode. A positive estimated coefficient suggests that females consider “comfort” factor more important.

[4] The base specification model was also estimated by the maximum likelihood method, which is more robust in the small sample. In general, the estimated coefficients are very close to the WLS estimates reported here, and still significant except for an estimated coefficient of travel time variable becoming insignificant. The Satorra-Bentler scaled chi-square, which is consistent for the maximum likelihood estimates with discrete variables, is 0.54 with a p-value equal to 1.00, indicating extremely good fit of model with the data.



Note: Observed endogenous variables (mc and ac) are latent continuous variables from PRELIS. A correlation between errors on UMC and UAC variables was estimated as shown on Table 2c, but is not shown on the path diagram.

FIGURE 2: Path diagram of base specification model (LISREL output)

The estimates for the coefficients of the structural equations (3b) and (3c) are presented in Table 2c. Four structural equations are actually estimated; two for revealed preference (RP) data and the other two for stated preference (SP) data, where RP data are travel cost and travel time at current conditions and SP data are those under a hypothetical condition. Since the coefficients on stated preference equations are constrained to be equal to coefficients on revealed preference equations, only estimated coefficients on revealed preference equations are presented. The R^2s for the utility functions of revealed and stated mode choice are 0.33 and 0.31, respectively, and those for the utility functions of revealed and stated activity choice are 0.19 and 0.19, respectively. Comparing estimated error variances of RP equations with those of SP equations, a scale parameter was computed as a square-root of the ratio of an estimated error variance of the RP equation to an estimated error variance of the SP equation for each of the structural equations (3b) and (3c): 0.985 for mode choice and 1.00 for activity choice. As expected the estimated scale parameters are no more than unity, but these estimates are noticeably much larger than other studies (e.g. Ben-Akiva and Morikawa, 1991).

The estimated coefficients of the mode choice equation indicate that a commuter is more likely to take a bus if his job does not require a car. As expected, the negatively significant estimated coefficient of travel time variable indicates that a longer travel time on a bus over driving alone makes a bus a less favorable travel mode and commuters less likely to take a bus. The estimated coefficient of the travel cost variable is insignificant and has an unexpected positive sign. In addition to observed personal characteristics and travel cost and time, the commuter's attitude has an important role in the mode choice decision. The utility of the bus mode choice is positively related to the attitude toward comfort of travel mode. This indicates that a person who considers comfortable travel to be important is more likely to use the bus and less likely to drive alone. Thus, a latent attitude factor is as important a determinant as observed personal characteristics. Although gender is not a direct determinant of mode choice, it affects the mode choice decision through the latent attitude variable of "comfort" of travel mode. Female commuters consider comfort of travel mode more important, so they are more likely to choose bus mode. For the activity choice equation, commuters are more likely to take extra stops and engage in additional activities if they are female, have fewer children, are frequent commuters, and their jobs require a car.

TABLE 2: Estimates of the base model

(a) Measurement equations

Endogenous variables	Comfort factor (t-statistic)	R^2	
S1. Protection from weather.	1.0	0.75	Equation (4a)
S2. Having a seat.	1.05 (24.09)	0.83	Equation (4b)
S3. Short wait time.	0.95 (25.67)	0.68	Equation (4c)

(b) Structural equation: attitude

Independent variable	Equation (3a) Comfort factor (t-statistic)
SEX	0.35 (8.35)
R^2	0.16

(c) Structural equations: utility functions

Independent variable		Equation (3b) Utility for bus mode [UMC] (t-statistic)	Equation (3c) Utility for extra stops [UAC] (t-statistic)
Comfort factor		0.16 (2.64)	
SEX			0.18 (2.48)
CHLD			-0.21 (-3.10)
DAY			0.29 (4.89)
CAR		0.50 (8.44)	-0.21 (-2.89)
RTC and STC		0.027 (1.08)	
RTT and STT		-0.085 (-3.72)	
R^2	Revealed preference	0.33	0.19
	Stated preference	0.31	0.19
Var(ε)	Revealed preference	0.67	0.81
	Stated preference	0.69	0.81
	Scale parameter (μ)	0.985	1.0
Error covariance between mode and activity choices		-0.45 (-5.98)	

