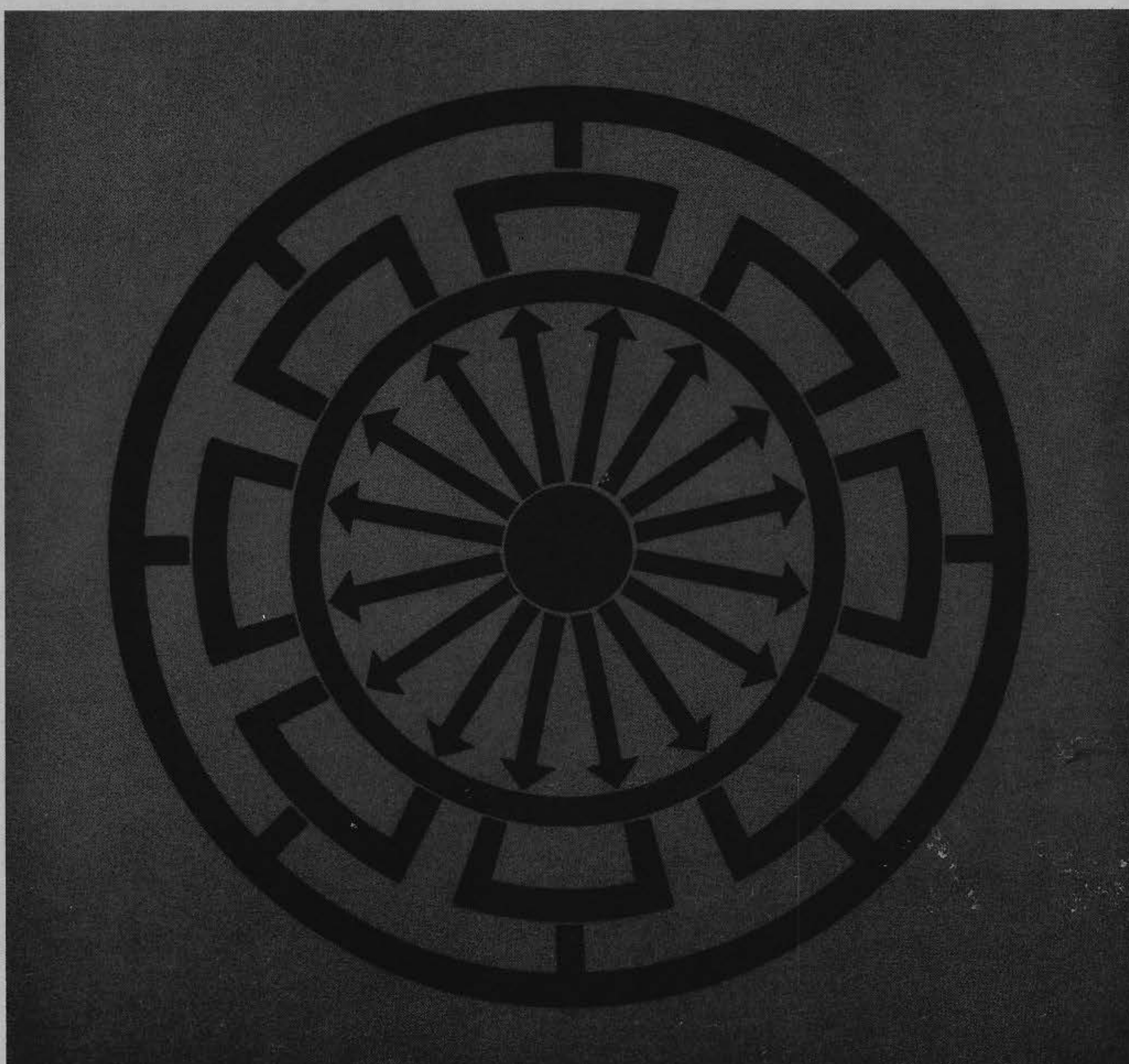
U.S. Department
of Transportation

**Urban Mass
Transportation
Administration**

Guide to Forecasting Travel Demand with Direct Utility Assessment

September 1982



NOTICE

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
UMTA-NH-11-0001-82-1		

4. Title and Subtitle	5. Report Date / 6. Performing Organization Code / 8. Performing Organization Report No.
GUIDE TO FORECASTING TRAVEL DEMAND WITH DIRECT UTILITY ASSESSMENT	5. September 1981 6. 8.
7. Author(s) Kocur, George, Adler, Tom, Hyman*, William and Aunet*, Bruce	
9. Performing Organization Name and Address Resource Policy Center Thayer School of Engineering Dartmouth College Hanover, NH 03755	10. Work Unit No. (TRAIS) UPP-35 11. Contract or Grant No. NH-11-0001
12. Sponsoring Agency Name and Address U.S. Department of Transportation Urban Mass Transportation Administration 400 Seventh Street, S.W. Washington, D. C. 20590	13. Type of Report and Period Covered University Research, July 1980-September 1981 14. Sponsoring Agency Code

15. Supplementary Notes *Division of Planning and Budget, Wisconsin Department of Transportation, P.O. Box 7913, Madison, WI 53707

16. Abstract

Direct utility assessment (DUA) is a demand modeling technique based on obtaining responses to a series of hypothetical situations which have been constructed using an experimental design. (The technique is also known as conjoint analysis.) The responses to the experiment are analyzed with multiple linear regression and can produce satisfactory models in many cases. However, such models are based entirely on stated behavior, not actual behavior.

It is possible to validate the regression models on actual data, and this second validation step is also discussed in the report. The validation uses a logit framework.

The report describes the construction of experimental designs, the development and administration of surveys, and analysis of survey responses. Appendices A through D provide tables of plans, examples of pretested instruments, and sample programs for data analysis. Other chapters of the report describe default models currently available for use by local agencies, and techniques of quick policy analysis using DUA.

