

External Validity Test for Discrete Choice
Transportation Forecasting Models based on the
Stated Choice Approach

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16. Abstract <p>A Constrained Conditional Logit Model based on the hypothesis that the existed resource constraints have significant effect on individual's mode switching is developed. Theoretical and empirical studies reported here have supported the validity of this hypothesis.</p> <p>Data were collected on traveler demographics and commuter modal choice in response to parking charges at two major urban New Jersey corporate sites.</p> <p>Several developmental contributions and advancements are reported, including: 1. The development of the Constrained Conditional Logit Model (CCLM) which explicitly includes the resource constraint into the decision making process and then a switching probability function, therefore providing a tool for evaluating the effect of various constraints; 2. An advance on the model estimation, which not only improves the efficiency of the estimation but also provides a tool on the study of transferability of empirical models; and 3. A cross-sectional design that makes an external validity test available in the situation where researchers have no opportunity to manipulate both test and control conditions in the actual experiment.</p> <p>This study shows that the CCLM model can successfully forecast the mode split change associated with a parking charge imposition for the single occupancy vehicle and public transit modes.</p>					
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CHAPTER 1

INTRODUCTION

Transportation policy research assesses the effect of policy changes, such as the imposition of a parking charge or the augmentation of passenger rail service, on individuals travel behavior. Over the last few decades, the Conditional Logit Model (CLM) has risen to be the theoretical and analytical model of choice for transportation policy studies. However, the current use of the discrete choice theory underlying the Conditional Logit Model may be flawed. The issue is the reported low levels of accuracy on forecasting individual travel behavior by the empirical models formed by current data. Horowitz (1985) indicates based on his study that few existing discrete mode choice models can explain as much as 40% - 50% of observed variation in choices, and many explain less than 30%. The low accuracy of prediction explains that current empirical models have significant biases or errors.

The utility derived from each potential travel alternative is assumed as the basis for a traveler's mode choice decision. Different from the utility function used in classical economics, the utility term used in the discrete choice models is expressed as indirect utility function (Ben-Akiva & Lerman, 1985). An indirect utility function is a derived utility function under given constraints. Explicit inclusion of constraint into indirect utility function is necessary if economic theory is to be fully incorporated in the discrete choice models. The report will unfold in the following fashion.

Chapter 2 presents a detailed review of the advances related with the Conditional Logit Model. It includes the development of theoretical model and relevant empirical findings.

Chapter 3 proposes the hypothesis. The null hypothesis states that there is no difference between treating the effect of resource constraint as a random utility term and as a component of systematic utility term. The alternative hypothesis states that

constraints explicitly exist in an individual's travel mode switching behavior and therefore significantly affect individual mode switching behavior. Ignoring these constraints in the systematic utility term will cause the biases in the model calibration.

The alternative hypothesis is based on a modified or extended theoretical model, the Constrained Conditional Logit Model (CCLM). Chapter 4 gives a detailed description about the formation and inclusion of constraints in utility term. The CCLM model explicitly incorporates constraints on individual travel mode switching. It is noteworthy that constraints that govern travel mode switching behavior are no longer limited to monetary and time budgets in this report as in classical utility maximization framework in economics, but are extended generally to the all resources which are consumed on the travel.

Through the simulation described in Chapter 5, the internal validity of the Constrained Conditional Logit Model is examined. The result shows that the Constrained Conditional Logit Model is capable of recovering the effects of constraints if these constraints do exist. The simulation result also shows that ignoring of these effects would cause significant biases in estimation and evaluation of the effects of a travel environmental change.

An empirical study is made to test the hypothesis about the existence of constraints. The empirical study involves Stated Choice surveys (SC) administered to the commute employees working at two sites in Newark, New Jersey. Chapter 6 introduces a detailed information about the survey sites and the survey process. The surveys were administered through pencil and paper questionnaires which were sent to respondents from the two sites.

Chapter 7 describes the empirical model's calibration and the hypothesis testing. The Hypothesis proposed in Chapter 3 is tested by χ^2 and t tests. The χ^2 test is for the equality of the coefficients underlying the CCLM model and the CLM model. The test results show that CCLM model's coefficients are significantly different from those

generated by the CLM model. The t test is used as a significance test for the constraints. The t test result shows that effects of the constraints on travel cost and time exist in individual commute mode switching behavior.

As the two surveys were performed on the same CBD, a series of joint estimations were conducted with different trials for the scale factor ratios. A test was executed to examine if the two samples can be accepted as drawn from the same target population. The tests include two sub-test topics :

- a) parameter estimate identity for the two samples, and
- b) variance identity for the random terms of the two samples.

The both test results show that the two samples have identical parameters in the systematic utility terms, but different variances of the random utility terms. The scale factor ratio or the variance ratio between the two samples is 1.3 in this study. After the adjustment by means of scale factor ratio, a unique empirical model was obtained using the pooled data matrix.

External validity test for the jointly estimated model is executed in Chapter 8. A commute mode switching and mode split analysis is made based upon the comparison of the forecast and real mode shift due to pressure formed by a \$3 parking charge. The cross-sectional experimental design is used in the external validity test. The WP employees are considered as the sub-sample assigned to the control condition as free parking currently prevails there. The MBL employees, on the other hand, are considered as the sub-sample assigned to the test condition because the actual parking charge is \$3 there. The CCLM model successfully predicts the effect of a parking charge difference on the use of single occupant vehicles for commuting purposes.

Finally, Chapter 9 presents the conclusion related to the constraints in individual commute mode switching. The Constrained Conditional Logit Model can effectively correct the biases and errors caused by exclusion of constraints in indirect utility function.

The Constrained Conditional Logit Mode is identified to be a helpful tool for assessing the effect of transportation policy.

CHAPTER 2

LITERATURE REVIEW

Discrete mode choice theory underlying the travel demand study has been developed in recent years as the advances of the relevant sciences, such as microeconomics, psychology and sociology. Therefore, modern travel demand analysis is considered as an extension of these branches of science. This chapter offers a brief review of the theoretical and methodological advances of the discrete mode choice on these relative fields.

2.1 Rationality in Decision Making

Economic theory, since it become systematic, has been based on some notion of rationality. "It seems to be asserted that a theory of the economy must be based on rationality, as a matter of principle. Otherwise, there can be no theory" (Arrow ,1986). Human behavior is almost uniformly considered as a rational activity because "everyone agrees that people have reasons for what they do. They have motivations, and they use reason (well or badly) to respond to these motivations and reach their goals" (Simon, 1986). "Capitalists choose to invest in the industry yielding the highest rate of return, and individuals always choose the alternative which is the best one for their interest" (Arrow, 1986).

Reitz (1977) defines the rationality in individuals behavior: "traditional economic theory postulates an economic man, who, in the course of being economic is also called rational. This man is assumed to have comprehensive knowledge of the relevant aspects of his environment which, if not absolutely complete, is at least impressively clear. He is assumed also to have a well-organized and stable system of preferences, and a skill in

computation that enables him to calculate, for the alternative courses of action that are available to him, which of these will permit him to reach the highest attainable point on his preference scale.”

The rationality in decision making process is generally interpreted as “the maximization of utility for the individual under a budget constraint” (Arrow, 1986). Here, utility is defined as the benefit derived from the alternative. Based upon this definition, an individual’s demand, as a function of all attributes of utility, is an immediate implication and becomes a most important formula in economics. Utility formation becomes the most essential element in various models of demand function.

The application of rationality theory has been criticized in some fields. Burnett and Hanson (1982) argue that “the assumption that intra-urban travel is the outcome of a rational decision-making process, even with limited information, seems to be dubious since increasing evidence indicates that travel is a stable daily routine, also a constrained choice for most likely a deep-seated avoidance behavior for many, too.”

As a summary, Mauheim’s (1979) description about the limitation of rational decision making process is presented here;

- 1) *The alternatives*: Do consumers really perceive all of the available alternatives? Do they consciously and deliberately consider every one of them? Or do they scan the set of alternatives and only examine carefully a small number? How does past experience influence which alternatives a consumer will consider explicitly?
- 2) *The consequences*: How do consumers perceive consequences? What consequences do they consider important? What kinds of biases are there in their perceptions of those consequences? How are these perceptions biased by individual experiences, word of mouth, or other information?

- 3) *The decision process*: Does the consumer go through a careful analysis and calculation of each alternative to reach a decision? Does he really formalize his preferences explicitly in the form of an indifference curve? Does he even behave as if he had formalized his preferences in this way? Does he choose among all alternatives in a single step or in a sequence of decisions?
- 4) *The static nature of the model*: Don't consumers change their information, and their preferences, over time? Don't they "learn" from actual experiences and sometimes shift choices?

If the above assumption about the decision making process is true, whether a certain behavior is "rational" or "reasonable" can be reached only by viewing the behavior in the context of a set of premises or "givens"(Simon,1986). These givens include the situation in which the behavior takes place, the goals it is aimed at realizing, and the computational means available for determining how the goals can be attained. An individual's activity should not always be thought as rational behavior because individual sometimes

- 1) recognize only a limited number of possible alternatives,
- 2) be aware of only a few of the consequences of each alternative, and
- 3) have access to only a limited, approximate, simplified model of the real situation.

In corresponding to the rational decision making process, some modifications have been made in the recent years. "The decision maker satisfies, rather than maximize, the alternatives under imperfective information awareness; that is, he looks for a course of action that is 'good enough', to meet a minimal set of requirements"(Simon, 1976). A business person, for example, often decides to invest in a new enterprise if he expects it to return a "satisfactory profit," without bothering to compare it with all the alternative investments open to him.

As the consequence of limited computation ability, when deciding among alternative courses of action, individuals use simple, local and myopic choice procedures

which adapt choice behavior to their capacity limitations. “The simplified approach fits the limited information-processing capacities of human beings.” The world is peopled by creatures of “bounded or limited rationality”, he says, and these creatures constantly resort to gross simplifications when dealing with complex decision problems.

Palma, Myers and Papageorgiou (1994) develop a myopic adjustment model for an individual imperfect ability. The decision principle underlying this model is that instead of finding at once the best allocation of resources, an individual myopically adjusts his current allocation toward higher utility. Switching to a particular alternative is assumed as the consequence of comparing different utility increments.

Another suggestion is proposed by Sonis (1986). He indicates that “by different way from a totally egoistic omniscient creature who is supposed to accomplish a rational free choice between different competitive alternatives on the basis of the individual’s utility maximization principle, homo socialis is an individual whose behavior is based on the interaction among choice-makers and on the limitation and learning within an active uncertain environment.” The choice behavior of homo socialis is directed by the subjective mental evaluation of the marginal temporal utilities. Finally he proposes: “a decision-maker dose not choose an alternative on the basis of a comparison of utilities, but on the basis of a comparison of the temporal marginal utilities (interpreted as the expectations of a gain in the future) which may be influenced by social interaction, imitation and learning processes between choice makers.”

Many other theories which are quite different from utility maximization have also been devised. Habit formation, for example, was made into a theory. “For a given price-income change, the individual chooses the bundle that satisfies the bundle constraints and that which requires the least change from the previous consumption bundle. It is different from utility maximization” (Constantinides, 1990).

2.2 Discrete Choice Model -- Application of Consumer Theory

Travel mode choice models are the application of the probability decision theory (Ben-Akiva and Lerman, 1985). This theory recognizes the imperfect information attainment for decision makers. A random or probabilistic element is included into decision process (Palma, Myers, and Papageorgiou, 1994). The randomness can be incorporated in a number of ways and many models are therefore developed in travel demand analysis (Bovy and Bradley, 1985, Golob and Meurs, 1987). The techniques that extend decision theory of microeconomics to the choices among the discrete sets of alternatives are provided by a class of mathematical models called discrete choice models (Ben-Akiva and Lerman, 1985, Domencich and McFadden, 1975). These models, like other standard models in microeconomics, assume that an individual's preferences among the possible alternatives can be described by a utility function. An individual selects the alternative with the greatest utility. However, these models differentiate themselves from other discrete choice models by accounting for the effect of uncertainty of human behavior using a random component ϵ . Mauheim (1979) lists the factors which have contributions to this randomness.

- 1) There may be service attributes that are important to some consumers but have not been explicitly represented in our estimation of their utilities. For example, comfort, perception of security, or other non-quantifiable attributes.
- 2) Consumers may not perceive all the alternatives open to them or may not have correct information on the attributes of the alternatives. For example, because of poor marketing, consumers are often not aware of route and schedule information that might influence their decision.
- 3) There may be essentially random elements in the consumer's behavior, in that his preferences vary from day to day or are influenced by external events. For example, the weather or the availability of the family car.

The most practically used discrete choice model, exemplified by the Conditional Logit Model, is developed by Domencich and McFadden (1975). The rationality is still executed by optimization of the utility function. Utility is interpreted as the satisfaction obtained from each alternative. The attractiveness of a particular alternative i for individual n can be quantified in terms of a “perceived attractiveness” utility function U_{ni} .

The utility function in discrete choice models usually consists of two components, systematic utility term V_{ni} and random term ε_{ni} . The former can be expressed by a function of explanatory attributes regarding the alternatives. The latter is used to present omitted attributes and un-explanatory attributes for the uncertainty in individual's behavior. The utility can be written as :

$$U_{ni} = V_{ni} + \varepsilon_{ni} \quad (2.1)$$

The form of the joint probability distribution describing the ε_{ni} decides the form of choice probability function. Now, the probability of choosing a particular alternative i can be converted to the probability $P_n(i)$ that the utility derived from alternative i is greater than any other alternative j for individual n .

$$\begin{aligned} P_n(i) &= P(U_{ni} > U_{nj}, \text{ for all } j \neq i, \text{ for individual } n) \\ &= P(V_{ni} - V_{nj} + \varepsilon_{ni} > \varepsilon_{nj}, \quad \text{for all } j \neq i) \end{aligned} \quad (2.2)$$

For a particular ε_{ni} , the conditional probability $P_n(i | \varepsilon_{ni})$ can be derived :

$$P_n(i | \varepsilon_{ni}) = \prod_j \int_{-\infty}^{V_{ni} - V_{nj} + \varepsilon_{ni}} f_{nj}(\varepsilon_{nj}) d\varepsilon_{nj} \quad (2.3)$$

where $f_{nj}(\varepsilon_{nj})$ is the probability density function of ε_{nj} . Hence, the probability of choosing alternative i can be obtained as ;

$$P_n(i) = \int_{-\infty}^{\infty} f_{ni}(\epsilon_{ni}) \left\{ \prod_j \int_{-\infty}^{V_{ni} - V_{nj} + \epsilon_{ni}} f_{nj}(\epsilon_{nj}) d\epsilon_{nj} \right\} d\epsilon_{ni} \quad (2.4)$$

The random variable ϵ_{ia} has joint distribution $f_n(\epsilon_{n1}, \epsilon_{n2}, \dots, \epsilon_{nJ})$ and the variance matrix can be expressed as

$$\Sigma = \begin{pmatrix} \sigma_{n11}^2 & \sigma_{n21}^2 & \dots & \sigma_{nm1}^2 \\ \sigma_{n12}^2 & \sigma_{n22}^2 & \dots & \sigma_{nm2}^2 \\ & & \dots & \\ \sigma_{n1m}^2 & \sigma_{n2m}^2 & & \sigma_{nmm}^2 \end{pmatrix} \quad (2.5)$$

where, σ_{nii} is the variance of random variable ϵ_{ni} and can be simplified as σ_{ni} , and σ_{nij} is the co-variance between ϵ_{ni} and ϵ_{nj} .

Generally, the integration in equation (2.4) is not tractable, and an approximation or numerical method has to be used to obtain the result. Some special functions can make the integration tractable. McFadden uses the Gumbel Distribution function as the joint probability function and variables ϵ_{ni} ($i=1,2,\dots,J$) are assumed to be independent and identically distributed (*IID*) across individual n as well as alternative i . The probability function is given by Equation (2.6),

$$F(\epsilon_{ni}) = \exp[-\exp(-\mu_{ni}(\epsilon_{ni} - \delta_{ni}))] \quad (2.6)$$

where

δ_{ni} -- position parameter

μ_{ni} -- scaling factor which is a function of variance σ_{ni}^2 with relationship:

$$\mu_{ni}^2 = \pi^2 / (6\sigma_{ni}^2) \quad (2.7)$$

Now, the probability of choosing alternative i can be derived (see appendix *A*) when δ_{ni} is assumed to be θ .

$$P_n(i) = \frac{\exp \mu_{ni}(V_{ni})}{\sum_{j=1}^J \exp \mu_{nj}(V_{nj})} \quad (2.8)$$

This model is called the Conditional Logit Model and has been widely applied in transportation planning. This model has become something of a standard in transportation planning. McFadden (1974) derives the asymptotic properties of the maximum likelihood estimator of the Conditional Logit Model in the linear parameter case.