5.2. Alternative specification models and tests of RP-SP data

The estimated model implicitly assumes that the mode choice and activity choice are made independently, as evident from lack of interaction terms in the mode and activity equations, while allowing correlation between error terms to take into account any unobserved common factors. Four alternative specification models, based on different underlying decision-making processes, are also estimated. Table 3 presents the estimated coefficients of interactive variables in different specification models and the overall goodness-of-fit statistics. In all alternative specification models which include an interaction term(s) between mode and activity equations, a correlation between error terms of two equations is omitted due to the under-identification problem (i.e., LISREL estimate of the model with both the interaction term and the error correlation resulted in negative estimated error terms, indicating a specification problem). First, the alternative specification models 1 and 2 show a negatively significant effect between the mode choice variable and the activity choice variable. Although the formal likelihood ratio test cannot be performed because these models have exactly the same number of parameters to be estimated as the base specification model, noticeably deteriorating chi-squared statistics of these alternative specification models (i.e. larger chi-squared statistics indicate less fit of model to the data) indicate that the alternative specifications with one-way interaction term do not explain the relationship between the mode choice and activity choice variables well as compared with the base specification model with the error correlation. A negative estimated coefficient on the interaction term may suggest that the interaction term in these alternative specification models simply mimics a negative error correlation between two dependent variables. Secondly, the alternative specification model 3, which includes two-way interaction terms, also results in deteriorating chi-squared statistics over the base specification model. The likelihood ratio test, based on the chi-square statistics and degrees of freedom of the alternative specification model 3 and the base specification model, clearly rejects the alternative specification model 3 against the base specification model at 5% level of significance.[5] The AIC (Akaike Information Criterion), a commonly used model-fit index for comparing models, also indicates that the base specification model is best specified among all tested specifications.[6] Finally, the importance of error correlation was formally tested on alternative specification 4, which was easily rejected at 1% level of significance against the base specification model. Thus, the data clearly suggest that the mode choice and activity choice decisions are made independently, and that unobserved common factors affect both mode and activity choice decisions. This confirms Bhat's (1997) finding of a significant unobserved common factor affecting mode and activity choice decisions in the seemingly unrelated regression analysis of the logit model. However, by assumption Bhat did not examine nor test statistically an interaction between the mode and activity decisions.

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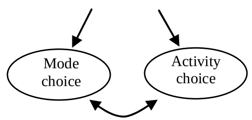
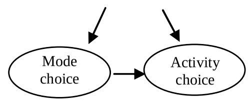
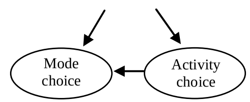
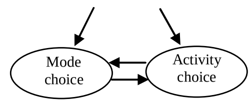
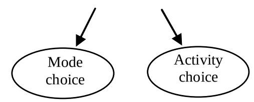
[5] A statistic, a difference in chi-square statistics between the basic specification model and the alternative specification models, has a chi-square distribution with a degree of freedom equal to the difference in degrees of freedom of the two models. See Bollen (1989, pp. 292) for details.

[6] AIC is similar to the adjusted R-square. The chi-square statistic will always decrease when a new relationship is added to the structural equations model, just as an R-square always increases as another variable is added on a regression equation. AIC takes into account the degree of freedom and compares the benefit of adding a relationship (lower chi-square statistic) with the cost (loss of degree of freedom and redundancy of the relationship) as an adjusted R-square does in a regression analysis.