17. Key Words	18. Distribution Statement
Demand modelling Urban transportation Transportation planning Attitudinal modelling	Available to the Public through the National Technical Information Service, Springfield, Virginia 22161.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified		

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Report UMTA-NH-11-0001-82-1

GUIDE TO FORECASTING TRAVEL DEMAND WITH DIRECT UTILITY ASSESSMENT

George Kocur
Tom Adler
William Hyman
Bruce Aunet

RESOURCE POLICY CENTER
THAYER SCHOOL OF ENGINEERING
DARTMOUTH COLLEGE
HANOVER, NH 03755

FEBRUARY, 1982

FINAL REPORT

Document is available to the U.S. public through the
National Technical Information Service,
Springfield, Virginia 22161

Prepared for

U.S. DEPARTMENT OF TRANSPORTATION
URBAN MASS TRANSPORTATION ADMINISTRATION
Office of University Reserach
Washington, D.C. 20590

PREFACE

Traditional travel demand forecasting methods are based on the actual past behavior of travellers under varying circumstances of income, auto ownership, travel time, cost and other observable factors. Surveys to establish such past behavior, "origin-destination" surveys, are quite expensive and cover only the narrow range of factors that are prevalent at the time of the survey.

In many other disciplines, notably the social sciences and market research, there is a strong tradition of using the expressed intentions of the individuals rather than their past behavior to estimate how they would react under future circumstances. Transportation planners have tried some relatively crude, "What would you do if . . .," surveys that have generally produced unusably inaccurate results.

For several years, transportation researchers have been exploring more sophisticated methods for designing and analyzing such surveys. These methods fall in the general category of attitudinal research, more specifically called "non-commitment response" or "behavioral intentions" approaches. Reports of some of the more promising efforts have appeared in the research literature, but these lack the "how to" detail that planning practitioners would require before attempting such a new approach in an operating environment.

This report goes a long way toward filling the need for practical guidance in this area. It is a product of the UMTA University Research Program and is based on the author's experience gained in applying behavioral intentions methods in studies in Georgia and Wisconsin. The report is not a "cook book" but does cover all the elements of survey design, administration, and model development.

Whether or not such "behavioral intentions" methods are superior to models based on actual past behavior has been debated for years. This report is being distributed to foster new attempts to apply these methods and to evaluate whether and for what purposes this approach is more effective. A limited number of additional copies of this report are available from UMTA, Methods Division, URT-41.

EXECUTIVE SUMMARY

Direct utility assessment (DUA) is a demand modeling technique based on obtaining responses to a series of hypothetical situations which have been constructed using an experimental design. The responses to the experiment are analyzed with multiple linear regression and can produce satisfactory models in many cases. However, such models are based entirely on stated behavior, not actual behavior.

It is possible to validate the regression models on actual data, and this second validation step is also discussed in the report. The validation uses a logit framework.

The report describes the construction of experimental designs, the development and administration of surveys, and analysis of survey responses. Appendices A through D provide tables of plans, examples of pretested instruments, and sample programs for data analysis. Other chapters of the report describe default models currently available for use by local agencies, and techniques of quick policy analysis using DUA.

Experience with DUA models suggests that they are able to play a useful role in forecasting and analyzing travel demand in many cases. DUA models can contain variables which are not measured or do not vary in current data sets, modes or other alternatives which do not currently exist, and other effects which are difficult to treat in traditional demand models. Many current

issues (such as energy policy, new transit services, or bike lanes) involve forecasting issues for which DUA is well suited. Validation experience of DUA models has been encouraging, and the link with logit formulations in validation offers many possibilities for "hybrid" models.

Thus, DUA is a useful tool for local planning. It is also possible to conduct DUA studies with limited budgets and time schedules, often in weeks or months. This manual is an early step in bringing DUA to the attention of local planners.

ACKNOWLEDGEMENTS

This study has benefited greatly from a long association with the Division of Planning and Budget at the Wisconsin Department of Transportation (WisDOT). We wish to acknowledge William Hyman, Bruce Aunet and James Etmanczyk, who actively participated in the development and analysis of the urban and intercity surveys used in the report. Chapters 3, 4 and 9 of this report draw heavily on a report prepared for WisDOT by Bill Hyman, Bruce Aunet and George Kocur. Joleen Nelson performed much of the data processing for that effort. We also acknowledge Roger Schrantz and Don Revello of WisDOT for their support of these efforts. A debt of thanks is also owed to Dr. Jordan Louviere of the University of Iowa, who first introduced us to these techniques, and on whose earlier work parts of this report rest. We also wish to thank Lee Jones, of the UMTA Office of Planning Methods and Support, our technical monitor, and Dr. Robert Dial and Gran Paules of the same office. Philip Hughes and Cara Gossard were very understanding contract monitors for the Office of University Research.

We wish to thank Dr. Gerald J. Hahn and the General Electric Company for permission to use materials included in Appendix A. We also thank National Analysts, a division of Booz-Allen, Hamilton, Inc., for permission to use one of the examples in Appendix B.

Patty Gordon prepared this report; we thank her for the efficiency and dispatch with which it was done.

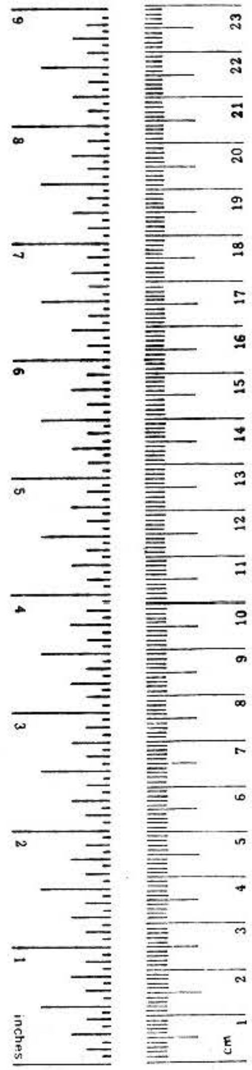
The opinions, findings and conclusions expressed or implied in the report are those of the authors only. The responsibility for any errors is ours.