It is worthwhile to indicate that “Presumably, modal choices also depend on the socioeconomic characteristics (say, s) of the individual making the decision. Logically, s would be attached to all the choices of a given commuter; but it is easily seen that the effect of this specification is that it is then impossible to estimate the impact of s on choice.”..... “ It is therefore conventional to attach these characteristics to one of the modes, and to define the corresponding places in the characteristics vector of the other modes to be zero” (Viton, 1989).

In addition to the Conditional Logit Model, multinomial probit model is also studied and applied in some cases. The major difference of probit model from logit model is the assumption about distribution of the random term in utility function U_n . Ben-Akiva & Lerman (1985) gives a expression of binary probit model as:

$$\begin{aligned} P_n(i) &= pr(\varepsilon_{nj} - \varepsilon_{ni} \leq V_{ni} - V_{nj}) \\ &= \int_{\varepsilon=-\infty}^{V_{ni}-V_{nj}} \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2}\left(\frac{\varepsilon}{\sigma}\right)^2\right] d\varepsilon \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{(V_{ni}-V_{nj})/\sigma} \exp\left(-\frac{1}{2}u^2\right) du \\ &= \Phi\left(\frac{V_{ni} - V_{nj}}{\sigma}\right) \end{aligned} \quad (2.9)$$

Since random term ε_{ni} is assumed as a multivariate normal distributed variable with a vector of means 0 and a $J \times J$ variance-covariance matrix Σ_ε , probit model can be

used to incorporate effect of the correlation between different alternatives to avoid the problem associated to *IID*. However, only very limited applications have appeared in travel demand literature (Daganzo, Bouthelier, and Sheffi, 1977), and there is still no evidence to suggest in which situations the greater generality of multinomial probit is worth the additional computational problems resulting from its use.

2.3 Dynamic Behavior Model and Panel Data

Although the Conditional Logit Model achieved great success, it is necessary to indicate that the fourth question proposed by Mauheim (1979) is still existed. Travelers actually change their information and their preferences over time, and they “learn” from actual experiences.

The interest in the study of travel behavior dynamics has grown considerably in recent years. This is because more and more empirical studies show that some attributes regarding travel mode choice change over time, as well as individuals and alternatives. “Continuing sub-urbanization, improvement of communication and traffic conditions, and air pollution policy, influence individuals' travel mode choice. On the other hand, changes in reaction patterns of individuals, household's size, income, and even car ownership, also contribute to the travel mode choice. Therefore, decision makers are very often required to make continuous decisions” (Kitamura,1990).

In addition to the exogenous attributes described above, endogenous attributes would also be responsible for the dynamic characteristics of individual's behavior. Endogenous attributes comprise characteristics arising from previous decisions and choices and are conceptually quite different from exogenous attributes. The importance of such endogenous attributes may be adduced from several broad areas of social science theory. For example, notions of cumulative inertia and cumulative stress have variously

informed theoretical work on such diverse decisions as job quitting, divorce, and residential move. Thus a decision to quit a job, divorce, or move home is postulated to be dependent upon the time interval since commencing the job, marrying, or the previous residential move, respectively.

Perhaps the most obvious fact contributing to the dynamic behavior is the time lags on decision making. Kitanura (1983) summaries: “not immediately acquired information, small magnitude change which not prompted any action, and constraints imposed on the household may all lead to apparent response lags.” The dynamic discrete choice models, in corporation with panel date analysis, are to evaluate the impact of a change in transportation system as well as the impact of endogenous attribute on individual’s behavior.

From a statistical viewpoint, panel data has definite advantage. Panel data offers accurate estimate of changes than would cross-sectional data. The essence of panel data is the information on a fixed sample of decision-makers across time so that the statements can be made about behavioral response at individual level (Fischer and Nijkamp, 1987). Panel data may be obtained by classical panel surveys which involve the repeated measurements on the same individuals at different points in time. The great potential of panel data for dynamic modeling stems from both the temporal nature of data and the data linkage for each decision maker. Panel data enables one to explicitly recognize the inter-temporal nature of choice outcome, especially the role of state dependence and serial correlation. Therefore, there is no doubt that dynamic models of discrete choice have to be based on panel data.

The simplest dynamic discrete choice model is the non-stationarity or temporal independence model. This model is based on the assumption that the decisions made at different time points are independent each other. Rust (1988) regards recurrent choice as a sequence of static utility maximizing choices by decision makers. Let $t = 1, 2, \dots, T$

denote an exogenously given sequence of time periods and assume that conditional on explanatory attributes matrix $(X_{ni1}, \dots, X_{nit}, \dots, X_{niT})$, the sequence of decision $(i_1 \dots i_t \dots i_T)$ obeys a multinomial choice process with a conditional density function given by:

$$P_n(i_1, \dots, i_T) = \prod_{t=1}^T \frac{\exp \mu_{ni}(V_{nit})}{\sum_{j=1}^J \exp \mu_{ni}(V_{njt})} \quad (2.10)$$

In corresponding to the non-stationarity, two other situations, structural dependence and serial correlation, are more complex. Structural state dependency refers to the dependency of current individual choice probabilities on preceding individual history. Structural state dependence may arise due to a number of reasons. “Choice outcomes may depend on previous choice (Markovian effect), on the length of time the current state has been occupied (duration dependence effects), on previous inter-choice times (lagged duration dependence effect), and on the number of times different states have been occupied (occurrence dependence effects)” (Fischer and Nijkamp, 1987).

Serial correlation refers to the variation among individuals due to both observed and unobserved external influences including variation caused by censoring of the panel data base. Unobserved attitudes towards alternatives may play a major role in serial correlation (Morikawa, 1994). In mode choice analysis, for instance, latent attitudes towards modes, such as I love driving a car, can predominantly influence mode choice behavior.

Tardiff (1980) is one of the first who made an attempt to extend discrete choice methodology by introducing structural state dependence and heterogeneity in utility functions as:

$$U_{nit} = \sum_{k=1}^K \beta_k x_{nikt} + \sum_{j=1}^J \gamma_{ij} d_{nj(t-1)} + \varepsilon_{ni} + \zeta_{nit}^* \quad (2.11)$$

* In order to keep inconsistency with the notes used in this report, we replace the sub-index.

where, $d_{nj(t-1)}$ is a dummy variable. If individual i chooses mode j in previous period $t-1$, $d_{nj(t-1)} = 1$, and $d_{nj(t-1)} = 0$ otherwise. The ε_{ni} refers to unobserved time-invariant effects (fixed effects of unobserved variables) and ζ_{nit} varies among the decision makers and time periods. By putting various terms in Equation (2.11) equal to zero, Tardiff (1980) considers two special cases of the general data discrete choice model: model with structural state dependence and model with serial correlation. If we assume the transfer parameter $\gamma_{ij} = 0$ for all individuals and alternatives, Equation (2.11) becomes structural serial correlation model, since the choices depend upon observed serial correlation effect. Remove ε_{ni} , Equation (2.11) becomes a structural state dependence model, because the effects of previous choices upon current choices are explicitly considered.

Daganzo, Bouthelier, and Sheffi (1977) performs a case study of serial correlation model and structural state dependence effects by a two-periods binary probit model. ($i = -1, 1$ and $t = 1, 2$) Let X_{it} stand for the attribute vector of the i th alternative and time t , and assume parameter β_t in utility function as a normal distributed variable:

$$\beta_t \sim MVN(\beta_t, \Sigma_{\beta_t}) \quad (2.12)$$

The correlation between β_1 and β_2 may be specified if the joint distribution of between β_1 and β_2 is defined as:

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} \sim MVN \left[\begin{pmatrix} \bar{\beta}_1 \\ \bar{\beta}_2 \end{pmatrix}, \begin{pmatrix} \sum_{\beta_1} & \text{cov}(\beta_1, \beta_2) \\ \text{cov}(\beta_1, \beta_2) & \sum_{\beta_2} \end{pmatrix} \right] \quad (2.13)$$

Another fact needed to pay an attention to is the habitual in the discrete choice behavior. Goodwin (1977) defines habit in individual's behavior; "It is convenient to use the word 'habit' to signify various sources of resistance to a change, that, on purely economic or 'rational' ground, would be made. These sources include a reluctance to upset an ordered and well-understood routine, perception thresholds below which changes in the relative attractiveness of the modes are not noticed, and barriers to the

relevant information reaching the individual. ... I would be expected that such effects will be time-dependent, although it is not clear how”.

Pollak (1970) is one of the first who incorporate habit into utility function. One of the utility function family is

$$U = \sum_{k=1}^n a_k \log(x_k - b_k) \quad (2.14)$$

where, x_k stands for the level of consumption of the k th good. a_k and b_k are parameters.

The dynamic models have been used in some transportation case studies (Basmann 1994 and Hartgen 1974). The results of these studies show that dynamic models represent travel behavior more accurately and meaningfully, because dynamic assumption about the decision making environment and behavior is much closer to the real behavior than that in static models. Much more data about individual’s behavior and alternatives has been employed in the establishment of these models. However, how to capture dynamic process in a quantitative model for travel behavior has not been well addressed and empirical examinations have not been made as much as the study for the case of static choice models.

2.4 Revealed Preference, Stated Preference and RP/SP Combination

In dynamic discrete choice models, a special case is that the first term and the third term of right side of Equation (2.11) equal to zero, which leads to a first-order Markov model of spatial choice. If previous choice is alternative j , the probability of choosing alternative i is called switching probability and is expressed as ;

$$Prob(j,i) = P(Y_n(t)=i/Y_n(t-1)=j) = P_n(i/j) \quad (2.15)$$

“An empirical examination showed that while the estimated models based on stated preference data tend to over-estimate the actual modal switching behavior due to the changes in transport services it is very important to incorporate the state dependence effects into disaggregate modal choice models”, Hirobata and Kawakami (1990) indicate. Their conclusion is based upon their study of switching behavior by a mode switching model on an intention data or stated preference data.

The survey of stated preferences (SP) is an alternative source of data on switching behavior instead of revealed panel data (RP). In contrast to the revealed preference survey which records traveler’s actual choice and relative explanatory attributes, a traveler is presented with a planned or a potential future change in the transportation system and is asked if and how he intends to modify his current choice in response to the change.

Stated preference models and data were introduced to transportation researchers by Louviere (1988). Stated preference models have been applied successfully in a variety of transport contexts such as route choice analysis (Bovy and Bradley, 1985). Morikawa (1994) studies and presents different characteristics of RP and SP data as follows:

- 1) RP data are cognitively congruent with actual behavior, but SP data may not be,
- 2) SP methods can directly treat non-existing services and alternatives,
- 3) Trade-off among attributes are more clearly observable from SP data, and
- 4) Individual-specific coefficient values may be estimable from SP data.

Despite considerable progress in designing SP experiments and estimating stochastic choice models from them, the question of relating the results to behavior in the real market of interest remains open. One of the central issues is that distribution of random term ε_{ni} could not be expected as identical to that which presents in RP experiments. This is because that the factors, such as learning, boredom, or anchoring to

earlier tasks, may distort the measurement of preferences. In addition, respondents may deliberately give biased responses in the hope of affecting the outcome of the analysis.

Bates (1988) indicates that “If we now assume that the distribution of error appropriate to estimation applies to forecasting, we will be making estimates of the ‘pseudo’ utility rather than of the ‘true’ utility: in other words, we are making estimates of relative preferences as expressed in a stated preference experiment rather than of what would occur in the market.”

Bates also thinks that “the simplest case is when ε , which we are using to relate to the kind of error which is compatible with models fitted to RP data, and η , which relates to the inability of the respondent to reply to the SP exercise in a way which corresponds with his actual behavior, are independently distributed with the same type of distribution, and differ only in their variances. Suppose the variance are σ_ε and σ_η , respectively.”

Morikava (1994) presents an approach to estimate the bias effect of a SP data. He assumes that both revealed and stated preferences can be modeled by random utility models with discrete choices such as the Conditional Logit Model. Then the utility functions and choice probabilities are given as follows:

$$\begin{aligned}
 \text{RP model:} \quad & U_{ni}^{RP} = V_{ni}^{RP} + \varepsilon_{ni}^{RP} \\
 & P_n^{RP} = \frac{\exp(V_{ni}^{RP})}{\sum_{j=1}^J \exp(V_{nj}^{RP})} \quad (2.16)
 \end{aligned}$$

$$\begin{aligned}
 \text{SP model:} \quad & U_{ni}^{SP} = V_{ni}^{SP} + \varepsilon_{ni}^{SP} \\
 & P_n^{SP} = \frac{\exp(V_{ni}^{SP})}{\sum_{j=1}^J \exp(V_{nj}^{SP})} \quad (2.17)
 \end{aligned}$$

where, all terms are same as before, and super-index RP and SP refer to RP and SP models, respectively. One fundamental assumption is that the trade-off relationship

among major attributes is common to both RP and SP models. After introducing a scale factor ratio λ that represents the ratio of standard deviations of ϵ_{ni}^{RP} and ϵ_{ni}^{SP} ,

$$Var(\epsilon_{ni}^{RP}) = \lambda^2 Var(\epsilon_{ni}^{SP}) \quad (2.18)$$

and, assume ϵ_{ni}^{RP} and ϵ_{ni}^{SP} have *IID* property, Equation (2.17) can be written as:

$$P_n^{SP} = \frac{\exp(\lambda \cdot V_{ni}^{SP})}{\sum_{j=1}^J \exp(\lambda \cdot V_{nj}^{SP})} \quad (2.19)$$

Note that scale factor ratio λ in Equation (2.19) is different from scale factor μ_{ni} in Equation (2.8). The former is the ratio of variance of SP and RP data, and the latter is the scale factor in random term distribution.

Now, we can use both RP and SP data to jointly estimate scale factor ratio λ . The approaches can be found in some relative literature (Adamowicz, Louviere, and Williams, 1994):

- 1) separate estimation of both RP and SP models. Then, concatenate both data sets after re-scale SP data relative to RP data and conduct a joint estimation.
- 2) compare the joint likelihood to the sum of the separate likelihoods for SP and RP models. Accept the null hypothesis that the re-scaled parameters are identical if the joint and summed separate likelihoods do not differ statistically.

In summary, stated preference data, combined with revealed preference data, can be used to increase the accuracy of parameter estimation.

CHAPTER 3

PROBLEM STATEMENT AND HYPOTHESIS

Travel mode switching is defined as a particular kind of travel mode choice in Chapter 1, where an individual shifts his travel mode due to a change or changes in travel services, such as an increment in parking charge. An individual faces the option to either switch to alternative mode or stay with the current travel mode. The most meaningful characteristics of travel mode switching, comparing with some other travel mode choice issues such as travel mode choice for vacation, is that the decision maker has a current travel mode. The commuter needs to consider the benefit or the utility derived from the each alternative, as well as the feasibility of switching to another mode.

Can current travel mode choice theory and the Conditional Logit Model effectively be used to explain travel mode switching? As discussed in Chapter 2, consumer theory underlying the discrete choice models is based upon utility maximization. It is noteworthy that the arguments in the systematic utility term contain the resources consumed in travel through the various travel modes. The most meaningful examples of consumed resources are travel cost and travel time. Generally, the consumed resources are defined as the prices for consuming the corresponding travel mode. As distinguished from the utility function with arguments of quantities of commodities used in classical economics, the utility function with arguments of prices is called indirect utility function (Ben-Akiva & Lerman, 1985).

The quantities of commodities in the direct utility function are commonly replaced by the prices of commodities and income. The utility maximizing constraint function consists of:

$$F(q_{1k}, p_{1k}, q_{2k}, p_{2k}, \dots, q_{ik}, p_{ik}, \dots) = C_k \quad (k = 1, 2, \dots, K) \quad (3.1)$$

where, q_{ik} and p_{ik} are the quantity and the k th price for commodity i , and C_k is total available amount for resource k . Here, price p_{ik} is defined as the consumed k th resource on unit of commodity i .

Based upon the above analysis, total amount of resource C_k should be included into indirect utility function as a kind of constraint. Bates (1988) indicates the necessity of the inclusion of constraints into the indirect utility function, although he does not identify a theoretical model or an empirical model to test this supposition. He thinks that it is the kind of utility that is dealt with in discrete choice theory that causes the use of constraints in the models. Indirect utility in discrete choice models internalizes the constraints arising from income and other sources in the random utility term.