TABLE 3: Alternative decision-making processes and model specifications

	Base specification (Independent decisions and affected by common unobserved factors)	Alternative specification 1 (Mode decision first)	Alternative specification 2 (Activity decision first)	Alternative specification 3 (Joint decisions)	Alternative specification 4 (Independent decisions)
Model					
Coeff. (t-stat.)	MC→AC: AC→MC:	MC→AC: -0.58 (-5.42) AC→MC:	MC→AC: AC→MC: -0.44 (-5.77)	MC→AC: -1.25 (-7.04) AC→MC: 0.60 (3.72)	MC→AC: AC→MC:
Error cov.	-0.45 (-5.98)	____	____	____	____
χ^2(df)	76.91 (70)	83.08 (70)	86.95 (70)	80.40 (69)	126.15 (71)
AIC	200.91	207.08	210.95	206.40	248.15
ECVI	0.50	0.52	0.53	0.52	0.62
Likelihood ratio test	____	6.17 (df = 0)	10.04 (df = 0)	3.49 (df = 1) (p-value = 0.062)	49.24 (df = 1) (p-value = 0.000)

Another assumption imposed on the model is the equality of coefficients between the RP model and the SP model. It is possible that the coefficients of variables in the SP model are different from those of the RP model. The model was re-estimated with no equality constraint. The estimated coefficients of measurement equations for latent attitude variable (i.e. equations (4a) through (4c)) are almost identical between the RP and SP models, mainly because these variables are identical between the two models. However, there were noticeable differences in estimated coefficients on mode and activity choice equations between the RP and SP models. With no equality constraint, the overall model yields 51.30 of the chi-square statistic with 54 degrees of freedom. The model seems to fit better without equality constraints. Again, the likelihood ratio test is performed between the model with equality constraint and one without. The likelihood ratio test statistic is 25.61 (= 76.91 – 51.30). With 16 degrees of freedom (= 70 – 54), the p-value is 0.060, so the equality assumption cannot be rejected at 5% level of significance. Furthermore, the AIC statistic of the model without equality constraint is 207.30, which is greater than the AIC of the mode with equality constraint (200.91), indicating that the equality constraint is acceptable.

Although a large number of empirical works using the RP-SP data on the nested-logit model have supported the validity and usefulness of incorporating the SP data into the RP data, it is not yet known for the structural equations analysis. The base specification model and the data in this study are used to examine an effect of the SP data on the model estimate in the structural equations analysis. Because the RP-SP model and the RP-only model use different samples sizes (where the SP data are considered as additional samples with extra noise), standard statistical tests such as the likelihood ratio test cannot be applied to examine the validity of use of the SP data. Instead, the goodness-of-fit indices of the two models are compared to examine how well each model fits to its own data. The normed fit index (NFI), like the R-square on a regression model, measures how much better the model fits as compared to the null model (i.e., the model in which all observed variables are uncorrelated). This index is 0.96 for the RP-SP model and 0.98 for the RP-only model, indicating that the RP-only model fits better with its RP-only data than the RP-SP model with the combined RP-SP data. This result is no surprise, because the SP data inherently have greater noise than the RP data, so the SP data are expected to fit the model less. However, taking account of degree of freedom, the James-Mulaik-Brett parsimony normed fit index is 0.61 for the RP-SP model and 0.48 for the RP-only model, suggesting that additional data which increases the degree of freedom helps improve its fit. In addition, the expected cross-validation index (ECVI) is 0.79 for the RP-SP model and 0.86 for the RP-only model. Similar to the AIC, the lower the ECVI, the better the fit, taking into account the degree of freedom. Therefore, the SP data seems to help improve the estimate of the model.

6. CONCLUSIONS

This study extends previous structural equations models by incorporating both revealed and stated preference data in the same manner as the RP-SP nested-logit models do. The structural equations analysis is used to examine the various decision-making processes on mode and activity choices. The structural equations model can extract personal attitudes and perceptions and consider measurement errors. As an application example, the Puget Sound Panel Study data shows that (1) the decision regarding extra stops (activities) along the route and the decision on mode choice are affected by common unobserved factors, (2) the mode choice and activity choice decisions are made independently, (3) personal attitude and perception are indeed important determinants of mode choice, and (4) the RP-SP model can help improve the fit of the model over the RP-only model.