METRIC CONVERSION FACTORS

Approximate Conversions to Metric Measures

Symbol	When You Know	Multiply by	To Find	Symbol
		LENGTH		
in	inches	*2.5	centimeters	cm
ft	feet	30	centimeters	cm
yd	yards	0.9	meters	m
mi	miles	1.6	kilometers	km
		AREA		
in^2	square inches	6.5	square centimeters	cm^2
ft^2	square feet	0.09	square meters	m^2
yd^2	square yards	0.8	square meters	m^2
mi^2	square miles	2.6	square kilometers	km^2
	acres	0.4	hectares	ha
		MASS (weight)		
oz	ounces	28	grams	g
lb	pounds	0.45	kilograms	kg
	short tons (2000 lb)	0.9	tonnes	t
		VOLUME		
tsp	teaspoons	5	milliliters	ml
Tbsp	tablespoons	15	milliliters	ml
fl oz	fluid ounces	30	milliliters	ml
c	cups	0.24	liters	l
pt	pints	0.47	liters	l
qt	quarts	0.95	liters	l
gal	gallons	3.8	liters	l
ft^3	cubic feet	0.03	cubic meters	m^3
yd^3	cubic yards	0.76	cubic meters	m^3
		TEMPERATURE (exact)		
°F	Fahrenheit temperature	5/9 (after subtracting 32)	Celsius temperature	°C

*1 in = 2.54 (exactly). For other exact conversions and more detailed tables, see NBS Misc. Publ. 286, Units of Weights and Measures, Price $2.25, SD Catalog No. C13.10:286.



Approximate Conversions from Metric Measures

Symbol	When You Know	Multiply by	To Find	Symbol
		LENGTH		
mm	millimeters	0.04	inches	in
cm	centimeters	0.4	inches	in
m	meters	3.3	feet	ft
m	meters	1.1	yards	yd
km	kilometers	0.6	miles	mi
		AREA		
cm^2	square centimeters	0.16	square inches	in^2
m^2	square meters	1.2	square yards	yd^2
km^2	square kilometers	0.4	square miles	mi^2
ha	hectares (10,000 m^2)	2.5	acres	
		MASS (weight)		
g	grams	0.035	ounces	oz
kg	kilograms	2.2	pounds	lb
t	tonnes (1000 kg)	1.1	short tons	
		VOLUME		
ml	milliliters	0.03	fluid ounces	fl oz
l	liters	2.1	pints	pt
l	liters	1.06	quarts	qt
l	liters	0.26	gallons	gal
m^3	cubic meters	35	cubic feet	ft^3
m^3	cubic meters	1.3	cubic yards	yd^3
		TEMPERATURE (exact)		
°C	Celsius temperature	9/5 (then add 32)	Fahrenheit temperature	°F

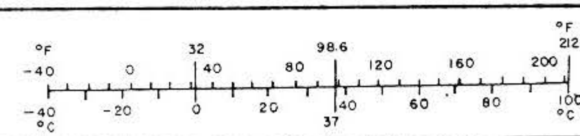


TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION AND SUMMARY

1.1 Overview.

This report describes a demand modeling technique called direct utility assessment (DUA).[1] DUA is a disaggregate modeling approach in that it uses individual survey responses to estimate the effects on behavior of different variables. It is different from other commonly used aggregate and disaggregate techniques in its use of behavioral intentions data. Most conventional modeling approaches use survey data which describe individuals' actual past choices or "revealed preferences." Behavioral intentions data describe individuals' stated preferences when presented with a hypothetical choice situation.

Models developed using direct utility assessment have unique advantages over conventional approaches in many applications. Hypothetical choice situations, or scenarios, can be structured in a way that allows clear distinctions to be made among the effects of different variables. Specifically, experimental designs can be constructed that result in no correlation among the independent variables. Also, scenarios can be specified which include some factor that may not be present in any existing situation. Figure

---

[1] Other authors call this technique functional measurement (Meyer et al., 1978) or conjoint analysis (Green and Srinavasan, 1978).

1.1 is an example of a "behavioral intentions" survey which could be used to develop a DUA model.

The advantages of DUA in travel demand forecasting relate closely to the characteristics of behavioral intentions survey data.

1) The scenarios can be designed to reduce to zero correlations among causal factors which in actual situations are quite high.

For example, two variables such as auto travel time and auto travel cost are very strongly correlated in most observed situations because they both vary directly with the length of the trip. This high correlation results in uncertain (low t-statistic) estimates of the independent effects of the two variables. An experimental design as shown below can be used in a DUA model to eliminate this.

Situation	Auto Time	Gasoline Cost ($/gallon)	Transit Service
1	15 min.	$1.00	.
2	25 min.	$1.00	.
3	15 min.	$1.50	(Several Variables)
4	25 min.	$1.50	.
			.

In this experiment (simplified from what might be used in practice), auto time and cost are totally uncorrelated. This is important in forecasting the impacts of gasoline price changes accurately; since auto time does not

FIGURE 1.1

Example of Experiment with Transit Operations-Oriented Variables

We want you to consider a set of situations in which there is an express bus from your neighborhood to your workplace. You have to walk 3 blocks to and from the bus stop at each end of the trip. The bus ride itself takes about 5 minutes longer than driving would. Please answer all eight questions.