However, should the constraints be limited to the income and time only as in the classic economics? Kitamura (1990) suggests that the constraints that govern travel behavior are not limited to monetary and time budgets as in classical utility maximization. The constraints may also include spatial and temporal fixity constraints associated with the respective activities, interpersonal linkage constraints, and other types of constraints that portray the travel environment of each individual.

Harvey (1985) further suggests that research on constraints should be extended to other fields as well. He explains that activity participation may depend on cognitive capacity, time constraints, exogenously-imposed schedules, physical needs, income, endowment, technology, cumulative experience, authority, morality and desire or need. For example, the need for shopping on the way home.

Up to now, the necessity of the inclusion of constraints has been recognized theoretically. Whether these constraints should be explicitly taken into the systematic utility term due to their significantly effects on an individual's mode switching behavior or they should be implicitly put into the random term still needs to be identified through an empirical study as well as a theoretical analysis.

As the hypothesis of this report, I propose that the existence of constraints in individuals' mode switching has to be considered when we structure a theoretical model with an indirect utility function. Furthermore, constraints are supposed to significantly affect an individual's travel mode switching; therefore, constraints can be measured by a discrete choice model which incorporates constraints in systematic utility term. Finally, the errors caused by ignoring the existence of constraints can be specified through the internal and external validity tests. In summary, the use of constraints in the analysis of individuals' travel mode switching behavior will be very helpful for correcting the biases in assessing the travel service changes.

CHAPTER 4

METHODOLOGY

This chapter presents the derivation of the theoretical model. This model replicates individuals' travel mode switching behavior under the constraints. This chapter also introduces an approach for estimating the coefficients in the model.

4.1 Formation of the Constrained Conditional Logit Model

Travel shares the individuals various resources with all other activities. If an individual's total activities are assumed arbitrarily as the combination of travel and other activities, the systematic utility V_n can be expressed for individual n by a function of consumed resources x_{nrk} and x_{nok} ($k=1,2,\dots,K$) as :

$$V_n = V_{nr}(x_{nr1}, \dots, x_{nrk}, \dots, x_{nrK}) + V_{no}(x_{no1}, \dots, x_{nok}, \dots, x_{noK})$$

where

V_{nr} -- systematic utility attained from travel r for individual n

V_{no} -- systematic utility attained from other activities o for individual n

x_{nrk} -- the resource k consumed by individual n in travel

x_{nok} -- the resource k consumed by individual n in all other activities

K -- the total number of measurable attributes (resources)

The all other factors affecting an individual's decision for assigning his resources are included in the decision process by a random utility term ϵ_n . The total utility can be expressed as:

$$U_n = V_{nr}(x_{nr1}, \dots, x_{nrk}, \dots, x_{nrK}) + V_{no}(x_{no1}, \dots, x_{nok}, \dots, x_{noK}) + \epsilon_n \quad (4.1)$$

Comparing Equation (4.1) with the utility function used in the derivation of the Conditional Logit Model, the same place is that total utility is the sum of systematic utility V_n and random component ϵ_n . The different place is that the former's systematic utility is the sum of travel systematic utility V_{nr} and other systematic utility V_{no} .

Based upon the assumptions made in Chapter 3, an individual myopically adjusts his current allocation of resources so as to obtain higher utility. But, instead of finding at once the best allocation of resources, utility increment maximization is used as the strategy to deal with the issue of travel mode switching. Therefore, an individual switches to the alternative which provides the maximum utility increment ΔU_n .

Generally assume that individual n switches travel mode from current mode c to alternative i . The travel mode switching causes the attribute change of Δx_{nrk} for travel and Δx_{nok} for all other activities($k=1,2\dots K$) simultaneously. The total utility increment ΔU_n due to a travel mode switching can be written approximately as:

$$\Delta U_n = \Delta V_{nr} + \Delta V_{no} + \Delta \epsilon_n \quad (4.2)$$

where ΔV_{nr} and ΔV_{no} are the systematic utility increment from travel and all other activities due to travel mode switching. $\Delta \epsilon_n$ is the random component increment for individual n due to the mode switching.

The above equation explicitly shows that a travel mode switching is the result of a reallocation of the resources, including the systematic utility change of all other activities as well as the systematic utility change for travel. For instance, a saving of travel time will increase the time spent on some other activities, such as reading or shopping, then will increase the total utility as well.

As indicated by Ben-Akiva & Lerman(1985), the utility acquired from all other activities can be thought of a continuous function of attributes. The systematic utility increment ΔV_{no} can be approximately expressed as:

$$\Delta V_{no} \approx \sum_{k=1}^K \frac{\partial V_{no}}{\partial x_{nok}} \Delta x_{nok} \quad (4.3)$$

where, $\frac{\partial V_{no}}{\partial x_{nok}}$ is the partial derivative of the utility function for all other activities with respect to attribute k . Consider the impossibility of attaining all information about individual's all other consuming activities while studying individual travel mode switching behavior, the systematic utility increment may be conveniently expressed by a

Taylor Series. The systematic utility increment ΔV_{no} can be written as: (approximately by the first two terms)

$$\frac{\partial V_{no}}{\partial x_{nok}} = \frac{\partial V(x_{no1}(0), \dots, x_{noK}(0))}{\partial x_{nok}} + \frac{\partial^2 V(x_{no1}(0), \dots, x_{noK}(0))}{\partial x_{nok}^2} dx_{nok} \quad (4.4)$$

The terms $\frac{\partial V(x_{no1}(0), \dots, x_{noK}(0))}{\partial x_{nok}}$ and $\frac{\partial^2 V(x_{no1}(0), \dots, x_{noK}(0))}{\partial x_{nok}^2}$ are the constants

related only to different individual n and attribute k . The following substitutions are used in the above expressions (4.4):

$$\phi_{nk} = \frac{\partial V(x_{no1}(0), \dots, x_{noK}(0))}{\partial x_{nok}} \quad (k=1, 2, \dots, K) \quad (4.5)$$

and

$$\beta_{nk} = \frac{\partial^2 V(x_{no1}(0), \dots, x_{noK}(0))}{\partial x_{nok}^2} \quad (k=1, 2, \dots, K) \quad (4.6)$$

Consider the systematic travel utility as a linear function as used in most of discrete choice models:

$$V_{nr} = \sum_{k=1}^K \alpha_{nk} x_{nrk} \quad (4.7)$$

the systematic utility increment ΔV_{nr} can be approximately expressed as:

$$\Delta V_{nr} = \sum_{k=1}^K \alpha_{nk} \Delta x_{nrk} \quad (4.8)$$

Take Equation (4.3) and (4.8) into Equation (4.2) and replace Δx_{nrk} and Δx_{nok} by dx_{nrk} and dx_{nok} , we obtain:

$$\Delta U_n = \sum_{k=1}^K \alpha_{nk} \Delta x_{nrk} + \sum_{k=1}^K \phi_{nk} \Delta x_{nok} + \sum_{k=1}^K \beta_{nk} (\Delta x_{nok})^2 + \Delta \varepsilon_n \quad (4.9)$$

Note that attributes can be grouped into two sets by the constraint types, these with resource constraint and these without resource constraint. The typical examples for the former are time and cost. For the latter, on the other hand, are gender or attitude. Adjust the order of attributes in systematic utility function so that the constrained attributes are listed as $k = 1, \dots, m$, and the unconstrained attributes are $k = m+1, \dots, K$.

Assume that constrained attributes subject to the following constraints:

$$x_{nrk} + x_{nok} = c_{nk} \quad (k=1,2,\dots,m) \quad (4.10)$$

where c_{nk} is the total available amount of resources k for individual n , such as budget or time limits. Differentiate function (4.10), the following equation can be derived,

$$dx_{nrk} + dx_{nok} = 0 \quad (k=1,2,\dots,m) \quad (4.11)$$

Differentiation dx_{nrk} and dx_{nok} are assumed to be approximately equal to increment Δx_{nrk} and Δx_{nok} , Equation (4.11) can be substituted by the following Equation (4.12):

$$\Delta x_{nrk} = -\Delta x_{nok} \quad (k=1,2,\dots,m) \quad (4.12)$$

It is worthy to indicate that the attributes without constraints do not subject to Equation (4.12). The travel attribute change Δx_{nrk} will not company the attribute change Δx_{nok} . For example, the change of a traveler's attitude for carpool will not definitely affect his attitude for pizza. Therefore, the allocation of attributes without constraints is assumed constant over the travel mode switching ($\Delta x_{nok} = 0, k = m+1 \dots K$).

Substitute Equation (4.12) into Equation (4.9),

$$\Delta U_n = \sum_{k=1}^K \alpha_{nk} \Delta x_{nrk} - \sum_{k=1}^m \varphi_{nk} \Delta x_{nrk} + \sum_{k=1}^m \beta_{nk} (\Delta x_{nrk})^2 + \Delta \varepsilon_n \quad (4.13)$$

Combine the first two terms on the right side of Equation (4.13),

$$\Delta U_n = \sum_{k=1}^K \gamma_{nk} \Delta x_{nrk} + \sum_{k=1}^m \beta_{nk} \Delta x_{nrk}^2 + \Delta \varepsilon_n \quad (4.14)$$

where

$$\gamma_{nk} = \begin{cases} \alpha_{nk} - \varphi_{nk} & k = 1, \dots, m \\ \alpha_{nk} & k = m+1, \dots, K \end{cases}$$

Through the substitutions above, sub-index o no longer appears. Therefore, from now the sub-index r will be omitted. All variables in equations are the attributes corresponding to travel unless where specific explanation is used.

Assume that individual n has a travel mode set with alternative $i = 1, 2 \dots J$, the total utility increment corresponding to the mode switching from current travel mode c to an alternative i can be re-written as

$$\Delta U_n(i) = \sum_{k=1}^K \gamma_{nk} \Delta x_{nik} + \sum_{k=1}^m \beta_{nk} \Delta x_{nik}^2 + \Delta \varepsilon_{ni} \quad (i=1,2,\dots,J) \quad (4.15)$$

where, sub-index i is used to stands for a particular switching from c to i . For example, x_{nik} in Equation (4.15) refers to the k th attribute corresponding to alternative i for individual n . The systematic utility which individual n attains from the current travel mode c is,

$$V_n(c) = \sum_{k=1}^K \gamma_{nk} x_{nck} \quad (4.16)$$

where x_{nck} is the k th attribute for individual n from the current travel mode c . For individual n , $V_n(i)$ is a constant for all switching alternatives. Consider the sum of the current systematic utility (4.16) and utility increment (4.2) as an approximate utility attained from alternative i , A new equation for the utility due to the travel mode switching is formed as follows;

$$\begin{aligned} \bar{U}_n(i) &= V_n(c) + \Delta U_n(i) + \varepsilon_{nc} \\ &= \sum_{k=1}^K \gamma_{nk} \Delta x_{nik} + \sum_{k=1}^K \gamma_{nk} x_{nck} + \sum_{k=1}^m \beta_{nk} \Delta x_{nik}^2 + \bar{\varepsilon}_{ni} \quad (i=1,2\dots J) \end{aligned} \quad (4.17)$$

where, $\bar{\varepsilon}_{ni}$ is the sum of random utility increment $\Delta \varepsilon_{ni}$ and ε_{nc} . Note that :

$$\Delta x_{nik} = x_{nik} - x_{nck} \quad (k=1,2\dots K) \quad (4.18)$$

and substitute Equation (4.18) into (4.17), we obtain

$$\bar{U}_n(i) = \sum_{k=1}^K \gamma_{nk} x_{nik} + \sum_{k=1}^m \beta_{nk} (x_{nik} - x_{nck})^2 + \bar{\varepsilon}_{ni} \quad (4.19)$$

Since the difference between $\Delta U_n(i)$ and $\bar{U}_n(i)$ is a constant which is not related to alternative i , maximizing $\bar{U}_n(i)$ will have same result as to maximize $\Delta \bar{U}_n(i)$. Now, travel mode switching process has been re-structured as the following maximization problem :

$$\begin{aligned} \text{Max: } \bar{U}_n(i) &= \sum_{k=1}^K \gamma_{nk} x_{nik} + \sum_{k=1}^m \beta_{nk} (x_{nik} - x_{nck})^2 + \bar{\varepsilon}_{ni} \\ &(i \in \text{travel Alternative } J) \end{aligned} \quad (4.20)$$

where

x_{nik} -- attribute k for alternative i

x_{ick} -- attribute k for current travel mode c

$\bar{\varepsilon}_{ni}$ -- the random term

γ_{nk} and β_{nk} -- parameters

Compare the above equation with maximization of travel utility in derivation for the Conditional Logit Model (assume systematic utility is linear function) :

$$\text{Max: } \Delta U_n(i) = \sum_{k=1}^K \alpha_{nk} x_{nik} + \varepsilon_{ni} \quad (i=1,2,\dots,J) \quad (4.21)$$

we can find that if we add maximization (4.21) with constraint condition

$$\text{Subject to: } H_{nci} = \sum_{k=1}^m \beta_{nk} (x_{nik} - x_{nck})^2 = 0 \quad (4.22)$$

the two maximization processes are identical. This is because constraint function H_{nci} is obtained as the inclusion of constraint conditions (4.10) into the total utility increment function. Now, make the following substitutions

$$V_{ni} = \sum_{k=1}^K \gamma_{nk} x_{nik}$$

and

$$H_{nci} = \sum_{k=1}^m \beta_{nk} (x_{nik} - x_{nck})^2 \quad (4.23)$$

into Equation (4.19), and assume that random term $\bar{\varepsilon}_{ni}$ is a *Weibull* distributed variable with the cumulative distribution function:

$$F(\varepsilon_{ni}) = \exp\{-\exp[-\mu_n(\varepsilon_{ni} - \lambda_{ni})]\} \quad (4.24)$$

the probability for switching travel mode from current c to alternative i can be acquired by the method developed by MacFadden (see appendix A):

$$\begin{aligned} P_n(c,i) &= \text{prob}(V_{ni} + H_{nic} + \bar{\varepsilon}_n > \text{Max}_{j \in B} (V_{nj} + H_{njc} + \bar{\varepsilon}_n) : j \in B \cap \bar{i}) \\ &= \frac{\exp(\eta_n V_{ni} + \mu_n H_{nic})}{\sum_{j=1}^J \exp(\mu_n V_{nj} + \mu_n H_{njc})} \\ &= \frac{\exp(\mu_n \sum_{k=1}^K \gamma_{nk} x_{nik} + \mu_n \sum_{k=1}^m \beta_{nk} (x_{nik} - x_{nck})^2)}{\sum_{j=1}^J \exp(\mu_n \sum_{k=1}^K \gamma_{nk} x_{njc} + \mu_n \sum_{k=1}^m \beta_{nk} (x_{njc} - x_{nck})^2)} \end{aligned} \quad (4.25)$$

where

x_{nik} -- attribute k for proposed alternative i for individual n

x_{nck} -- attribute k for current mode c for individual n

γ_{nk} and β_{nk} -- parameters for individual n

μ_n -- Scaling factor for individual n

If the parameters in the above equation is assumed as insensitive over individuals, sub-index n can be omitted from Equation (4.25) :

$$P(c,i) = \frac{\exp(\mu \sum_{k=1}^K \gamma_k x_{ik} + \mu \sum_{k=1}^m \beta_k (x_{ik} - x_{ck})^2)}{\sum_{j=1}^J \exp(\mu \sum_{k=1}^K \gamma_k x_{jk} + \mu \sum_{k=1}^m \beta_k (x_{jk} - x_{ck})^2)} \quad (4.26)$$

where

$P(c,i)$ -- the probability for switching travel mode from current mode c to proposed alternative i

By the derivation process above, a modified discrete choice model -- the Constrained Conditional Logit Model (CCLM) is developed.