The model presented in this study can be extended to the analysis of more complex decision-making processes involving more detailed information on modes, activities, and times. One limitation of the structural equations model is its difficulty to incorporate more than two choices. Each additional choice requires another equation and the corresponding coefficients to be estimated. An empirical model of even four choices (e.g. mode choices of drive-alone, car-pooling, bus or train, and bicycle) involves too many parameters to be estimated, requires much greater sample size, and becomes computationally intractable in estimation even with a moderate number of exogenous variables in the model. Another limitation of structural equations analysis is its use of polychoric, polyserial, and tetrachoric correlations. As mentioned earlier, it is analogous to a logit transformation in regression analysis, so it does not match to more sophisticated estimation methods like mixed logit. In addition, structural equations analysis examines only the correlation matrix of observed variables rather than individual observations, so it ignores any systematic variations among observations and is less efficient than generalized least squared estimators of regression models. Lastly, because there is only one observation for each of mode choice and activity choice, the empirical model was not able to estimate unobserved utilities (latent factors) associated with mode choice and activity choice in the structural equations. Multiple observations of commuters' mode and activity choices, or measurement of other indicators associated with these choices, may be used to identify these latent factors of interest. Alternatively, an integrated analysis of the structural equations model and the logit model developed by Walker (2001) and Ben-Akiva et al. (2002a,b) can be extended in the RP-SP framework to overcome these limitations, while maintaining many advantages of the structural equations analysis in this study.

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REFERENCES

Adler, T. and Ben-Akiva, M. (1979) A theoretical and empirical model of trip chaining behavior. Transportation Research Part B, 13, 243-257.

Arentae, T, Aloys, B., Maarten, P. and Timmermans, H. (2006) From activity-based modeling to social event-based modeling: conceptual framework and empirical results. In IATBR (International Association for Travel Behavior Research), 11th International Conference on Travel Behavior Research. Kyoto, Japan 16-20 August 2006.

Ben-Akiva, M. and Morikawa, T. (1991) Estimation of travel demand models from multiple data sources. In M. Koshi (ed.), Transportation and Traffic Theory, Proceedings of the 11th ISTTT, Elsevier Science, Amsterdam, pp. 461-476.

Ben-Akiva, M., Bradley, M., Morikawa, T., Benjamin, J., Novak, T., Oppewal, H. and Rao, V. (1994) Combining revealed and stated preferences data. Marketing Letters, 5, 335-350.

Ben-Akiva, M., Benjamin, J., Lauprette, G. and Polydoropoulou, A. (1996) Impact of advance public transportation systems of travel by Dial-a-Ride. Transportation Research Record, 1557, 73-79.

Ben-Akiva, M., McFadden, D., Garling, T., Gopinath, D., Walker, J., Bolduc, D., Borsch-Supan, A., Delquie, P., Larichev, O., Morikawa, T., Polydoropoulou, A. and Rao, V. (1999) Extended framework for modeling choice behavior. Marketing Letters, 10, 187-203.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D., Daly, A., de Palma, A., Gopinath, D., Karlstrom, A. and Munizaga, M. (2002a) Hybrid choice models: progress and challenges. Marketing Letters, 13, 163-175.

Ben-Akiva, M., Walker, J., Bernardino, A., Gopinath, D., Morikawa, T. and Polydoropoulou, A. (2002b) Integration of choice and latent variable models. In H. Mahmassani (ed.), Perpetual Motion: Travel Behavior Research Opportunities and Application Challenges, Elsevier Science, Amsterdam, pp. 431-470.

Benjamin, J. and Price, G. (1997) A multiple response conjoint analysis of regional urban transportation. In IATBR (International Association for Travel Behavior Research), 8th International Conference on Travel Behavior Research. Austin, Texas September 1997.