BUS FACTORS				YOUR RESPONSES				
How often the bus runs:	Your chances of getting a seat:	How close to schedule the bus usually arrives:	Whether there is a shelter at your stop:	How likely are you to use the bus: Very unlikely				Very likely
every 5 mins.	50%	within 1 min.	yes	1	2	3	4	5
every 10 mins.	100%	within 5 mins.	yes	1	2	3	4	5
every 15 mins.	50%	within 5 mins.	yes	1	2	3	4	5
every 15 mins.	100%	within 1 min.	no	1	2	3	4	5
every 20 mins.	100%	within 1 min.	yes	1	2	3	4	5
every 20 mins.	50%	within 5 mins.	no	1	2	3	4	5
every 5 mins.	100%	within 5 mins.	no	1	2	3	4	5
every 10 mins.	50%	within 1 min.	no	1	2	3	4	5

change, a model attributing some of the cost effect to time changes will underpredict the decrease in auto use. The DUA model can separate the two effects with a high degree of statistical confidence.

2) DUA models can be constructed which include factors which either do not exist or which exhibit no variability in existing situations.

Many factors that are of interest to transit planners fall into this category: reliability, seat availability, seat comfort, climate control, bus versus rail "image" or express bus versus local bus "image", provision of shelters, and so on. All these variables are felt to have impacts on transit patronage but we know very little about the extent of the effects. The design of scenarios for a DUA model offers many possibilities in exploring these issues. The variables can be incorporated into scenarios which can be presented to many groups of respondents; an example is shown in Figure 1.1. We may already know the coefficient of headway fairly well from previous work (DUA and others); this experiment gives us the weights people place on seat availability, one form of reliability, and shelters. Different groups of travelers (e.g., young versus old) will put different weights on these factors; the model can reflect these differences in its coefficients. Also, the tradeoffs between these variables are not likely to be constant, and the model can account for that. In fact, the very reason for considering provision of shelters is to produce a varying (i.e., lower) trade-off rate between wait time and travel time than would exist in the absence of shelters. Thus, the DUA model can provide useful information in addressing these issues.

3) The experimental designs used for DUA models allow considerable freedom in the specification of demand models, or the selection of variables to include in the model and their functional form.

Because all variables are uncorrelated in the experiment, we can find the coefficient of each independently, even if the variables are highly correlated or unmeasurable in real situations. Furthermore, we can test the form in which these variables enter the utility function (or demand model). Most current models use additive, linear utility functions which generally assume a constant tradeoff (between, say, time and cost) across all levels of the variables. Absence of correlation among variables allows this assumption to be easily relaxed and much of the completed DUA work indicates nonconstant tradeoffs to be important. For example, under some conditions, travel time and cost are not traded off at all. The situation graphed in Figure 1.2 is typical. At low fare levels

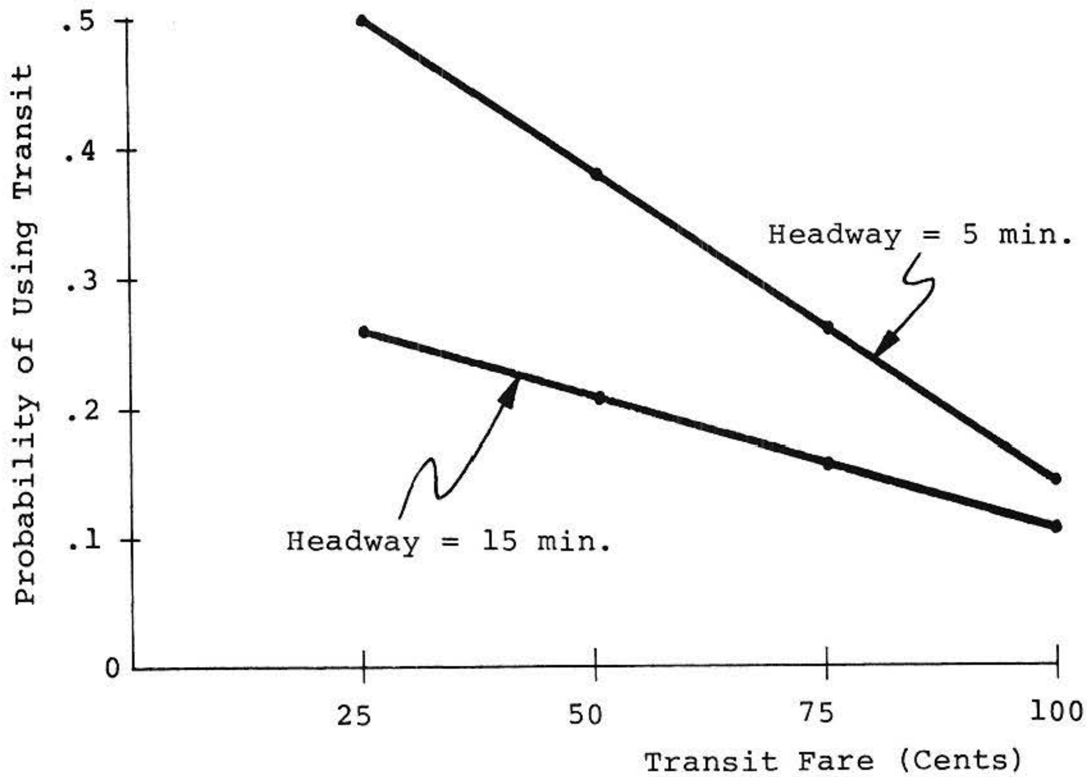


FIGURE 1.2

Example of Variable Tradeoff Rates

(e.g., 25 cents), the difference between 15-minute headways and 5-minute headways makes a large difference in mode split. At high fare levels, however, it makes little difference because the fare is already such a deterrent to transit use. DUA models such as the one whose behavior is illustrated in the figure, suggest that the levels of <u>all</u> variables (even, for example, comfort, which is not in the usual models) must be satisfactory to potential riders to gain an appreciable mode split.