4.2 Parameter Estimation

The estimation is performed by Maximum Likelihood Method (MLE). Given that individual n has a set of alternatives, the probability he switches travel mode from current mode c to a particular alternative i is expressed as Equation (4.25). If individuals' switchings are observed and the event of switching from mode c to alternative i by individual n is recorded as $Y_{nci} = I$, the probability that all events happen is expressed as :

$$\prod_n \prod_i \prod_c P_n(c,i)^{Y_{nci}} \quad (4.27)$$

The likelihood function, therefore, is :

$$\Lambda = Ln \prod_n \prod_i \prod_c P_n(c,i)^{Y_{nci}} = \sum_n \sum_i \sum_c Y_{nci} Ln P_n(c,i) \quad (4.28)$$

Assume the parameter γ_{nk} and β_{nk} in Equation (4.25) are all insensitive over individuals. To estimate the parameters, the following equations are required while maximizing Equation (4.28):

$$\frac{\partial \Lambda}{\partial \gamma_k} = \sum_n \sum_i \sum_c \frac{Y_{nci}}{P_n(c,i)} \frac{\partial P_n(c,i)}{\partial \gamma_k} = 0 \quad (4.29)$$

and

$$\frac{\partial \Lambda}{\partial \beta_k} = \sum_n \sum_i \sum_c \frac{Y_{nci}}{P_n(c,i)} \frac{\partial P_n(c,i)}{\partial \beta_k} = 0 \quad (4.30)$$

Take Equation (4.25) into the above equations :

$$\begin{aligned} \frac{\partial P_n(c,i)}{\partial \gamma_k} &= \frac{\partial}{\partial \gamma_k} \left(\frac{\exp(\mu_n \sum_k \gamma_k x_{nik} + \mu_n \sum_k \beta_k (x_{nik} - x_{nck})^2)}{\sum_j \exp(\mu_n \sum_k \gamma_k x_{njik} + \mu_n \sum_k \beta_k (x_{njik} - x_{nck})^2)} \right) \\ &= P_n(c,i) \left(\sum_j P_n(c,j) x_{njik} - x_{nik} \right) \end{aligned} \quad (4.31)$$

and

$$\begin{aligned} \frac{\partial P_n(c,i)}{\partial \beta_k} &= \frac{\partial}{\partial \beta_k} \left(\frac{\exp(\mu_n \sum_k \gamma_k x_{nik} + \mu_n \sum_k \beta_k (x_{nik} - x_{nck})^2)}{\sum_j \exp(\mu_n \sum_k \gamma_k x_{njik} + \mu_n \sum_k \beta_k (x_{njik} - x_{nck})^2)} \right) \\ &= P_n(c,i) \left(\sum_j P_n(c,j) (x_{njik} - x_{nck})^2 - (x_{nik} - x_{nck})^2 \right) \end{aligned} \quad (4.32)$$

Take Equation (4.31) and (4.32) into Equation (4.29) and (4.30) :

$$\begin{aligned} \frac{\partial \Lambda}{\partial \gamma_k} &= \sum_n \sum_i \sum_c Y_{nci} \left(\sum_j P_n(c,i) x_{njik} - x_{nik} \right) \\ &= \sum_n \sum_i \sum_c (P_n(c,i) x_{nik} - Y_{nci} x_{nik}) = 0 \quad (k=1, 2 \dots K) \end{aligned} \quad (4.33)$$

and

$$\begin{aligned} \frac{\partial \Lambda}{\partial \beta_k} &= \sum_n \sum_i \sum_c Y_{nci} \left(\sum_j P_n(c,j) (x_{njik} - x_{nck})^2 - (x_{nik} - x_{nck})^2 \right) \\ &= \sum_n \sum_i \sum_c (P_n(c,i) (x_{nik} - x_{nck})^2 - Y_{nci} (x_{nik} - x_{nck})^2) = 0 \\ & \quad (k=1, 2 \dots K) \end{aligned} \quad (4.34)$$

Take substitution (4.35):

$$h_{ncik} = (x_{nik} - x_{nck})^2 \quad (k=1, 2 \dots K) \quad (4.35)$$

into Equation (4.34), we can obtain :

$$\sum_n \sum_i \sum_c (P_n(c,i)h_{ncik} - Y_{nci}h_{ncik}) = 0 \quad (k=1,2,, K) \quad (4.36)$$

Take Equation (4.25) into Equations (4.33) and (4.36), we can compute the estimates for parameters γ_k and β_k ($k=1,2,, K$). Since Equation (4.33) and (4.36) are implicit functions of γ_k and β_k , estimates for parameters γ_k and β_k can only be obtained by the trial and error method as the products with scale factor μ_n , that is, the coefficients for parameters γ_k and β_k .

By the similar method developed by McFadden (1974), the maximum likelihood coefficient estimates for γ_k and β_k can be identified as consistent, asymptotically normal and asymptotically efficient.

CHAPTER 5

INTERNAL VALIDITY OF THE MODEL STRUCTURE

Although an extended structure model, the Constrained Conditional Logit Model, is derived, does this model make a difference from the Conditional Logit Model on the replication of actual travel mode switching? Whether can maximum likelihood algorithm recover the estimates that are significantly different from their parameters? An internal validity is conducted in this chapter by a Monte Carlo simulation to answer these questions, and to determine the impact of assuming a Conditional Logit Model where the actual model should be the Constrained Conditional Logit Model.

5.1 Data Generation

The first issue for the simulation is to determine the structure of systematic utility function. For the sake of convenience, the attainment from 1968 survey in the Washington, D. C., metropolitan area is used (Ben-Akiva & Lerman 1985). There are three travel modes in that survey, drive alone, transit bus and share carpool. The mode splits for the three travel modes are 57%, 16% and 27%, respectively. Three attributes included in the systematic utility function are travel time, travel cost and out-vehicle time. The average values for these attributes are presented in Table 5.1.

The next issue is data generation. For each observation, travel time for a particular travel mode is generated as an independent normal distributed variable. The average travel times for the three travel modes are 26.7, 56.5 and 36.7 as listed in Table 5.1. The standard deviation is 5.0.

Table 5.1 Average attribute value

	Travel Time (min)	Travel Cost (cents)	Out-Vehicle Time (min)
Auto	26.7	88.5	5.4
Bus	56.5	47.1	18.6
Carpool	36.7	35.4	10.4

Data obtained from 1968 survey in the Washington, D. C., metropolitan area

Travel costs are generated as three dependent variables on the travel times by the following equation :

$$Travel\ cost = (Travel\ time \times unit\ cost) + Normal\ distributed\ variable(0, 5.0) \quad (5.1)$$

where, the unit cost for the three travel modes are 6.15, 1.24 and 1.35 \$/min, respectively.

Out-vehicle times are generated as three independent normal distributed variables with average times of 5.4, 18.6 and 10.4. The standard deviation is 1.0.

The random utility term is a *Weibell* distributed variable with standard deviation of 1.28. The distribution function of random variable ϵ_{ni} is :

$$F(\epsilon_{ni}) = \exp[-\exp(-\mu_n \epsilon_{ni})] \quad (5.2)$$

where, μ_n is a scale factor defined as the function of variance σ_{ni} by Equation (2.7) in Chapter 2 (assume that μ_{ni} and σ_{ni} are insensitive over individuals).

$$\mu_n^2 = \pi^2 / (6\sigma_n^2)$$

In order to generate records for individual travel mode choices, the parameters for the corresponding attributes have to be pre-determined. Table 5.2 presents the pre-determined values for the parameters:

Table 5.2 Predetermined parameter value

Parameters	γ_1	γ_2	γ_3	β_1	β_2	β_3
True Value	-0.0389	-0.00725	-0.0121	-0.0054	-0.00012	-0.0112

In Table 5.2, γ_1 , γ_2 and γ_3 are the parameters for travel alternative specific attributes, travel time, travel cost and out-vehicle time and, β_1 , β_2 and β_3 are the parameters for the constraint variables imposed on the three travel alternative specific attributes.

5.2 Simulation Method

The performance of the Constrained Conditional Logit Model on replicating travelers' behavior is examined through the travel mode switching due to the designed travel service change. In the simulation, travel cost for driving alone is supposed to rise 50 cents for each observations. The all other attributes remain as the original ones. Traveler's mode switching due to the rising of travel cost is embodied by the Constrained Conditional Logit Model. The simulation is conducted by the following steps :

- 1) generate the travel specific alternative attributes by the approach described in the previous section,
- 2) compute the systematic utility terms and the random utility terms for the three alternatives,
- 3) choose the alternative with the largest sum of the systematic and random utility as the current travel mode c for observation i ,
- 4) compute the proposed travel specific alternative attributes according to the proposed travel cost rising,
- 5) compute the constraint functions for each switching alternative,
- 6) generate a *Weibull* random variable for each switching alternative,
- 7) compute the sum of systematic utility and random utility as the total utility for each switching alternative, and
- 8) choose the alternative with the largest total utility under the corresponding constraint condition as the switching choice i .

5.3 Simulation Result

The number of observations in the simulation is 200. Based on the switching database generated by the way described above, the coefficients are estimated by *ALOGIT* software. The control file is attached in Appendix B of this dissertation. The estimation result by the Constrained Conditional Logit Mode is listed in Table 5.3.

Table 5.3 Estimation by the CCLM model

Attribute Number	Attribute Name	Coefficient Estimate	Asymptotic Standard Error	t Test Statistic
1	Travel Time	-0.04483	0.03620	-1.2
2	Travel cost	-0.01123	0.00284	-4.0
3	Out-Vehicle Time	-0.00691	0.08490	-0.1
4	Travel Time Constraint.	-0.00689	0.00141	-4.9
5	Travel Cost Constraint.	-0.00014	0.000036	-3.9
6	Out-Vehicle Time Constraint	-0.01245	0.00696	-1.8

$\alpha(0) = -219.7225$
 $\alpha(\beta_c) = -90.6071$
 $\rho^2 = 0.5876$
 $\rho^2 = 0.5163$

The result shows that the null hypothesis of the parameter of Out-Vehicle Time can not be rejected even at a 0.10 level of significance. ($t = 1.65$).

The same database is used for the estimation by the Conditional Logit Model. Table 5.4 presents the estimation result:

Table 5.4 Estimation by the CLM model

Attribute Number	Attribute Name	Coefficient Estimate	Asymptotic Standard Error	t Test Statistic
1	Travel Time	-0.05815	0.0251	-2.3
2	Travel cost	-0.01183	0.0018	-6.5
3	Out-Vehicle Time	-0.00244	0.0548	-0.04

$\alpha(0) = -219.7225$
 $\alpha(\beta_l) = -189.5214$
 $\rho^2 = 0.1375$
 $\rho^2 = 0.0117$

The χ^2 test is used to examine the internal validity of the Constrained Conditional Logit Model. The test is performed by examining the null difference hypothesis between the estimated Constrained Conditional Logit Model and the estimated Conditional Logit Model under the situation where constraints exist in individuals' travel model switchings. The χ^2 test statistic L is computed by the following equation:

$$\begin{aligned}
 L &= -2 [\alpha(\beta_l) - \alpha(\beta_c)] \\
 &= -2 [-189.5214 + 90.6071] \\
 &= 197.8286
 \end{aligned}$$

where $\alpha(\beta_l)$ and $\alpha(\beta_c)$ are the likelihood values obtained for the Conditional Logit Model and the Constrained Conditional Logit Model as shown in Table 5.3 and Table 5.4.

The computation result shows that the null difference hypothesis for the two models can not be accepted even at a 0.05 level of significance as the critical value for a χ^2 distributed variable at three degree of freedom is 7.815. ($\chi^2_{0.1}(3) = 7.815$). Three constraint variables used in the constraint function is the sake of three degree of freedom.

The parameter estimates obtained for the Conditional Logit Model in Table 5.4 are identified as significantly different from the pre-determined parameter values as well

as the parameter estimates for the Constrained Conditional Logit Model listed in Table 3. In other words, if the Constrained Conditional Logit Model can capture the effects of constraints while these constraints do exist in individuals mode switching, the Conditional Logit Model will lost accurate estimates for these parameters.

Also, null hypothesis of the parameters for the corresponding constraint variables is rejected by a t test at a 0.10 level of significance ($t_{0.1} = 1.65$) for the three parameters and at a 0.05 level of significance for β_1 and β_2 . ($t_{0.1} = 1.96$)

The same conclusion can also be attained from the comparison of goodness-of-fit measures. Let us examine the likelihood ratio index (rho-squared bar) for both models. The entry of constraint attributes (h_{ci1} , h_{ci2} and h_{ci3}) causes index's rising from 0.0117 to 0.5163 . Therefore, entry of constraints appears capable of increasing sufficient explanation power to individuals mode switching behavior if constraints do exist.

Finally, Table 5 presents a summary for the pre-determined parameters, the estimates for the Conditional Logit Model, and the estimates for the Constrained Conditional Logit Model for the sake of easy comparison.

Table 5.5 Summary of parameter and estimate

<i>Parameters</i>	γ_1	γ_2	γ_3	β_1	β_2	β_3
Real Value	-0.03890	-0.00725	-0.01210	-0.00540	-0.00012	-0.01120
CLM Model	-0.05815	-0.01183	-0.00244			
CCLM Model	-0.04483	-0.01123	-0.00691	-0.00689	-0.00014	-0.01245

CHAPTER 6

SURVEY AND DATA COLLECTION

Through the simulation performed in Chapter 5, the validity of the Constrained Conditional Logit Model has been identified theoretically. This model can effectively replicate the effects of constraints on individuals' travel mode switching. However, an empirical study is still necessary for supporting this conclusion.

This chapter introduces the surveys conducted on the two sites in 1995. Each survey collects the travelers' current travel situation, travel mode usage and their preferences toward various scenarios of travel services.

6.1 Introduction of Survey Site

During the year 1995, the surveys of commuters at two employment sites were conducted in downtown of Newark, New Jersey. The respondents were the employees of the Mutual Benefit Life Corporation's (MBL) headquarters building on Broad Street, and the Prudential Insurance Corporation's Washington Plaza Building (WP).

According to two independent Employee Transportation Surveys administered in compliance with the U.S. Clean Air Act Amendments of 1991, as of September 26, 1994, total 893 employees of MBL Corporation worked in the MBL building everyday. Seven hundred and fifty six parking spaces were available in MBL building at a parking charge of 3.00 dollar per day. In addition, some street parking was available within three blocks. Bus stops were located within one block or approximately 50 yards of the building's entrance. During the morning commute, seven bus lines served the MBL building with headways of less than 15 minutes, and additional four lines have headways between 16-30 minutes. Two commuter railway stations and two subway stations are located within walking distance. According to the survey of 1994, travel modes used by the MBL employees can be categorized into drive alone, carpool/vanpool and public transport (bus,

subway and rail). About 60.5% of total employees drive alone to work. The market shares of carpool and public transport are approximately 14.5% and 25%, respectively. The average one-way commute distance for the all employees in MBL building is 18 miles.

The employees' commute travel to the Prudential - Washington Plaza Building (WP) is similar with that to MBL. The survey of September 26, 1994 shows that there are 893 employees working at the WP site on a daily bases, and 902 parking spaces are provided to the Prudential employees without parking fee. Also, additional 296 off-site parking spaces within a distance of three blocks are leased for the WP employees. Three bus lines serve the site with 15 minute morning headways, two lines have 30 minute headways, and one with more than 30 minute headways. Subway and commuter rail service are available within a three block or 10 minute walking distance. The 1994 survey also shows that the market shares of travel alone, carpool or vanpool, and public transport are 63.2%, 13.1% and 23.2%, respectively. The average one-way commute distance for the all employees in WP building is 19.06 miles. Figure 6.1 presents the travel distance distributions for the two sites.

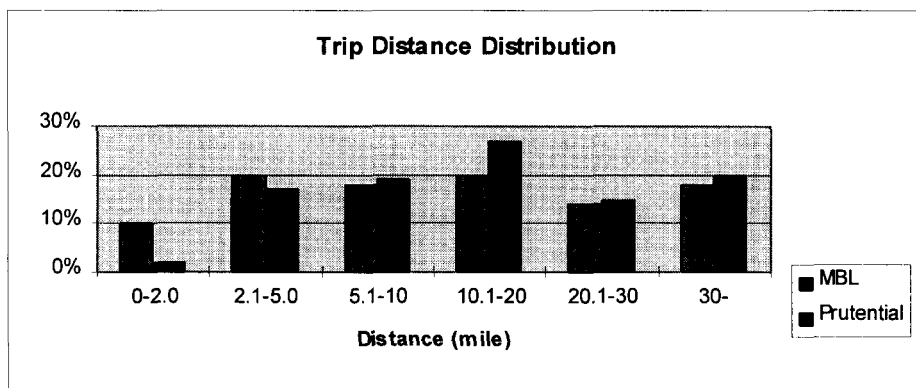


Figure 6.1 Distribution of travel distance

The 1994 surveys also supply the distributions of employee's home location. The following Table 6.1 gives the 10 most common home zip codes for the both sites.