Benjamin, J. and Sen, L. (1982) A Manual of Procedures to Analyze Attitudes toward Transportation (DOT-RSPA-DMA-50/82/16), USDOT, Washington D.C.

Benjamin, J., Kurauci, S., Morikawa, T., Polydoropoulou, A., Sasaki, K. and Ben-Akiva, M. (1999) Forecasting paratransit ridership using discrete choice models with explicit consideration of availability. Transportation Research Record, 1618, 60-68.

Bhat, C.R. (1995) A heteroscedastic extreme value model of intercity travel mode choice. Transportation Research Part B, 29, 471-483.

Bhat, C.R. (1997) Work travel mode choice and number of non-work commute stops. Transportation Research Part B, 31, 41-54.

Bhat, C.R. and Castelar, S. (2002) A unified mixed logit framework for modeling revealed and stated preferences: formulation and application to congestion pricing analysis in the San Francisco Bay Area. Transportation Research Part B, 36, 593-616.

Bollen, K. (1989) Structural Equations with Latent Variables. John Wiley & Sons, New York.

Brownstone, D., Bunch, D. and Train, K. (2000) Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transportation Research Part B, 34, 315-338.

Cao, X., Mokhtarian, P.L. and Handy, S.L. (2007) Do changes in neighborhood characteristics lead to changes in travel behavior? A structural equations modeling approach. Transportation, 34, 535-556.

Damm, D. (1982) Parameters of activity behavior for use in travel analysis. Transportation Research Part A, 16, 135-148.

de Lapperent, M. (2006) The choice of transportation for home to work trips in the French Parisian region; applications of mixed GEV models with non-linear utility functions. In IATBR (International Association for Travel Behavior Research), 11th International Conference on Travel Behavior Research. Kyoto, Japan 16-20 August 2006.

Golob, T. (1996) Model of household demand for activity participation and mobility. In T. Gärling, T. Laitilla and K. Westin (eds.), Theoretical Foundations of Travel Choice Modeling, Pergamon, Oxford, pp. 365-398.
Golob, T. and McNally, M. (1997) A model of activity participation and travel interactions between household heads. Transportation Research Part B, 31, 177-194.
Hanson, S. (1986) Dimensions of the urban transportation problem. In S. Hanson (ed.), The Geography of Urban Transportation, Guilford Press, New York, pp. 3-23.
Johansson, M., Heldt, T. and Johansson, P. (2006) The effects of attitudes and personality traits on mode choice. Transportation Research Part A, 40, 507-525.
Kelloway, K. (1998) Using LISREL for Structural Equation Modeling: A Researcher's Guide, Sage Publications, Thousand Oaks, CA.
Kitamura, R. (1983) A sequential trip chaining approach to trip chaining behavior. In TRB (Transportation Research Board), 63rd Annual Meeting, January 1983, Washington, D.C.
Kitamura, R. (1984) A model of daily time allocation to discretionary out-of-home activities and trips. Transportation Research Part B, 18, 255-266.
Kitamura, R. and Kermanshah, M. (1983) Identifying time and history dependencies of activity choice. Transportation Research Record, 944, 22-30.
Koppelman, F. and Pas, E.I. (1980) Travel-choice behavior: models of perceptions, feelings, preference, and choice. Transportation Research Record, 765, 26-33.
Lu, X. and Pas, E.I. (1999) Socio-demographics, activity participation and travel behavior. Transportation Research Part A, 33, 1-18.
Morikawa, T., Ben-Akiva, M. and McFadden, D. (2002) Discrete choice models incorporating revealed preferences and psychometric data. In P.H. Franses and A.L. Montgomery (eds.), Econometric Models in Marketing, Advances in Econometrics, Vol. 16, Elsevier Science, Oxford, pp. 29-55.
Murakami, E. and Ulberg, C. (1997) The Puget Sound transportation panel. In T. Golob, R. Kitamura, and L. Long (eds.), Panels for Transportation Planning: Methods and Applications, Kluwer, Norwell, MA, pp. 159-192.
Pas, E.I. (1986) The urban transportation planning process. In S. Hanson (ed.), The Geography of Urban Transportation, Guilford Press, New York, pp. 49-72.
Puget Sound Regional Council (1996) Puget Sound Transportation Panel Survey 1989 – 1994. PSRC, Seattle, WA.
Walker, J. (2001) Extended discrete choice models: integrated framework, flexible error structures, and latent variables. Ph.D. Massachusetts Institute of Technology.