4) <u>Development of DUA models is a relatively simple and inexpensive process</u>.

This report steps through many of the details of the model development process but, in essence, there are three steps:

A. Survey design and administration. This step requires development of a good initial idea of which are the important factors affecting behavior. These factors are then represented in a survey which includes an experimental design taken from one of the plans in Appendix A.

B. Specification and estimation of DUA model. Techniques as simple as cross-tabulation or multiple regression analysis can be used to estimate model coefficients.

C. Model validation. Individual or aggregate-level checks are used to ensure that the model is a good representation of actual behavior.

Travel demand model systems have been developed by consultants working with agency personnel in periods as short as five months (Kocur, 1981). The information contained in this report is sufficient to allow many agencies to develop a set of DUA models using only in-house capabilities.

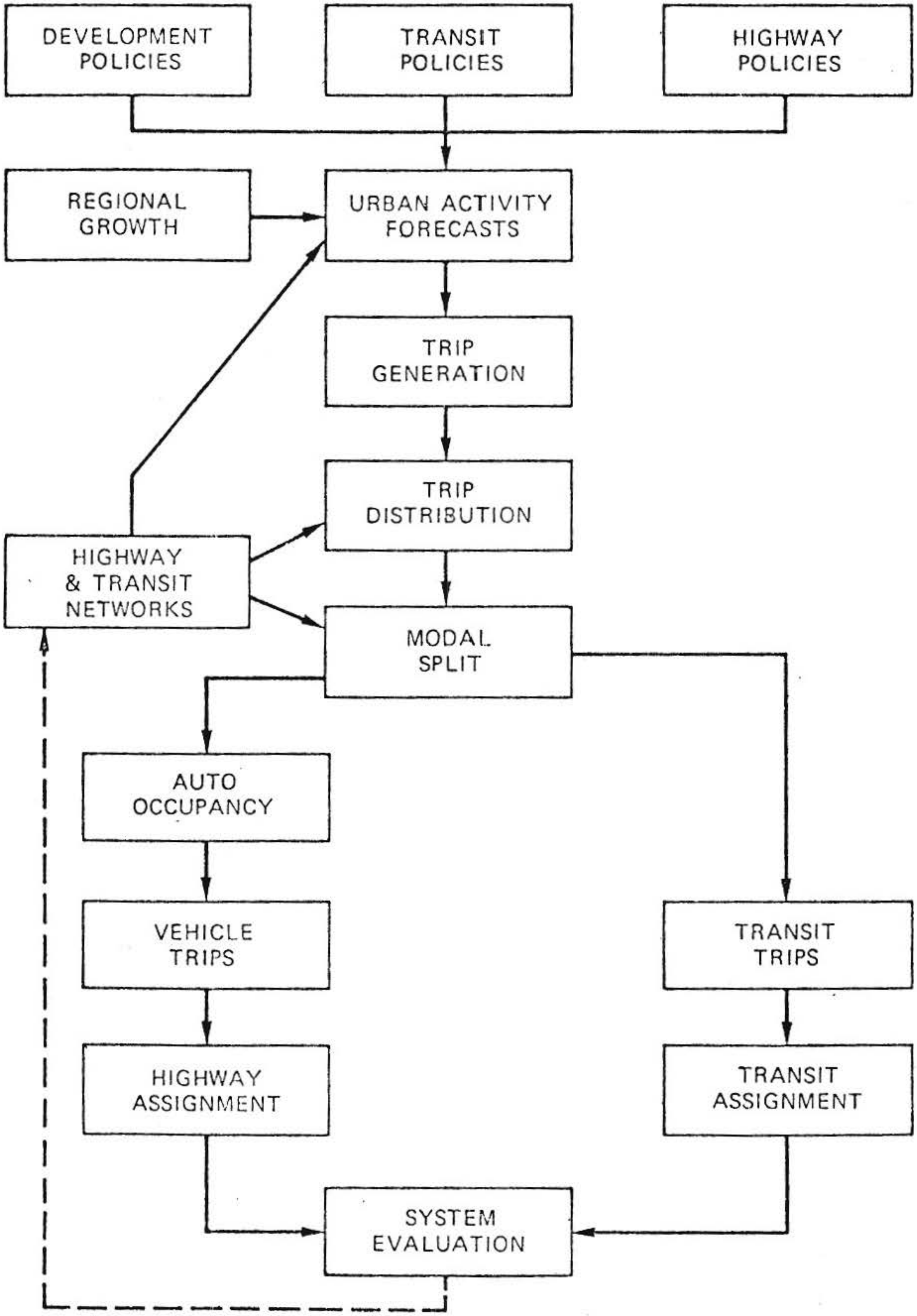
Although direct utility assessment has many advantages, it also has some drawbacks, both practical and theoretical. For example, it can be difficult to design surveys which measure the effects of a large number of factors but which are reasonable enough in length to ensure thoughtful responses. The most basic drawback is that responses indicating behavioral intentions do not necessarily correspond directly to actual future behavior. Careful use of validation techniques, as described in Chapter 6, can reduce the possible biases introduced by this problem. Overall, direct utility assessment is an appropriate and useful demand forecasting approach for many applications. Chapter 2 of this report elaborates on both the advantages and the drawbacks of DUA applied to travel demand forecasting.

1.2 Demand Analysis in the Transportation Planning Process.

In urban area transportation studies, a series of models is used to evaluate alternative transportation projects. These include land use, supply (or service), demand, network, cost and other impact models, all of which are tied together in a forecasting or analysis framework as shown in Figure 1.3. Development, transit and highway policies are specified by the analyst, and generally influence urban activity forecasts. These activity forecasts provide estimates of residential, industrial and commercial activities throughout the region, which in turn form the basis for transportation demand forecasts.