Table 6.1 Most common home zip code and percentage

Rank	The MBL Site		The WP Site	
	Home Zip	Percentage	Home Zip	Percentage
1	07111	4.40%	07111	3.00%
2	07032	4.00%	07083	2.00%
3	07109	3.80%	07032	1.80%
4	07003	3.10%	07003	1.60%
5	07029	2.10%	07052	1.40%
6	07108	2.00%	07205	1.40%
7	07104	2.00%	07109	1.40%
8	07050	1.80%	07040	1.30%
9	07103	1.70%	07018	1.30%
10	07106	1.70%	07110	1.30%

The surveys also provide the job classification for the employees on the two sites because this factor has been identified by some empirical studies as closely related to travel mode choice. Table 6.2 presents the job category.

Table 6.2 Job category

Job category.	The MBL Site	The WP Site
Clerical/Secretarial	21%	27%
Technical	6%	4%
Administrator/Manager	25%	20%
Sales/Associate	2%	1%
Service/Maintenance	3%	1%
Skilled Craft	1%	0%
Professional	36%	39%
Laborer	0%	1%
Others	6%	7%

6.2 Survey Instrument

The Constrained Conditional Logit Model is calibrated to a particular set of alternatives by the data obtained from the survey instrument. The survey instrument consists of two sections:

- a) the respondent's socioeconomic characteristics and current travel situation, and
- b) the scenarios of proposed travel alternatives and the respondent's choices.

First, the respondents are requested to report their current travel situation by answering a set of questions. These questions can be categorized into:

- 1) the questions about the respondent's current travel modes and associated attributes, such as current travel mode available to the respondent, his current using travel mode and associated travel time, cost, access time and access approach. The respondents are encouraged to report the information about the other travel mode's attributes values,
- 2) respondent's preferences to the existed and proposed travel modes, such as the attitude to the existed travel modes, and comfort and safety appraisalment for each travel mode. Each of the preferential questions consist of some level semantic scales, from extremely pleased to extremely displeased.
- 3) traveler's personal information related to the travel mode choice, such as traveler's family size, income, age, gender and job classification. Some of the questions in this section are presented as a category formation. For instance, the income of the respondent consists of five levels with the equal interval of \$25,000.

The commute mode choice scenarios were presented to the respondents with three commute alternatives: single occupant vehicle (SOV), carpool (CP) and public transport (PT). A total of 18 scenarios were designed for the respondents from both sites. Each scenario provides respondents with a set of attribute values for the each alternative.

Appendix C presents an example of scenarios. Table 6.3 presents the brief introduction of these attributes and their value ranges:

Table 6.3 Alternatives and associated attributes

ALTERNATIVES	ATTRIBUTES
Alternative 1, Single Occupant Vehicle	
Cost of tolls and gas per day	Current costs
Parking space charge per day	\$0.00, \$3.00, \$5.00
Alternative 2, Carpool	
Carpool costs per person per day	1/2 drive alone cost
Parking space charge per day	1/2 drive alone parking space charge
Pick up location	Home, parking lot, shopping center
Extra time required for carpooling	10 min, 20 min, 30 min
Guaranteed rider home	15 min waiting, 35 min waiting, none
Alternative 3, Public Transit	
Transit fare per day	Current value
Number of transfers	Current number
Extra time required for transit	15 min, 25 min, 45 min
Guaranteed rider home	15 min waiting, 35 min waiting, none
Transit subsidy paid to you per day	None, \$3.00, \$5.00

The sequence of 18 scenarios were randomly ordered and administered to respondents. The respondents are asked to choose just one travel mode according to their tastes or preferences. Respondents were selected through the volunteer process. The employee transportation coordinator of each firm asked for volunteers from the permanent employees working at the site. The survey questionnaires were delivered to the volunteer by corporate mails and total 74 respondents from MBL and 85 from WP

returned the questionnaires. Each respondent completed 18 choice tasks or observations. Respondents failing to answer the questions about their current commute mode were excluded from the following data analysis. The final data set contains 646 and 898 observations in MBL and WP data set, respectively.

CHAPTER 7

ESTIMATION AND TEST OF HYPOTHESIS

In this chapter, empirical evidence is used to test the hypothesis proposed in Chapter 3, that is, constraints should be explicitly included in decision makers' indirect utility functions. The hypothesis tests are conducted through the following steps:

- 1) The coefficients in systematic utility function are estimated by the Conditional Logit Model and the Constrained Conditional Logit Model. This process is conducted by ALOGIT software for MBL data and WP data separately.
- 2) A χ^2 test is performed for the null structural difference hypothesis and a t test is performed to test the null coefficient hypothesis for each constraint variable.
- 3) the two data sets are pooled and tested for a common underlying structural model.

7.1 Coefficient Estimation

Data matrix $[X_{ik}]$ was formed after a pre-analysis of MBL and WP survey data in accordance to the Constrained Conditional Logit Model. The sub-index n in Equation (4.25) is omitted since the coefficients in the empirical model are assumed to be insensitive to the different individuals in the samples.

$$P(c,i) = \frac{\exp(\mu V_i + \mu H_{ci})}{\sum_{j=1}^J \exp(\mu V_j + \mu H_{cj})} \quad (i=1,2,3)$$

and

$$\begin{aligned} V_i &= \alpha_i + \sum_{k=1}^K \gamma_k x_{ik} \\ H_{ci} &= \sum_{k=1}^K \beta_k h_{cik} = \sum_{k=1}^K (x_{ik} - x_{ck})^2 \end{aligned} \quad (7.1)$$

Sub-index i stands for the i th observation and k refers to the k th element in the data set. Each observation consists of 23 elements shown as Table 7.1.

Table 7.1 Element in each observation

Element No.	Variable
1	individual choice
2	travel time for SOV, x_{11}
3	travel cost for SOV, x_{12}
4	access time for SOV, x_{13}
5	travel time for CP, x_{21}
6	travel cost for CP, x_{22}
7	access time for CP, x_{23}
8	travel time for PT, x_{31}
9	travel cost for PT, x_{32}
10	access time for PT, x_{33}
11	attitude for SOV, x_{14}
12	attitude for CP, x_{25}
13	attitude for PT, x_{36}
14	traveler's age, x_{17}
15	traveler's family size, x_{18}
16	traveler's gender, x_{19}
17	traveler's annual income, x_{10}
18	designed travel time change for SOV, h_{c11}
19	designed travel cost change for SOV, h_{c12}
20	designed travel time change for CP, h_{c21}
21	designed travel cost change for CP, h_{c22}
22	designed travel time change for PT, h_{c31}
23	designed travel cost change for PT, h_{c32}

Equation (7.2) shows the systematic utility term including its elements and associated parameters.

$$(V_i) = (\alpha_i) + [X_{ik}] \gamma_k \quad (i = 1, 2, 3) \quad (7.2)$$

where, the vector (V_i) refers to the systematic utility derived from each commute alternative: single occupant vehicle (SOV), carpool (CP) or public transit (PT), respectively. The elements in the parameter vector (γ_k) are presented in Table 7.2.

Table 7.2 Parameter in systematic utility function

Number	The attribute which parameter is corresponding to
1	travel time (generic)
2	travel cost (generic)
3	access time (generic)
4	attitude for SOV
5	attitude for CP
6	attitude for PT
7	traveler's age for SOV
8	traveler's family size for SOV
9	traveler's gender for SOV
10	traveler's income for SOV

The parameter vector (α_i) stands for the alternative specific constant for the alternatives: SOV and CP. The design travel scenarios are mainly constructed in term of changes in travel time and travel cost, therefore, the variables in constraint term H_{ci} are designed to correspond the constraints on travel time and travel cost. The constraint function H_{ci} is formed in the form of Equation (7.3):

$$\begin{pmatrix} H_{c1} \\ H_{c2} \\ H_{c3} \end{pmatrix} = \begin{bmatrix} h_{c11} & h_{c12} \\ h_{c21} & h_{c22} \\ h_{c31} & h_{c32} \end{bmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} \quad (7.3)$$

where, β_1 and β_2 are the parameters corresponding to the two arguments in the constraint function. Appendix D presents the control files used in ALOGIT software. Table 7.3 and

7.4 present the Constrained Conditional Logit Model estimation results for the MBL and the WP sites, respectively.

Table 7.3 CCLM model estimation for the MBL site

Attribute number	Attribute Name	Coefficient estimate	Asymptotic Standard Error	t Statistic
1	Constant of SOV	-1.574	.562	-2.8
2	Constant of CP	.5770	.784	.7
3	Travel Time (generic)	-.1819E-01	.947E-02	-1.9
4	Travel cost (generic)	-.2179	.568E-01	-3.8
5	Access Time (generic)	-.9164E-02	.138E-01	-.7
6	Attitude to SOV	.3200	.585E-01	5.5
7	Attitude to CP	.3470	.713E-01	4.9
8	Attitude to PT	.5547	.738E-01	7.5
9	Age to SOV	.4110E-01	.127E-01	3.2
10	Family Size to SOV	.8326E-01	.393E-01	2.1
11	Gender to SOV	-.2226	.115	-1.9
12	Income to SOV	.9286E-01	.122	.8
13	Constraint on Travel Time(generic)	-.6632E-03	.154E-03	-4.3
14	Constraint on Travel Cost(generic)	.2371E-02	.479E-02	.5

Likelihood with Zero $\alpha(0) = -709.7053$

Final Likelihood $\alpha_c(\beta_m) = -555.8165$

Rho-Squared with Zero $\rho^2 = 0.2168$

Rho-Squared with constant $\rho^2 = 0.2050$

Table 7.4 CCLM model estimation for the WP site

Attribute number	Attribute Name	Coefficient estimate	Asymptotic Standard Error	<i>t</i> Statistic
1	Constant of SOV	1.468	.563	2.6
2	Constant of CP	0.359	.579E-01	6.2
3	Travel Time (generic)	-.1921E-01	.630E-02	-3.0
4	Travel cost (generic)	-.2509	.335E-01	-7.5
5	Access Time (generic)	.1508E-02	.708E-02	.2
6	Attitude to SOV	.2055	.534E-01	3.8
7	Attitude to CP	.3572E-01	.509E-01	.7
8	Attitude to PT	.5497	.562E-01	9.8
9	Age to SOV	-.2001E02	.835E-02	-.2
10	Family Size to SOV	.6713E-01	.297E-01	2.3
11	Gender to SOV	.4391	.109	4.0
12	Income to SOV	-.2219E-01	.675E-01	-.3
13	Constraint on Travel Time(generic)	-.4147E-03	.917E-04	-4.5
14	Constraint on Travel Cost(generic)	-.1941E-01	.506E-02	-3.8

Likelihood with Zero $\alpha(0) = -986.5538$
 Final Likelihood $\alpha_c(\beta_w) = -807.8917$
 Rho-Squared with Zero $\rho^2 = 0.1811$
 Rho-Squared with constant $\rho^2 = 0.1623$

In Table 7.3 and 7.4, $\alpha(0)$ is the maximum likelihood value where all the parameters are zero, and $\alpha_c(\beta_m)$ and $\alpha_c(\beta_w)$ are the maximum likelihood values for the final estimation results. ρ^2 and $\bar{\rho}^2$ are the factors for the goodness-of-fit measure.

First, discuss the estimates associated with the travel specific attributes, travel time, travel cost and access time. Both Table 7.3 and 7.4 above show that the estimates corresponding to travel time and travel cost are negative as expected. However, the *t* statistic values for the estimates corresponding to access time are very small for the two sites. As the *t* statistic values are less than the critical value of 1.28 under significant level of 0.1, the access time effect on the individuals travel mode switching can be put into the random utility term. According to the analysis to the data, this is because that the quite

more respondents in the two sites did not correctly answer the questions about their access time and approach, especially for the alternatives they did not use currently. The alternative specific constants for SOV are positive for both sites. The coefficient estimates for the attitudes are all positive as expected.

The traveler's annual income has very weak effect and this effect is contradictory for the two sites (0.8 and -0.3 for MBL and WP, respectively). This result can be explained as the respondents' reluctant to answer the question about their income, or deliberately supply the wrong answers.

Table 7.5 CLM model estimation for the MBL site

Parameter	Attribute	Coefficient estimate	Asymptotic Standard Error	t Statistic
α_1	Constant of SOV	-2.788	.863	-3.2
α_2	Constant of CP	.9085	.732	1.2
γ_1	Travel Time	-.4618E-01	.683E-02	-6.8
γ_2	Travel cost	-.2361	.406E-01	-5.8
γ_4	Access Time	-.4559E-02	.125E-01	-0.4
γ_5	Attitude to SOV	.3470	.574E-01	6.0
γ_6	Attitude to CP	.3171	.701E-01	4.5
γ_8	Attitude to PT	.5302	.711E-01	7.5
γ_9	Age	.3823E-01	.126E-01	3.0
γ_{10}	Family Size	.7370E-01	.391E-01	1.9
	Gender	-.2363	.114	-2.1
	Income	.1442	.120	1.2
$\alpha(0) = -709.7053$				
$\alpha(\beta_m) = -567.5669$				
$\rho^2 = 0.2003$				
$\bar{\rho}^2 = 0.1881$				

It is noteworthy that the coefficient estimates for the constraint variables are negative. This result means that the existence of constraints encourages the traveler to stay or switch to an alternative with smaller attribute changes.

Table 7.5 and 7.6 present the estimation for the Conditional Logit Model using ALOGIT software for the two sites. The results show that the t statistic values corresponding to access time and traveler's annual income are also less than the critical value of 1.28.

Table 7.6 CLM model estimation for the WP site

Parameter	Attribute	Coefficient estimate	Asymptotic Standard Error	t Statistic
α_1	Constant of SOV	.6232	.524	1.2
α_2	Constant of CP	2.877	.493	5.8
γ_1	Travel Time	-.3397E-01	.534E-02	-6.4
γ_2	Travel cost	-.1794	.252E-01	-7.1
γ_3	Access Time	-.2154E-02	.706E-02	-0.3
γ_4	Attitude to SOV	.2566	.530E-01	4.8
γ_5	Attitude to CP	.3194E-01	.511E-01	4.6
γ_6	Attitude to PT	.5165	.534E-01	9.7
γ_7	Age	-.1256E-02	.825E-02	-0.2
γ_8	Family Size	.4787E-01	.285E-01	1.7
γ_9	Gender	.4524	.109	4.2
γ_{10}	Income	-.1565E-02	.666E-01	0.0
$\alpha(0) = -986.5538$				
$\alpha_l(\beta_w) = -831.4445$				
$\rho^2 = 0.1572$				
$\bar{\rho}^2 = 0.1378$				

7.2 Hypothesis Testing

The hypothesis that constraints will significantly affect the individuals travel mode switching behavior is tested by:

- a) a χ^2 test performed for examining the null difference hypothesis.

The null difference hypothesis suggests that the Constrained Conditional Logit Model has same underlying structural parameters as the Conditional Logit Model. In

other words, the coefficients are not significantly different statistically for the two models.

$\alpha_l(\beta_m)$ and $\alpha_l(\beta_w)$ in Table 7.5 and 7.6 are the likelihood values obtained by the Conditional Logit Model, and $\alpha_c(\beta_m)$ and $\alpha_c(\beta_w)$ in Table 7.3 and 7.4 are by the Constrained Conditional Logit Model. The χ^2 test statistic λ for the MBL site and the WP site is computed as:

$$\lambda_m = -2 (\alpha_l(\beta_m) - \alpha_c(\beta_m))$$

or

$$\lambda_w = -2 (\alpha_l(\beta_w) - \alpha_c(\beta_w)) \quad (7.4)$$

If either χ^2 test statistic: λ_m or λ_w , is larger than the critical value $\chi^2_{s(n)}$, the null hypothesis will be rejected. Sub-index s stands for significant level and n refers to degree of freedom. The alternative hypothesis that the two models are significantly different from each other will be accepted.

The χ^2 test statistic λ_m for MBL data is computed as:

$$\lambda_m = -2 (-567.5669 + 555.8165) = 23.5008$$

As the critical value under the significance level of 0.05 with two freedom (two freedom is the result of two new parameters) is 5.991, the null difference hypothesis of structural parameters for the two models is rejected for MBL sample. This means that the equation estimated by the Constrained Conditional Logit Models are significantly different from the equation estimated by the Conditional Logit Model.

By the same way as the above, the null difference hypothesis of the structural parameter estimates is rejected for WP sample as well as MBL sample. The χ^2 test statistic λ_w is computed:

$$\lambda_w = -2 (-831.4445 + 807.8917) = 47.1056$$

- b) a t test performed for the null hypothesis of each coefficient in constraint function if the null hypothesis in χ^2 test is rejected.