APPENDIX 1. DEFINITION OF VARIABLES

Variables		Name	Description
Socio-demographic variables	SEX	Gender of respondent	1=Male, 2=Female
	CHLD	Number of children	Numeral
	DAY	Number of days work	Numeral
	CAR	Job require car	1=Yes, 2=No
Mode-specific variables	TC	Difference in travel cost	Bus cost (bus fare) minus car cost (gasoline cost and parking fee)
	TT	Difference in travel time	Bus travel time minus car travel time
Dependent variables	MC	Mode choice	1 = Bus, 0 = Car (SOV)
	AC	Activity choice	1 = Extra-stop(s), 0 = No extra-stop
	S1 – S3	Importance rating statements	1 for "Not important at all" and 7 for "Extremely important."

APPENDIX 2. STATED PREFERENCE DATA OF PUGET SOUND STUDY

A2.1 Stated preference questionnaire

A2.1.1 Mode choice question

If all theses statements were true: Gasoline is $.90/gallon and parking at work is free, you could drive/ride in a carpool with one man who is a friend or co-worker and share the costs, and the bus fare is $.50 each way, the time between each bus is 10 minutes and riding the bus takes 10 minutes longer than driving alone, would you:
Drive alone, Carpool or Take the bus.

A2.1.2 Activity choice question

After leaving work, would you be likely to make:
No stops on the way home or _____ number of stops on the way home.

A2.2 Factors and levels of experimental data

Factor	Level
1. Gasoline Price	$0.90, 1.10, 1.50. 2.00
2. Parking Fee	Free, $6.00
3. Number of Riders	2, 3
4. Rider Gender	Female, Male
5. Car pool Rider	Friend/Co-worker, Ride-match
6. Bus Fare	$0.50, 1.00, 1.50, 2.00
7. Bus Headway	10 minutes, 20 minutes
8. Added Bus Time	10 minutes, 20 minutes

APPENDIX 3. PERCEPTION AND NEEDS SURVEY QUESTIONS

Please rate how important each of these items is to you in deciding how to **travel to work** by circling a number from “1” to “7”. A “1” means “not important at all” to you and a “7” means “extremely important to you”.

	Not important at all			Neutral			Extremely important
A. Ability to arrive on time	1	2	3	4	5	6	7
B. Ability to travel without changing vehicle	1	2	3	4	5	6	7
C. Not having to deal with traffic congestion	1	2	3	4	5	6	7
D. Short travel time	1	2	3	4	5	6	7
E. Day-to-day costs like gas, parking, bus	1	2	3	4	5	6	7
F. Protection from weather	1	2	3	4	5	6	7
G. Having a seat	1	2	3	4	5	6	7
H. Short wait time	1	2	3	4	5	6	7
I. Ability to read while traveling	1	2	3	4	5	6	7
J. Ability to travel when desired	1	2	3	4	5	6	7
K. Flexibility to change plans	1	2	3	4	5	6	7
L. Making few stops	1	2	3	4	5	6	7
M. Parking availability	1	2	3	4	5	6	7
N. Safety of vehicle from accidents	1	2	3	4	5	6	7
O. Freedom from threats to personal safety	1	2	3	4	5	6	7
P. Avoiding stress	1	2	3	4	5	6	7
Q. Minimizing pollution	1	2	3	4	5	6	7