The demand models used in urban studies typically consist of three components: trip generation, or how many trips will be made; trip distribution, or where the trips begin and end; and mode choice, or whether auto or transit (or some other mode) is to be used. While these three demand modeling components are the central focus of this report, the techniques described have applications to many other transportation and non-transportation demand modeling problems.

The three component transportation demand models accept as input information on urban activity patterns, the socio-economic characteristics of urban residents, and the service levels of alternative travel modes to various destinations. They produce estimates of travel mode and destination; trips are then assigned to networks to find passenger and vehicle flows. Finally, impact models are used to estimate the costs, emissions, noise levels and other impacts of the system which, along with demand and network



THE TRADITIONAL TRAVEL DEMAND FORECASTING PROCESS
FIGURE 1.3

Source: Spear (1977).

information, form the basis for evaluation.

The process outlined in Figure 1.3 is used to analyze alternatives involving significant construction or other investment. Significant resources and time are required to use this traditional transportation planning process. For many short-range or operational issues (often called transportation systems management or TSM) a streamlined version of the model system is used in which only the demand models are exercised. Simplified techniques are then used to estimate other impacts primarily based on the demand model results.

Direct utility assessment can produce models that can be used in either the full model system or in simplified approaches.

1.3 Outline of the Report.

This report is structured in three parts. The first part, including Chapters 1 and 2, presents an overview description of the technique of direct utility assessment and its applications. The second part includes Chapter 3: Design of Experiments and Survey, Chapter 4: Survey Administration, Chapter 5: Analysis of Survey Responses, Chapter 6: Model Validation, and Chapter 7: Advanced Design and Analysis Procedures. Together, these chapters outline the fundamental approach to DUA model development. Chapters 8 and 9: Default Models and Policy Analysis, respectively, describe application models and approaches for travel demand forecasting. The report concludes (Chapter 10) with a brief statement of areas of further work in developing the DUA technique. The appendices include survey instruments, several computer analysis procedures, and tables of experimental designs that could be used in demand forecasting projects.

CHAPTER 2

BASIC CONCEPTS OF DIRECT UTILITY ASSESSMENT APPLIED TO TRAVEL DEMAND FORECASTING

2.1 The Direct Utility Assessment Technique.

Direct utility assessment (DUA) is a technique for assessing the effects on consumer behavior of policy changes. Information on consumer preferences is obtained by presenting a survey respondent with a series of situations, and asking what he or she would do under each. The series of situations is selected according to an experimental design, so that the causal factors influencing the respondent can be easily inferred from his or her responses to the situations.

The technique is very flexible and can handle a variety of qualitative and quantitative policies and behavior responses. The resulting model can also be validated against actual behavior in most cases, so the analyst can use it in a predictive fashion with a reasonable degree of confidence. Finally, the technique is relatively easy to apply from a technical perspective, and requires little effort and time compared to many other techniques.

A sample DUA survey is given in Figure 2.1. Each respondent is asked to consider various hypothetical travel scenarios and state his or her choice for each scenario. DUA is termed a behavioral intentions technique because it relies on an analysis of stated choice preferences, and not on decisions observed in

FIGURE 2.1

SAMPLE DUA SURVEY

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR SHARE A RIDE (CAR POOL/VAN POOL) TO WORK?

Consider that you are going to work and that driving alone or sharing a ride in a car pool or van pool are your only choices.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or share a ride to work.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or share a ride to work.

	AUTO FACTORS			CAR POOL/VAN POOL FACTORS		PLEASE– ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE ALONE OR SHARE A RIDE? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Parking Cost to Drive Alone	People You Share A Ride With	Employee Work Schedule	Always Drive Alone	Probably Drive Alone	In-different	Probably Share A Ride	Always Share A Ride
SITUATION 1	Ample Supply	$1.30/gallon	Free	Co-Worker/ Neighbor	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	Free	General Public (Carpool Matching)	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 3	Ration of 10 gallons/week*	$2.00/gallon	$30/month	Co-Worker/ Neighbor	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 4	Ample Supply	$2.60/gallon	$30/month	Co-Worker/ Neighbor	Fixed 8 hour day	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$1.70/gallon	Free	Co-Worker/ Neighbor	Fixed 8 hour day	1	2	3	4	5
SITUATION 6	Ample Supply	$2.00/gallon	Free	General Public (Carpool Matching)	Fixed 8 hour day	1	2	3	4	5
SITUATION 7	Ample Supply	$1.70/gallon	$30/month	General Public (Carpool Matching)	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 8	Ration of 10 gallons/week*	$1.30/gallon	$30/month	General Public (Carpool Matching)	Fixed 8 hour day	1	2	3	4	5

***If your car gets 15 miles per gallon, you can travel 150 miles per week.**

OVER →

T-277D-80

real situations.

A travel alternative in a DUA survey is represented by a group of attributes. For example, Figure 2.1 shows a survey which offers a choice between driving alone to work or sharing a ride. It uses three attributes to describe auto travel in general: gas availability, gas price, and parking cost when driving alone. In addition, two factors relate specifically to ride sharing: relationship with the other riders and work schedule flexibility. The attribute values vary over the eight situations. In the example, all attributes have two levels or values except for gas price which has four values, ranging from $1.30 to $2.60.

The pattern of levels that appears in Figure 2.1 is based on an experimental design in which every variable is completely uncorrelated (orthogonal) with every other variable. These designs have been worked out for a wide variety of situations and an abbreviated catalog of them is presented in Appendix A. Thus, survey design is primarily a matter of looking up a design that meets a particular need.