This test is to examine which constraint's effect is significant statistically. If the null hypothesis for a particular coefficient is rejected, we accept the alternative hypothesis that this constraint exists in the travel mode switching behavior.

The null hypothesis of constraint coefficients is rejected as the t statistics for coefficients 13 and 14 in Table 7.3 and 7.4 are both larger than the critical value of 1.28 under the significant level of 0.1. This result shows that the constraints on the travel time and travel cost both exist.

In summary, through the tests performed by the two data sets, a conclusion is reached. As expected, constraints exist and affect individuals' travel mode switching.

7.3 Joint Data Estimation and Sample Identity Testing

The 1994 surveys for the MBL and WP sites show that the individuals of the two sites have similar geographic and sociological characteristics as well as the actual commute mode alternatives. On the surface, the two experiment sites appear identical for all other travel attributes with the exception of a difference in parking charge. Both sites hold financial service headquarters. Both sites are in the CBD of the same city. Both are located near the same transportation centers. However, whether these two data can be accepted as the two samples drawn from the same population is still needed to be examined statistically.

On the view of discrete mode choice model, two samples drawn from the same population should statistically have the same parameters for the systematic utility components and same random utility distribution. As the estimation of the model supplies the coefficient estimates, the discussion should be start from the identity of coefficients.

The discussion in Chapter 2 shows that the calibrated coefficient τ_n is the product of parameter vector γ_n corresponding to the attributes in the systematic utility function

and the scale factor μ_n which is related to the variance of the random utility term. Sub-index n (1 or 2) here stands for the different sample; the MBL or the WP sample.

$$\mu_n \times \gamma_n = \tau_n \quad (7.5)$$

The sufficient condition for the equivalence of coefficients for the two samples: $\tau_1 = \tau_2$, is that μ_1 equals to μ_2 and γ_1 equals to γ_2 . However, this does not mean that different coefficients: $\tau_1 \neq \tau_2$, will definitely result in different parameters: $\gamma_1 \neq \gamma_2$ and different scale factors: $\mu_1 \neq \mu_2$.

Assume the variances of the two samples in this study are σ_1^2 for the MBL and σ_2^2 for the WP and they can be expressed as:

$$\sigma_1^2 = \zeta^2 \sigma_2^2 \quad (7.6)$$

where λ is a factor called the scale factor ratio. Now, the requirement for the identity of scale factors is transferred to be $\zeta = 1$. Therefore, we obtain:

$$\mu_1 = \zeta \mu_2 \quad (7.7)$$

where sub-index 1 and 2 refer to the sample 1 and sample 2. Providing that the scale factor μ_1 of sample 1 is arbitrary assumed as 1.0, we can calculate the scale factor μ_2 and ζ according to the coefficients τ_1 and τ_2 if the parameters are identical for the two samples. The important point is to test if the two samples have same parameters.

The test for the hypothesis of the two samples identical is performed by two sub-test as follows:

- a) test the null difference hypothesis for the two sample's parameters, and
- b) test the null difference hypothesis for the two samples scale factors, that is, scale factor ratio is 1.0 while the parameters of the two samples are equal.

A approach which was designed to test the identity of stated preference (SP) and revealed preference (RP) data is used in this report (Swait & Louviere, 1993). The key point of the test for hypothesis (a) above is to find the scale factor ratio by a grid search. The grid search is conducted in the following few steps:

- 1) compute separately the coefficients τ_1 and τ_2 for the two samples,

- 2) set a reasonable range for the scale factor ratio λ , and determine a unified interval to obtain a set of trail scale factor $\lambda^{(l)}$. Parameter $\lambda^{(l)}$ stands for the different trail value for λ ,
- 3) concatenate both data sets as a joint data set $[X_{ik}(m) \lambda^{(l)} X_{ik}(w)]^T$ with a trial scale factor ratio $\lambda^{(l)}$. $X_{ik}(m)$ and $X_{ik}(w)$ for the data matrix for MBL sample and the WP sample.
- 4) estimate coefficients using the joint data set with different scale factor ratio $\lambda^{(l)}$, and
- 5) repeat step 3) and 4) until a maximum likelihood value is achieved.

The $\lambda^{(l)}$ corresponding to the maximum likelihood value is the scale factor ratio estimate. After the estimate and its corresponding likelihood are computed, the test for parameter equality is executed by comparing the likelihood for the joint data set with the sum of the separate likelihoods for the two samples. Accept the null hypothesis that both samples have the same parameters in the systematic utility function if the joint and summed separate likelihoods are not significantly different.

If the above null hypothesis is accepted, compare the maximum joint likelihood to the joint likelihood with scale factor ratio of 1.0, and accept hypothesis (b) if the maximum joint likelihood and likelihood with 1.0 of scale factor ratio are not different statistically.

The separate estimations for the two samples have been finished in section 7.1 and the coefficient estimates are listed in Table 7.3 and 7.4. Therefore, grid search was performed by a series of joint estimations with different scale factor ratios using ALOGIT program. The control file for the joint estimation is attached in Appendix E of this report. The WP data matrix was multiplied by a particular scale factor ratio λ_i and concatenated with MBL data matrix to form a joint data matrix. The grid search result is presented by Figure 7.1.

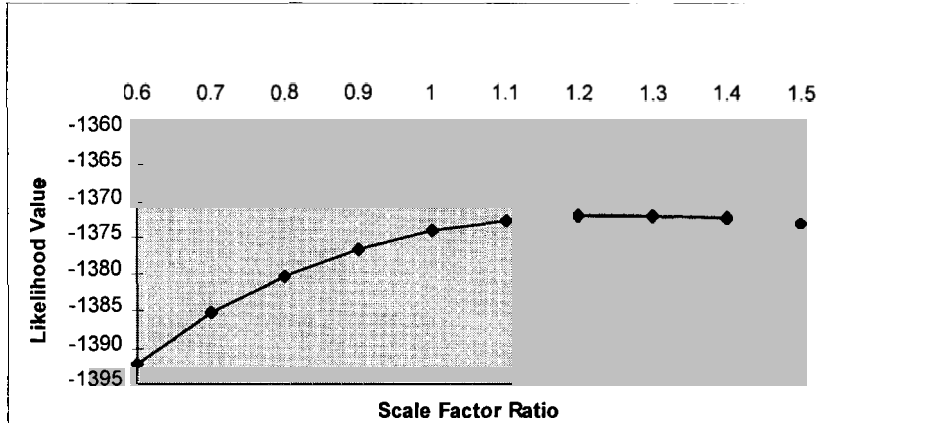


Figure 7.1: Grid search of scale factor ratio

The likelihood value $\alpha_c(\beta_p)$ corresponding to the scale factor ratio of 1.0 is -1374.0999; the estimation model for this value is not shown. The maximum likelihood value $\alpha_c(\beta_{\mu})$ found by the grid search is -1370.5652 at the scale factor ratio of 1.3. Table 7.7 presents the estimation result with the scale factor ratio of 1.3 using the Constrained Conditional Logit Model.

The test for the parameter identity of the two samples is conducted based upon the separate estimations in Table 7.3 and 7.4 and the joint estimation in Table 7.7. The χ^2 test statistic L_a for hypothesis of parameter identity is computed as:

Table 7.7 Joint estimation by the CCLM model

Attribute number	Attribute Name	Coefficient estimate	Asymptotic Standard Error	t Statistic
1	Constant of SOV for the MBL	-2.203	.812	-2.7
2	Constant of CP for the MBL	1.028	.709	1.4
3	Constant of SOV for the WP	1.581	.543	2.9
4	Constant of CP for the WP	3.193	.503	6.4
5	Travel Time (generic)	-.1715E-01	.478E-02	-3.6
6	Travel cost (generic)	-.2159	.253E-01	-8.5
7	Access Time (generic)	-.1402E-02	.601E-01	-0.2
8	Attitude to SOV	.3266	.571E-01	5.7
9	Attitude to CP	.3258	.701E-01	4.7
10	Attitude to PT	.5527	.720E-01	7.7
11	Age to SOV	.3925E-01	.126E-01	3.1
12	Family Size to SOV	.7972E-01	.389E-01	2.0
13	Gender to SOV	-.2112	.114	-1.9
14	Income to SOV	.1180	.120	1.0
15	Constraint on Travel Time(generic)	-.4961E-03	.719E-4	-6.9
16	Constraint on Travel Cost(generic)	-.5284E-02	.252E-2	-2.1

Scale Factor Ratio $\lambda = 1.3$

Likelihood with Zero $\alpha(0) = -1696.2574$

Final Likelihood $\alpha_c(\beta) = -1370.5652$

Rho-Squared with Zero $\rho^2 = 0.1920$

Rho-Squared with constant $\rho^2 = 0.1795$

$$\begin{aligned}
 L_{aj} &= -2 [\alpha_c(\beta_{\mu}) - (\alpha_c(\beta_m) + \alpha_c(\beta_w))] \\
 &= -2(-1370.5652 - (-555.8165 - 807.8917)) \\
 &= 13.714
 \end{aligned}$$

Critical Value with df=9 is 19.675.

where, $\alpha_c(\beta_{\mu})$ is the maximum likelihood value of joint data estimation in Table 7.7, $\alpha_c(\beta_m)$ and $\alpha_c(\beta_w)$ are the maximum likelihood values of the separate estimations for the MBL sample and the WP sample shown in Tables 7.3 and 7.4.. The critical value under

the significance level of 0.05 with degree of freedom equal to 9 is 19.675. The degree of freedom number is $K+1$, where K is the number of common parameters in joint model as well as the separate models. The null hypothesis states that the parameters underlying both models are identity.

The hypothesis of scale factor identity is tested by computing test statistic L_b

$$\begin{aligned} L_b &= -2 [\alpha_c(\beta_p) - \alpha_c(\beta_\mu)] \\ &= -2(-1374.0999+1370.5652) \\ &= 7.0694 \end{aligned}$$

Critical value with $df=1$ is 3.841

where, $\alpha_c(\beta_p)$ is the likelihood value of joint data estimation with scale factor ratio of 1.0 shown in Figure 1. The critical value under the significance level of 0.05 with degree of freedom of 1 is 3.841. (the one degree of freedom is the result of the restriction on the scale factor $\mu_1 = \mu_2$)

The two test results show that the parameters in the systematic utility functions are identical for the two samples, but the variances of random components and therefore the scaling factor are different. Finally, based on the joint estimation result in Table 7.7, the joint Constrained Conditional Logit Model was calibrated as follows:

$$P_n(c,i) = \frac{\exp(\mu_n V_i + \mu_n H_{ci})}{\sum_{j=1}^3 \exp(\mu_n V_j + \mu_n H_{cj})} \quad (c, i = 1, 2, 3)$$

and

$$\begin{Bmatrix} V_1 \\ V_2 \\ V_3 \end{Bmatrix} = \begin{Bmatrix} -2.203E_1 + 1.028E_2 \\ 1.581E_1 + 3.193E_2 \\ 0 \end{Bmatrix} +$$

$$+ \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & 0 & 0 & x_{17} & x_{18} & x_{19} & x_{10} \\ x_{21} & x_{22} & x_{23} & 0 & x_{25} & 0 & 0 & 0 & 0 & 0 \\ x_{31} & x_{32} & x_{33} & 0 & 0 & x_{36} & 0 & 0 & 0 & 0 \end{bmatrix} \begin{Bmatrix} -0.0172 \\ -0.2159 \\ -0.0014 \\ 0.3266 \\ 0.3258 \\ 0.5527 \\ 0.0393 \\ 0.0797 \\ -0.2112 \\ 0.1180 \end{Bmatrix} \quad (7.8)$$

$$\begin{pmatrix} H_{c1} \\ H_{c2} \\ H_{c3} \end{pmatrix} = \begin{bmatrix} (x_{11} - x_{c1})^2 & (x_{12} - x_{c2})^2 \\ (x_{21} - x_{c2})^2 & (x_{22} - x_{c2})^2 \\ (x_{31} - x_{c1})^2 & (x_{32} - x_{c2})^2 \end{bmatrix} \begin{Bmatrix} -0.0005 \\ -0.0053 \end{Bmatrix}$$

where, E_1 is 1 for MBL and 0 for WP individuals, and E_2 is 0 for MBL and 1 for WP individuals. Parameter μ_n is 1 for MBL and 1.3 for WP individuals. The term $(x_{ik} - x_{ck})$ stands for the designed k th attribute change if commuter switches from current mode c to alternative i .

The coefficients in the constraint terms (H_{ci}) are all negative in Equation (7.8). For example, the coefficient for travel time change term is -0.0005 . This result shows that the constraints for travel time and cost tend to encourage individuals to remain in their current commute modes, instead of switching to an alternative. However, some variable's contributions to the mode switching behavior, such as access time and income, are still vague in that their t statistic values are less than the critical value. Additional study on these variables is necessary.

7.4 Discussion

In summary, empirical evidence has identified the existence of the constrained resources, such as cost and time, on individual mode switching behavior. These constraints are identified to significantly affect individual mode switching behavior. Ignoring the effects

of these constraints, when estimating the model, will cause biased coefficient estimates. The Constrained Conditional Logit Model can correct these biases and errors.

In addition, correcting the biases in the estimation of the coefficients makes the transferability of the empirical models possible. As the joint estimation improves the estimation efficiency as well as the accuracy of the estimates.

CHAPTER 8

EXTERNAL VALIDITY AND DISCUSSION

Chapter 7 tests the Constrained Conditional Logit Model and presents evidence of its superior performance when compared to the Conditional Logit Model. However, the evidence is limited to construct validity tests and is therefore limited to a test of internal validity.

Forecast and policy models are prepared to predict states of systems after attributes have been changed. A model may succeed in demonstrating internal validity, but this does not guarantee high quality predictions. A useful model must also be examined for its external validity. According to Rosnow and Rosenthal (1996), external validity is a model's performance in predicting actual states of affairs. This chapter presents the methodology and the external validity test for carrying out the analysis.

8.1 Ideal Experimental design for external validity test

An external validity test of the CCLM model examines a model's ability to predict travel mode switching behavior associated with a designed change in travel conditions, such as a parking charge imposition. Ideally, an external validity test should be performed by measuring the difference between predicted travel mode switching and real mode switching following a change in a travel attribute identical to that specified in the forecasting model.

One of the most important issue in external validity test is the experimental design for obtaining the actual mode switching data. A statistically appropriate number of individuals should be randomly selected from a target population, and the characteristics of their travel situations relative to the travel modes available, such as travel time, cost ...etc., as well as their current choices of travel modes recorded. Then, by an equality principle these individuals should be randomly assigned to two different experimental

conditions, the test condition and control condition. Individuals assigned to the control condition should face a set of unchanging travel conditions and, therefore, be called the control sub-sample. The individuals assigned to the test condition would have one attribute changed to test the effect of the attribute change on the mode switching.

On the other hand, mode switching prediction should be made in corresponding to the difference between the control and test conditions identical with the experiment and be compared with the real outcome of the experiment. The comparison usually be conducted by a particular statistical approach.

Let us take an imposition of a parking charge as an example. The external validity test could include:

- 1) randomly select a set of individuals and record their current travel modes and associated travel attributes for each travel alternative,
- 2) randomly assign these individuals to either the control condition or to the test condition. The control condition maintains the individuals current travel conditions while, the test condition imposes a designed parking charge.
- 3) observe and record the real mode choice for the two sub-samples before and after the designed parking charge is imposed. The market share differences between the two sub-samples are accepted as the effect of parking charge imposition after removal of confounding effects,
- 4) predict travel mode switching behavior associated with the designed parking charge imposition identical with the experiment condition using the CCLM model,
- 5) test the null difference hypothesis. The null hypothesis -- the mode split obtained by the forecast model is statistically identical to the mode split obtained under the real world conditions.

If the null difference hypothesis is accepted, the hypothesis that the CCLM model prediction is identical to actual controlled switching behavior can not be rejected. In other word, the CCLM model is externally valid.

8.2 Actual Experimental Design for External Validity Test

An ideal external validity test is seldom supported by real world condition. The ideal experimental design is therefore necessarily modified to be practical for the circumstances surrounding actual research condition. The practical experimental design must incorporate cause and effect reasoning. This implies that the two phenomenon covary, the cause precedes the effect and confounding factors are eliminated.

A longitudinal design conforms to at least one of the three criteria for cause and effect reasoning since this design can effectively guarantee the control sample and the test sample identical by observing the sample sample's behavior before and after the test condition is executed. The data used in longitudinal design is called panel data as discussed in Chapter 2.