After examining the attributes of a given situation, the respondent indicates on a scale his or her likely behavior. In Figure 2.1, the situations are rated on a scale of one to five. Each response is defined by a relative term, such as "always", "probably", or "indifferent". The response scale may correspond to specific choice probabilities, or only to relative likelihoods (this is discussed in detail in Chapter 6). In addition to mode choice, the response scale may be used to analyze other travel decisions, such as trip frequency. An example of a survey with both mode choice and trip frequency response scales is given later.

The DUA survey results are analyzed by deriving a utility function across the various attributes for each respondent, based on that person's responses to each scenario. In this way, the attributes which are most important in the travel choice process can be identified. The individual utility functions may be aggregated across the entire sample, or grouped according to socio-economic variables also obtained from the survey. The methods used in analyzing the survey responses range from manual techniques, such as cross tabulation and graphing to computer-based techniques, such as multiple linear regression or logit estimation.

Because the survey response scale generally does not correspond to a pre-defined probability scale, these results by themselves do not provide a sufficient basis to predict the respondents' actual decision (e.g., mode choice). To do this, we must also know the relationship between their behavioral intentions as stated on the survey and their actual behavior. This relationship is obtained by including at least one situation on the survey which closely corresponds to the status quo or actual choices currently facing the respondents. By comparing actual current behavior with stated behavior in the situations closest to the status quo in the survey, a true probability can be attached to each point on the survey response scale. Once this is done, the model can be used for forecasting.

2.2 Comparison of DUA with Other Demand Model Techniques.

The most widely used type of travel demand model is estimated using revealed preference data. This technique uses data based on actual travel behavior, measured by surveys, and actual attribute levels for available alternatives. The analyst attempts to select variables based on theory and goodness-of-fit which produce a model that accurately describes the travel behavior.

Direct utility assessment (also called functional measurement) is one of several techniques which use behavioral intentions or "laboratory simulation" response data. These techniques attempt to simulate choice scenarios in order to infer the importance of different factors in the choice process. This contrasts with other "attitudinal" approaches in which respondents are asked to directly rate or rank the importance of these factors.

In DUA, the response scale is assumed to have a metric interpretation; that is, the difference in preference between "3" and "5" is twice the difference between "3" and "4". This assumption separates DUA from conjoint measurement (or tradeoff analysis) which is one of several other techniques using behavioral intentions data. In conjoint, the scale is interpreted as giving information only on the ranking of preferences; that is, one only knows that "5" is preferred over "4" and that "4" is preferred to "3", but there is no implication that there are equal differences between these points.[2] An alternative rated "5"

---

[2]Some authors use "conjoint analysis" to describe all techniques based on experimental design.

could be only slightly preferred over an alternative rated "4", but the "4" could be greatly preferred to an alternative rated "3". DUA is the only behavioral intentions technique which has a clearly defined error theory allowing statistical tests of model validity (Louviere et al., 1981).

Both the revealed preference and the different behavioral intentions approaches have advantages in specific circumstances and are by no means mutually exclusive. In the case of DUA, elements of both revealed preference and behavioral intentions techniques can be used. However, before either approach is used, it is important to understand their strengths and limitations.

2.2.1 Comparison of DUA and Revealed Preference. There are many issues which should be considered when choosing a demand modeling approach for a specific project or study. Among the most important are:

- Availability of data on current or past behavior and alternatives
- Variation in measures of policy interest
- Availability of measures of key variables
- Time and resources available to build and use the model
- Theoretical validity

Each is discussed in turn in the following sections.

Availability of Data. To estimate coefficients of a revealed preference model, data on past choices from among the alternatives of interest must be available. This, of course, implies that the alternatives (e.g., a bus service) already exist. The most interesting and relevant forecasting issues, however, often revolve around new alternatives which do not currently exist. For already-existing options, policymakers often feel they have sufficient information to make decisions just based on a summary of the existing system's performance; the need for a model does not always exist. However, for assessing new alternatives or scenarios, a model can provide useful information.

There are two approaches to modeling the demand for new services. One is to use a revealed preference model, which describes the choice of a similar alternative, and then to make some assumptions to apply the model to the new alternative. Although certain attributes of new systems, such as reduced travel time or costs, can be captured in a revealed preference model, other attributes may simply not exist in past systems.

The alternative approach is to use a DUA model which is calibrated specifically to describe the choice between the new alternative and some existing alternative.

Variation in Measures of Interest. Many variables of policy interest exhibit little or no variability in the cross-sectional data sets used to estimate urban travel demand models. For example, fuel availability and price will be almost the same for all residents in an area surveyed on the same day. It is therefore impossible to include this variable in a model estimated using cross-sectional revealed preference data. One can obtain variability in fuel availability and price by collecting a time-series data set, but it could take several years to observe significant changes. DUA can incorporate variables such as fuel price and availability directly, as shown in Figure 2.1.

Another issue related to variation in key measures is multi-collinearity. In this case, two or more variables in a data set are so closely correlated that their effects on behavior cannot be separated. An example is auto operating costs and travel times in areas with no parking charges and little congestion. Both trip cost and time will be very strongly correlated with trip distance. In DUA, all variables within the experimental design are completely uncorrelated, and therefore their separate effects on behavior can always be determined.

Availability of Measures of Key Variables. There are many variables affecting travel behavior which are difficult to quantify or isolate. Subjective aspects such as safety, reliability, and convenience are very hard to determine from the numerical data used in revealed preference studies. Factors which have "random" variability, such as weather or availability of a seat are also lost in most travel data. DUA accommodates these qualitative attributes by using verbal descriptions to define them. For instance, "convenience" could be given two levels: "bus scheduled to leave at desired departure time," and "bus scheduled to leave one-half hour before desired departure time."

Any variable which can be verbally understood by the respondent can be included in a behavioral intentions model.