However, panel data was not available in that the researchers had no opportunity to manipulate both test and control conditions in the actual experiment. Alternatively, two samples may be selected based on their location in a same central business district (CBD) and their operation in the same type of business to replace the panel data. This data is called cross-sectional data and a cross-sectional design is then developed in this situation to replace the longitudinal design. The principle and process of this design will be discussed in section 8.2.1.

Data was collected in this study for the external validity test as well as for both the CLM and the CCLM estimation of explanatory models. The CCLM explanatory model developed in Chapter 7 is used to produce a forecast of mode split change associated with a change in parking charge. To remove confounding effect in cross-

sectional experimental design, all other variables (covariates) in the explanatory model are held unchanged in the forecast.

In correspondence, a truth set was formed by combining the WP sample with adjusted covariates and the MBL sample for completing the external validity test. The confounding effect removal and relevant covariate adjustment will be discussed in detail in section 8.2.2.

The external validity test will be performed by generating a mode split forecast by the CCLM explanatory model. The forecast method for the external validity test will be discussed in section 8.2.3. Finally the difference between the forecast values and the truth set's mode split values will be tested using standard hypothesis testing procedures.

8.2.1 Experiment samples

In this study, two employment sites, WP and MBL, were chosen in combination to reflect a natural experiment occurring on the sites. On the surface, the two experiment sites appeared identical for all other travel attributes with the exception of a difference in parking charge. Both sites hold financial service headquarters. Both sites are in the same CBD of a major city. Both are located near the same transportation center. The only significant difference was the parking condition facing the respective employees.

The natural experiment arose as a result of financial problems experienced by one of the experimental sites. The MBL headquarter site was the center of a bankruptcy action in 1991. This action forced the management to impose \$3.00 parking charge on its employees who use its parking lot. In contrast, the Washington Plaza headquarter site of the Prudential Issuance Corporate has had fully subsidized parking for over two decades. The Washington Plaza headquarters site was selected as the control sites based on its \$0.00 parking charge. In neither case was alternative parking a feasible option.

The validity of the selection of the two samples is supported in Chapter 7 by the finding that the two samples were drawn from a population reflecting the same underlying mode switching structural model.

8.2.2 Confounding effect and truth set formation

In the ideal world, the control sub-sample and the test sub-sample are formed through a random assignment of elements taken from a random sample derived from the target population. Random assignment guarantees that the two sub-samples have identical attribute distributions although the two sub-samples are made up of different individuals.

Theoretically, cross-sectional experimental designs should also meet the equal distribution requirement. In this study, equal attribute distribution requirements implies that the WP sample and MBL sample should have identical covariate distributions with the only exception of the parking charge. If normal distribution is accepted as the distribution function for the covariates, the identical distribution requirement is explained as the same average covariate values and associated standard deviations. Take travel time as an example. The two samples are required to have the same average travel time and standard deviation of travel time.

However, initial examination of descriptive statistics taken from the two sites reveals that the means and variances of the two sites are different across many variables; different average travel time, different average income etc. The difference between direct observations of the two samples' mode split will include a confounding effect as well as a parking charge impact.

To remove the confounding effect, an adjustment of the covariate values is required. The WP sample's covariate values are changed and this change is reapplied into a implicit change in the mode split. Take travel time as an example. The following Figure 8.1 presents the different SOV travel time distributions for the MBL sample and the WP sample.

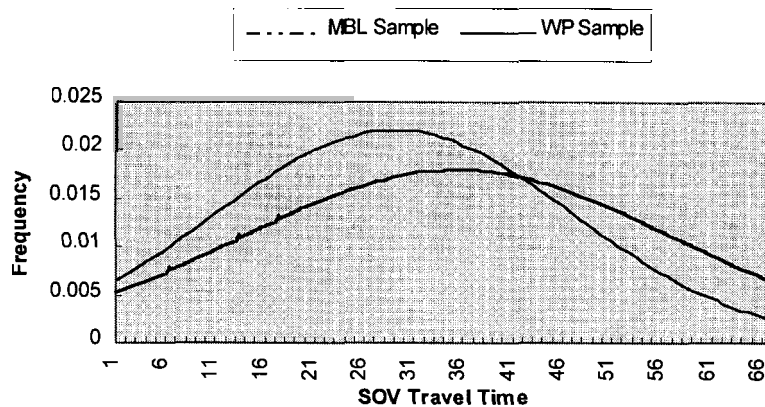


Figure 8.1 Travel time distributions of two samples

Assume the travel time is a normally distributed variable for each travel mode. The adjustment process will continue with the change of average SOV travel time and associated standard deviation for the WP sample. Using the MBL sample's average travel time and the standard deviation as the parameters, a set of normally distributed elements can be generated by the random generator in Microsoft EXCEL for the WP sample. The number of the elements in the adjusted WP sample is the same as the number of individuals in the original WP sample.

Next is the method used to assign these elements to each individual in the WP sample. There are $n!$ ways to assign these elements to the total of $\{n\}$ individuals. A practical travel time adjustment process is used for this assignment. The objective is to attain the least change between each WP individual's current travel time for SOV and the element assigned to this individual.

This objective is completed by minimizing the square of the sum of travel time changes for all individuals in the WP sample. This objective is expressed by a function G_k :

$$\text{Min: } G_k = \sum_{j=1}^K (y_j - x_i)^2 \quad (k=1,2,\dots,K) \quad (8.1)$$

where,

y_j -- the j th element for the adjusted travel time and

x_i -- the original travel time before the adjustment for individual i

k -- the k th combination

The minimization process has been compiled as a computer program and this program is attached in Appendix F.

After the assignment of the elements to each individual in the WP sample, these elements form the adjusted travel time for the SOV mode of the WP sample. Using the same procedure, all other covariates are adjusted for the three travel modes.

Then, these adjusted covariates are used to produce the adjusted mode choice for the individuals in the WP sample. The mode choices were produced through a Monte Carlo simulation using the explanatory CCLM model based on the adjusted covariate values. The simulation is conducted by the following steps:

- 1) Compute the systematic utility for the three travel modes, SOV, Carpool and Transit, using adjusted covariate values for each individual of the WP sample,
- 2) Generate a Weibull distributed variable as the random utility term,
- 3) Compute the constraint values based on the original and adjusted covariate values,
- 4) Choose the travel mode with the largest sum of systematic and random utility term under the corresponding the constraints.

The truth set has now been formed by assembling the MBL sample and the WP sample with adjusted covariates. The mode split obtained from the test sub-sample of the truth set is considered as the experiment result m_r and will be compared with the forecast result by the CCLM model.

8.2.3 Forecast and External Validity Test

The forecast of the impact of a \$3.00 parking charge on mode split is conducted by the explanatory CCLM model with the following process;

- 1) Taken as given, each WP individual's adjusted covariate values for the three travel modes as well as their personal information are used to compute the systematic utility and the corresponding constraints.
- 2) Using the explanatory CCLM model, compute each WP individual's probabilities to switch to each proposed travel alternative following a \$3.00 parking charge imposition.
- 3) Add all WP individuals' switching probabilities and then divide this sum by the total number of individuals in the WP sample. This final result is the aggregate mode split forecast m_p .

Based on the work above, the mode split in the real world, m_r , and the mode split forecast m_p are obtained. The last step is the external validity test. The hypothesis for the external validity is the null difference between the actual mode split values and the forecast values. The t test is used to test the null hypothesis H_o ,

$$H_o: \quad m_r = m_p \quad (8.2)$$

The mode split in the real world is assumed statistically identical to the mode split forecast. As an alternative hypothesis, H_I is listed below for the situation where two mode split are not equal.

$$H_I: \quad m_r \neq m_p \quad (8.3)$$

The test statistic θ is a t distributed variable and its values in this test can be computed by Equation (8.4):

$$\theta = \frac{|m_p - m_r|}{\sigma / \sqrt{n}} \quad (8.4)$$

where,

m_r -- the actual mode split obtained from the test sub-sample of the truth set

m_p -- the predicted mode split based on the control sub-sample and designed parking charge imposition

σ -- the standard deviation for the aggregate mode split forecast

n -- individual number in the sample.

This test has to be performed for the three travel modes, respectively. If θ is less than the pre-determined two-tail critical value $t_{s/2}(n-1)$ under the $n-1$ degree of freedom with significance of s , the external validity of CCLM model can not be rejected.

Based on the discussion above, external validity test is summarized as the following process;

- 1) Observe and record the MBL sample's mode split as the truth set's behavior to the parking charge imposition.
- 2) Adjust the WP sample's covariate distributions so that the WP covariate's distribution has the same statistical values for the travel attributes and personal information as those of the MBL sample.
- 3) Use WP sample's adjusted travel attributes and personal information to make a forecast of mode split under a \$3.00 parking charge imposition.
- 4) Test the null hypothesis between the mode split forecast and truth set's mode split observed from the MBL sample.

8.3 Empirical Test

This section presents the external validity test result for the CCLM model using the cross-section experimental design described in the above section.

A total of 58 individuals were selected from the WP site. The actual commuter mode split for the three travel modes: SOV, Carpool and Transit, were recorded based on the 1995 survey and are presented in the Table 8.1. The second column lists the numbers of individuals of the sample using each commute mode and the third column presents the mode split values.

Table 8.1 Actual un-adjusted historical mode split of the WP sample: July,1995

Travel mode (1)	Mode Share (2)	Mode Split (3)
SOV	40	68.97 %
CP	3	5.17 %
PT	15	25.86 %
TOTAL	58	100.00 %

A second 58 individuals were selected from the MBL. The mode split values for the three travel modes were recorded and presented in Table 8.2.

Table 8.1 Actual un-adjusted historical mode split for MBL sample: July,1995

Travel mode (1)	Mode Share (2)	Mode Split (3)
SOV	38	65.51 %
CP	7	12.07 %
PT	13	22.41 %
TOTAL	58	100.00 %

Table 8.3 presents the average covariates and associated standard deviations for the covariates of the two samples.

Table 8.3 Covariate averages for the two samples

Covariate	The MBL Sample		The WP Sample		<i>t</i> test Statistic
	Average	Sta. Dev.	Average	Sta. Dev.	
Travel time for SOV	35.57	22.10	29.12	18.04	1.72
Travel Cost for SOV	5.88	3.09	2.81	2.57	5.81**
Access Time for SOV	4.22	1.83	4.69	1.31	1.59
Travel time for CP	47.53	24.24	41.09	21.86	1.50
Travel Cost for CP	3.18	1.74	1.89	1.92	3.79**
Access Time for CP	6.21	4.52	6.33	6.75	0.11
Travel time for Transit	61.84	26.19	47.76	31.98	2.59**
Travel Cost for Transit	4.03	2.71	3.24	2.76	1.56
Access Time for Transi	13.20	13.10	9.63	9.95	1.65
Attitude for SOV*	3.59	1.95	2.38	1.61	3.64**
Attitude for CP*	4.33	1.78	4.33	1.67	0.00
Attitude for Transit*	5.14	1.91	4.76	1.75	1.12
Age Category*	2.84	0.41	2.13	0.53	8.07**
Income Category*	3.48	1.05	2.38	1.18	5.30**

*These variables are rank order variables in the survey and assumed to belong to an underlying continuous distribution in the survey.

** The values are larger than the critical value of 2.0 for two tailed t distribution at 0.05 level of significance.

For ease of computation, the underlying distributions of the variables shown in Table 8.3 are all assumed to act as continuous variables. The values in the parentheses are the standard deviations. It can be seen that some covariates, such as travel cost for the SOV and CP, attitude for the SOV, Age category and income category, differ with statistical significance between the MBL site and the WP site.

The average covariate values and standard deviations for MBL were used to adjust the covariate distributions for the WP sample to form a truth set. The SOV travel time is taken as an example. The original travel time values are listed in the second row in Table 8.4. Using the average travel time for the MBL sample and the associated standard deviation: 35.57 and 22.10, adjusted travel time for the WP sample were obtained and

assigned to each individuals in the WP sample. The adjusted travel time are listed in the third row of Table 8.4.

Table 8.4 SOV travel time adjustment for individuals in the WP sample

Individual No.	1	2	3	4	5	6	7	8
Original SOV Travel Time	25	40	35	70	45	110	45	30
Adjusted SOV Travel Time	31	48	46	79	63	92	67	40

Table 8.4 (continued)

9	10	11	12	13	14	15	16	17	18
65	60	40	25	25	15	15	35	15	30
78	74	49	39	38	14	12	46	14	41

Table 8.4 (continued)

19	20	21	22	23	24	25	26	27	28
10	20	20	60	45	50	20	40	25	40
10	25	28	74	67	71	22	51	31	49

Table 8.4 (continued)

29	30	31	32	33	34	35	36	37	38
30	45	45	20	32.5	40	15	50	45	20
39	64	63	29	43	47	20	71	60	29

Table 8.4 (continued)

39	40	41	42	43	44	45	46	47	48
30	15	20	45	42.5	25	25	25	10	30
42	16	28	57	54	38	37	37	10	40

Table 8.4 (continued)

49	50	51	52	53	54	55	56	57	58
15	6	20	20	17.5	20	20	45	25	10
14	7	28	27	21	26	26	56	29	9

A Monte Carlo simulation was next conducted, using the explanatory CCLM model and the adjusted covariate values, to produce the individual mode choice. The mode split values for the three travel modes were then computed by averaging the individuals mode switching data. The mode split values with adjusted covariate values for the WP sample are listed in the second column of Table 8.5 as well as the MBL mode split values in the third column. The mode split data listed in Table 8.5 form the mode split observation of the truth set which will be used in the external validity test.

Table 8.5 WP sample mode split with adjusted covariates

Travel mode	WP Mode Split Value (Adjusted Covariate)	MBL Mode Split Value
(1)	(2)	(3)
SOV	75.31 %	65.51 %
CP	10.86 %	12.07 %
PT	13.83 %	22.41 %
TOTAL	100.00 %	100.00 %

Table 8.6 presents the forecast values and the external validity test result. The adjusted mode split values for the truth set associated with the test condition are listed in the second column and mode split forecast values are listed in the third column of Table

8.6. The mode split forecasts are obtained by the explanatory CCLM model derived in Section 7.3.

In fact, all WP individual's mode switching probabilities for each mode are averaged as the sample's mode split values. The standard deviations are listed in the parenthesis in the third column of Table 8.6 based on the average of 58 individuals in the sample for the need of computation of statistic values. Column 4 lists the absolute values of the differences between the truth set values and the forecast values. The *t* statistic values in column 5 are computed by Equation (8.4).

Table 8.6 Adjusted mode split values and forecast value comparison

Mode	Mode Split Values (Truth Set)	Mode Split Values (Forecast)	Forecast Error	<i>t</i> Test Statistic
(1)	(2)	(3)	(4)	(5)
SOV	65.51 %	66.65 % (5.75 %)	1.14 %	1.5100
CP	12.07 %	12.78 % (2.37 %)	0.71 %	2.2815
PT	22.41 %	20.57 % (7.37 %)	1.84 %	1.9014

The two-tail critical value for the significance of the 0.05 level with degrees of freedom of 57 is 2.0; therefore, the null difference hypothesis can not be rejected for the SOV and PT modes. The null difference hypothesis for CP can be rejected. The reason for the rejection of the null difference hypothesis for the CP mode is that very few individuals in the two sites use carpool as their commute mode. The small number of observation causes a loss of accuracy when computing the mode split values for carpool. However, the mode split forecast for the WP sample generated by CCLM model is statistically identical with the adjusted observation for the MBL sample for the SOV and PT modes.

8.4 Comparison with Other Research

The cross-section experimental design and the empirical work conducted in the above section can be compared with the before and after research design and external validity test conducted by Beaton (1997). That study for the SC model by before and after design shows that the predicted market share for SOV changes from 100% in 1993 to a predicted 83.2 % in 1995. The actual 1995 value reported from the subset of 1995 respondents is 82.2 %. The difference between forecast for switching behavior and actual switching behavior is 1 %.

8.4 Summary

This chapter has presented the study results of an external validity test using a cross-section experimental design for the CCLM model. The experimental technique used in this study certifies that

- 1) cross-sectional experimental design can be used in external validity test where panel data is not available. The two samples used in the cross-section experimental design must be identified as drawn from the same target population, and
- 2) to remove confounding factor, the covariates of two samples must be adjusted to have identical Distribution.

The CCLM model has been identified valid through internal and external validity test. This study shows that the CCLM model can successfully forecast the mode split change associated with a parking charge imposition for the SOV and public transit modes.

CHAPTER 9

CONCLUSION

This report develops the Constrained Conditional Logit Model based on the hypothesis that the existed resource constraints have significant effect on individual's mode switching. Theoretical and empirical studies made in this report have supported the validity of this hypothesis.

The first contribution of this report is the development of the CCLM model which explicitly includes the resource constraint into the decision making process and then the switching probability function. This advance gets the discrete choice theory underlying travel mode choice consistent with the classical economic theory although the assumption of inclusion of constraints has been proposed in some papers described in Chapter 2. The explanatory model estimation and the internal and external validity study in this report shows that the Constrained Conditional Logit Model can successfully address this issue without increasing the complexity on the model estimation.

This model therefore provides a tool for evaluating the effect of various constraints. These constraints are no longer limited within time and cost, but extended to a broad field. This advance makes it possible to analyze the effect of other constraints, such as exogenously-imposed schedules, physical needs, authority and morality.

The second contribution is the advance on the model estimation. A factor grid searching approach which was developed originally in SP and RP data combination has been successfully applied on the joint estimation by the combination of two samples. This process not only improves the efficiency of the estimation but also provides a tool on the study of transferability of empirical models.

As the Constrained Conditional Logit Model corrects the errors caused by failing to incorporate constraints in the indirect utility function, more precise estimates for the attributes in systematic utility becomes passable. These improvement can help us to

promote the accuracy on predicting the individuals' mode switching on the different site and situation.

The third contribution is the improvement on the experimental design for external validity test. A cross-sectional design was used in this study to replace the longitude design which is usually used with panel data in the external validity test. The cross-sectional design makes external validity test available in the situation where researchers have no opportunity to manipulate both test and control conditions in the actual experiment.

The cross-sectional design can also avoid the time effect in the longitude design, such as individual's taste change with time. However, the cross-section experimental design can only be used under the following conditions:

- 1) the two samples used in the cross-section experimental design must be identified as drawn from the same target population, and
- 2) the two samples's covariates distribution must be identical. Otherwise, the mode split values must be adjusted.

If the above two conditions are not true in the real situation, confounding factor will affect the observation of the actual mode switching behavior. The confounding effect caused by using two samples to form a truth set has been studied in this report. The adjustment of the covariate values of the two samples is another important contribution. Without removal of the confounding effect by the covariate values adjustment, cross-sectional design has seldom opportunity to be applied since it is impractical to expect the two samples with identical distributions of attributes in the real world.

Further work is still needed to improve the approach for establishing empirical models. As indicated in the above chapters, how to design the proposed travel alternatives and the associated attributes so as to avoid the errors related to RP and SP combination is one of the existed issues. Further study about the survey method and data collection is necessary.

The analysis of the effects of other constraints, such as physical and morality, on the individual travel mode switching is needed by more empirical studies.

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APPENDIX A

DERIVATION OF CONDITIONAL LOGIT MODEL

The utility used in discrete choice models is assumed as the sum of a systematic utility term V_{ni} and a random term ε_{ni} . Sub-index n and i here stand for individual n and alternative i .

$$U_{ni} = V_{ni} + \varepsilon_{ni} \quad (\text{A.1})$$

Given that the random term ε_{ni} is a *Weibull* distributed variable. The density distribution function and the cumulative distribution function of ε_{ni} are written as:

$$f(\varepsilon_{ni}) = \mu_n \exp[-\mu_n(\varepsilon_{ni} - \lambda_{ni})] \exp\{-\exp[-\mu_n(\varepsilon_{ni} - \lambda_{ni})]\} \quad (\text{A.2})$$

and

$$F(\varepsilon_{ni}) = \exp\{-\exp[-\mu_n(\varepsilon_{ni} - \lambda_{ni})]\} \quad (\text{A.3})$$

where, μ_n and λ_{ni} are the scale factor and position factor. If term ε_{ni} is assumed to vary independently and identically (*IID*) for all alternatives and individuals, the probability that the utility obtained from alternative i is larger than all other alternatives can be written as :

$$P_n(i) = \text{Prob}(U_{ni} > \max(U_{nj})) = \text{Prob}(V_{ni} + \varepsilon_{ni} > \max(V_{nj} + \varepsilon_{nj}))$$

where, J is the total number of the alternatives available. Compute the probability of $\max(V_{nj} + \varepsilon_{nj})$:

$$\begin{aligned} \text{Prob}[\max(V_{nj} + \varepsilon_{nj}) < \varepsilon] &= \prod_{j=1}^J \text{Prob}(V_{nj} + \varepsilon_{nj} < \varepsilon) \\ &= \prod_{j=1}^J \exp[-\exp(-\mu_n(\varepsilon - V_{nj} - \lambda_{nj}))] \\ &= \exp\left\{-\sum_{j=1}^J \exp[-\mu_n(\varepsilon - V_{nj} - \lambda_{nj})]\right\} \end{aligned} \quad (\text{A.4})$$

Then write $\max(V_{nj} + \varepsilon_{nj})$ to be $V_n^* + \varepsilon_n^*$. The probability can be written as

$$\begin{aligned} \text{Prob}(V_n^* + \varepsilon_n^* < \varepsilon) &= \text{Prob}(\varepsilon_n^* < \varepsilon - V_n^*) \\ &= \exp\{-\exp[-\mu_n(\varepsilon - V_n^* - \lambda_n^*)]\} \end{aligned} \quad (\text{A.5})$$

Compare Equation (A.4) with (A.5), we obtain

$$\exp[\mu_n(V_n^* + \lambda_n^*)] = \sum_{j=1}^J \exp[\mu_n(V_{nj} + \lambda_{nj})] \quad (\text{A.6})$$

The probability of choosing alternative i is obtained as:

$$\begin{aligned} & \text{Pr ob}(\varepsilon_n^* - \varepsilon_{ni} < V_{ni} - V_n^*) \\ &= \int_{\varepsilon_n^* - \varepsilon_{ni} < V_{ni} - V_n^*} f(\varepsilon_{ni}, \varepsilon_n^*) d\varepsilon_{ni} d\varepsilon_n^* \\ &= \int_{\varepsilon_n^* - \varepsilon_{ni} < V_{ni} - V_n^*} \frac{\partial^2 F(\varepsilon_{ni}, \varepsilon_n^*)}{\partial \varepsilon_{ni} \partial \varepsilon_n^*} d\varepsilon_{ni} d\varepsilon_n^* \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\varepsilon_{ni} + V_{ni} - V_n^*} \frac{d}{d\varepsilon_{ni}} [F_i(\varepsilon_{ni})] \frac{d}{d\varepsilon_n^*} [F_{j^*}(\varepsilon_n^*)] d\varepsilon_{ni} d\varepsilon_n^* \\ &= \int_{-\infty}^{\infty} \frac{d}{d\varepsilon_{ni}} [F_i(\varepsilon_{ni})] \left\{ \int_{-\infty}^{\varepsilon_{ni} + V_{ni} - V_n^*} \frac{d}{d\varepsilon_n^*} [F_{j^*}(\varepsilon_n^*)] d\varepsilon_n^* \right\} d\varepsilon_{ni} \\ &= \int_{-\infty}^{\infty} \frac{d}{d\varepsilon_{ni}} [F_i(\varepsilon_{ni})] \{ F_{j^*}(\varepsilon_{ni} + V_{ni} - V_n^*) \} d\varepsilon_{ni} \end{aligned} \quad (\text{A.7})$$

Take Equation (A.3) into Equation (A.7), we obtain :

$$\begin{aligned} & \text{Pr ob}(\varepsilon_n^* - \varepsilon_{ni} < V_{ni} - V_n^*) \\ &= \int_{-\infty}^{\infty} \mu_n \exp[-\mu_n(\varepsilon_{ni} - \lambda_{ni})] \exp\{-\exp[-\mu_n(\varepsilon_{ni} - \lambda_{ni})]\} * \\ & \quad * \exp\{-\exp[-\mu_n(\varepsilon_{ni} + V_{ni} - V_n^* - \lambda_n^*)]\} d\varepsilon_{ni} \\ &= \frac{\exp[\mu_n \lambda_{ni}]}{\exp(\mu_n \lambda_{ni}) + \exp[-\mu_n(V_{ni} - V_n^* - \lambda_n^*)]} \int_{-\infty}^{\infty} d\{\exp[-\exp(-\mu_n \varepsilon_{ni})] * \\ & \quad * [\exp(\mu_n \lambda_{ni}) + \exp(-\mu_n(V_{ni} - V_n^* - \lambda_n^*))]\} \\ &= \frac{\exp(\mu_n \lambda_{ni})}{\exp(\mu_n \lambda_{ni}) + \exp[-\mu_n(V_{ni} - V_n^* - \lambda_n^*)]} (1 - 0) \\ &= \frac{\exp[\mu_n(V_{ni} + \lambda_{ni})]}{\exp[\mu_n(V_{ni} + \lambda_{ni})] + \exp[\mu_n(V_n^* + \lambda_n^*)]} \end{aligned} \quad (\text{A.8})$$

Take Equation (A.6) into Equation (A.8), we obtain :

$$P_n(i) = \frac{\exp[\mu_n(V_{ni} + \lambda_{ni})]}{\exp[\mu_n(V_{ni} + \lambda_{ni})] + \sum_{j=1, j \neq i}^J \exp[\mu_n(V_{nj} + \lambda_{nj})]}$$

$$= \frac{\exp[\mu_n(V_{ni} + \lambda_{ni})]}{\sum_{j=1}^J \exp[\mu_n(V_{nj} + \lambda_{nj})]} \quad (\text{A.9})$$

Assume that position factor λ_{ni} in the above equation is zero, the probability of choosing alternative i by individual n is obtained as :

$$P_n(i) = \frac{\exp(\mu_n V_{ni})}{\sum_{j=1}^J \exp(\mu_n V_{nj})} \quad (\text{A.10})$$

Equation (A10) is the ordinary form of the Conditional Logit Model.

APPENDIX B

CONTROL FILE FOR SIMULATION

The following control file was used in the estimation for the Constrained Conditional Logit Model in Chapter 5.

****Estimation for the Constrained Conditional Logit Model****

DATA 19,1
PRINT 80,63,3
END

- Parameter Definition

01 Travel_Time
02 Travel_Cost
03 Out-Veh_Time
04 Constraint_on_Travel_Time
05 Constraints_on_Travel_Cost
06 Constraint_on_Out-Veh_Time

- Systematic Utility Function (1-Single Occupant Vehicle, 2-Carpool, 3-Transit)

util001= p01*d02+p02*d03+p03*d04+p04*d11+p05*d12+p06*d13
util002= p01*d05+p02*d06+p03*d07+p04*d14+p05*d15+p06*d16
util003= p01*d08+p02*d09+p03*d10+p04*d17+p05*d18+p06*d19

The following control file was used in the estimation for the Conditional Logit Model in Chapter 5.

****Estimation for the Conditional Logit Model****

DATA 19,1
PRINT 80,63,3

END

- Parameter Definition

01 Travel_Time

02 Travel_Cost

03 Out-Veh_Time

- Utility Function (1-Single Occupant Vehicle, 2-Carpool, 3-Transit)

util001= p01*d02+p02*d03+p03*d04

util002= p01*d05+p02*d06+p03*d07

util003= p01*d08+p02*d09+p03*d10

APPENDIX C

SURVEY QUESTIONNAIRES

Please consider each scenario independently and do not compare with others. (Values in bold change in each scenario)

Alternative 1, Single Occupant Vehicle

Cost of tolls and gas per day	Your current cost*
Parking space charge per day	\$5.00/day(\$100/month)

Alternative 2, Carpool

Carpool costs per person per day	1/2 your current drive alone cost*
Parking space charge per day	1/2 your drive alone parking space charge
Pick up location	A shopping center parking lot
Extra time required for carpooling	10 min. for each one way trip
Guaranteed rider home	Yes, 15 minute wait
Carpool subsidy paid to you per day	\$0.00

Alternative 3, Public Transit

Transit fare per day	Current values*
Number of transfers	Current number*
Extra time required for transit	25 min. for each one way trip
Guaranteed rider home	Yes, 15 minute wait
Transit subsidy paid to you per day	\$0.00/day(\$0.00/month)

After comparing the characteristics of the three alternatives shown above, I choose:

Please check one and only one alternative

Drive alone	()
Carpool	()
Transit + MBL van service	()

APPENDIX D

CONTROL FILE FOR ESTIMATION

The following control file was used in the estimation for the Constrained Conditional Logit Model in Chapter 7.

Estimation for the Constrained Conditional Logit Model

DATA 27,1
PRINT 80,63,3
END

- Parameter Definition

01 SOV_constant
02 CP_constant
03 Travel_Time
04 Travel_Cost
05 Access_Time
07 Attitude_SOV
08 Attitude_CP
09 Attitude_Transit
10 Age
11 Familiar
12 Gender
13 Income
14 Travel_Time_Constraint
15 Travel_Cost_Constraint

- Systematic Utility Function (1-Single Occupant Vehicle, 2-Carpool, 3-Transit)

util001=p01+p03*d02+p04*d03+p05*d04+p07*d12+p10*d15+
+p11*d16+p12*d17+p13*d18+p14*d19+p15*d20
util002= p02+p03*d05+p04*d06+p05*d07 +p08*d13 +p14*d22+p15*d23

util003= p03*d08+p04*d09+p05*d10+p09*d14 +p14*d25+p15*d26

The following control file was used in the estimation for the Conditional Logit Model in Chapter 7.

**** Estimation for the Conditional Logit Model****

DATA 27,1
PRINT 80,63,3
END

- Parameter Definition

01 SOV_constant
02 CP_constant
03 Travel_Time
04 Travel_Cost
05 Access_Time
07 Attitude_SOV
08 Attitude_CP
09 Attitude_Transit
10 Age
11 Familiar
12 Gender
13 Income

- Systematic Utility Function (1-Single Occupant Vehicle, 2-Carpool, 3-Transit)

util001=p01+p03*d02+p04*d03+p05*d04+p07*d12+p10*d15+
+p11*d16+p12*d17+p13*d18
util002= p02+p03*d05+p04*d06+p05*d07 +p08*d13
util003= p03*d08+p04*d09+p05*d10+p09*d14

APPENDIX E

CONTROL FILE FOR JOINT ESTIMATION

The following control file was used in the estimation for the joint Constrained Conditional Logit Model in Chapter 7.

**** Estimation for Joint Constrained Conditional Logit Model****

DATA 31,1
PRINT 80,63,3
END

- Parameters

01 SOV_Constant_for_MBL
02 CP_Constantfor_MBL
03 SOV_Constant_for_WP
04 CP_Constant_for_WP
05 Travel_Time
06 Travel_Cost
07 Access_Time
11 SOV_Attitude
12 CP_Attitude
13 Transit_Attitude
14 Age for SOV
16 Family_size for SOV
18 Gender for SOV
20 Income for SOV
50 Travel_time_Constraint
51 Travel_cost_Constraint

- Systematic Utility Function (1-Single Occupant Vehicle, 2-Carpool, 3-Transit)

util001= p01*d02+p03*d04+p05*d06+p06*d07+p07*d08+p11*d16+
+p14*d19+p16*d20+p18*d21+p20*d22+ p51*d23+p52*d24

util002= p02*d03+p04*d05+p05*d09+p06*d10+p07*d11+p12*d17 +p51*d26+p52*d27
util003= p05*d12+p06*d13+p07*d14+p13*d18+p51*d29+p52*d30

APPENDIX F

PROGRAM FOR ATTRIBUTE ASSIGNMENT

Program Assignment

```
implicit none
integer::l(58),i,j
real::old_value(58),new_value(58),hold
open(unit=13,file="oldvalue.txt",status="old")
read(13,*) old_value
open(unit=14,file="newvalue.txt",status="old")
read(14,*) new_value
do i=1,58
  l(i)=i
end do
do i=1,58
  do j=i+1,58
    if(old_value(i)<old_value(j)) then
      hold=old_value(j)
      old_value(j)=old_value(i)
      old_value(i)=hold
      hold=l(j)
      l(j)=l(i)
      l(i)=hold
    end if
    if(new_value(i)<new_value(j)) then
      hold=new_value(j)
      new_value(j)=new_value(i)
      new_value(i)=hold
    end if
  end do
end do
do i=1,58
  do j=1,58
    if(l(j).eq.i) old_value(i)=new_value(j)
  end do
end do
```

```
end do
open(unit=15,file="result.dat",status="old")
write(15,*) old_value
stop
End Program Assignment
```