Time and Resources Available to Build Model. DUA models can be prepared more quickly than revealed preference models if a suitable data set for revealed preference is not already available, and if extensive validation data collection is not required. While resources required for both types of models may be comparable in some cases, DUA has a quick-response capability not available in revealed preference models. The reason is that DUA surveys are self-contained, requiring no data collection beyond that obtained through the survey. For example, it is not necessary to use network skim trees for travel time/cost data. If validation is required, some external data must be collected; however, validation will not be required in many cases.

Due to the controlled nature of data collection through laboratory simulation, the data[3] are likely to be more reliable. Revealed preference modeling efforts can be hindered by incomplete information due to aggregation over large areas of the sample. DUA models treat each respondent individually and can provide more precise and complete information. This is especially true for variables such as travel time and distance to transit stops, which are often averaged over zones in large data sets.

Furthermore, the DUA analysis procedure is predefined by the survey design, so the analysis is very straightforward. Most

---

[3] That is, the stimuli or actual variables influencing choice.

demand models used in practice require very comprehensive data collection. Also, the analysis of conventional data sets requires complicated computer models. A great deal of time is spent specifying the mathematical form of the model, whereas DUA's underlying behavioral theory dictates the model form. Coefficients of DUA models can, in the extreme, be estimated with pencil and paper, although this is not recommended either for large samples or complex models.

Theoretical Validity. The most commonly criticized aspect of behavioral intention models is the potential deviation between intended and actual behavior. People who say they would switch to transit in a certain hypothetical situation might not respond in that way to real stimuli. How do we know if experimental responses would occur in real situations? We must rely on behavioral theory to guide the development of the models, and on statistical error theory to judge their validity. In this last respect, previous studies have shown behavioral intentions models to be quite successful.

Real observations on revealed preference are rarely in error. In behavioral intentions models, however, biases between intended and actual behavior might be introduced. Since all situations are verbally described, imprecise wording may not give the full information about the decision being analyzed. In addition, the set of attributes used to define the scenarios may be lacking an important factor. However, pretesting of the survey can minimize these problems.

Also, there are clearly many situations for which revealed preference models are completely adequate. When analyzing incremental changes to existing systems in variables which are properly measured, exhibit variability, and for which an existing data set is available, revealed preference models should be used. Even if one or more of these conditions is not met, the shortcomings of the revealed preference model may be outweighed by the principal shortcoming of the DUA technique, possible bias in the survey responses.

Both techniques have value in different forecasting and analysis situations; by using each in situations where it best fits study objectives, demand analysis can be made a more useful tool in aiding decisions.

2.2.2 Comparison of DUA and Other Behavioral Intentions Models. Behavioral intentions modeling techniques range from very qualitative to very rigorous. The simplest type of survey is that which uses single-answer questions administered to a cross-sectional sample. Slightly more detailed is the technique of multidimensional scaling or "preference mapping", which arranges a number of alternatives on axes which correspond to the most important attributes (e.g., points on a graph of travel speed vs. distance between stops). This technique is useful for grouping similarly perceived alternatives.

Several techniques measure the simultaneous tradeoffs of two or more factors in the choice process. Although these methods are sometimes called conjoint measurement, this term is used here only for methods which use ordinal (rank-order only) response data. When just two factors are considered, a matrix format is often used in the survey. The term tradeoff analysis is usually used for this format, but this term may also refer to conjoint studies of more than two variables. The most statistically rigorous technique is DUA, also called functional measurement. This technique is identical to conjoint measurement, except that cardinal (metric) responses are required. There are several criteria to be considered in choosing among these behavioral intentions techniques.

Forecasting of travel demand requires a statistically accurate model. This means that the model must be based on individually accurate probability choice functions, and that there must be an error theory to measure this accuracy. The use of metric response scales rather than ranking of alternatives provides both of these properties.

In analyzing decisions where a certain choice probability applies, such as likelihood of selecting a transit mode or likelihood of taking a trip, it will be most accurate to have each individual specify that probability. Eventually, ordinal response techniques require that the rankings be transferred to a metric scale for forecasting. So, when it is feasible for the respondent to supply this scaled information himself, the model becomes a more powerful forecasting tool: a measure of likelihood is a more precise predictor than a measure of preference.

Models based upon metric response (such as DUA) seem to be most consistent with the actual decision process. If there is one factor in the decision which greatly outweighs all other factors, DUA will show the extent to which this variable outweighs all others. Preference ranking, on the other hand, will show only that this variable is the most important, with little insight as to the relative magnitude of this difference in importance.

An additional advantage of metric over rank-order scales is the existence of a conventional error theory. DUA provides a specific measure of variance, whereas ordinary conjoint analysis relies on a measure called "stress", which is peculiar to that technique (Kruskal). A measurement of error is vital to the correct specification of a model form (discussed in Chapter 7) and of the comparison of the accuracy of different modeling techniques.

DUA's scenario survey format has advantages over other related survey designs. First, the format handles qualitative variables well. Second, with the scenario format used in DUA one can obtain a large amount of data in a small amount of space. This economy of design is quite important, especially when personal data must also be collected. A survey with several matrix-type tradeoff designs or long lists of two-factor combinations can appear quite formidable to potential respondents. The experimental designs of DUA are the most compact surveys which allow independent analysis of several factors.

There are some cases in which techniques other than DUA can be used, however. The use of metric response scales may be inappropriate or difficult to apply to certain decisions. If, for example, an experiment is meant to determine rider preference to alternative types of carpools, then an ordinal ranking would be appropriate. It may be difficult for a respondent to state the likelihood of choosing one type of carpool over another, while it might be quite easy to state which types are preferred. This model, however, would not predict what percentage of drivers would switch from private autos to carpools in each case as would DUA.

There is some question of a person's ability to evaluate many factors simultaneously while making a decision. Some theories suggest that people have a hierarchy of factors when contemplating a decision, starting at the most important factor and proceeding to factors of decreasing importance. The scenario format accommodates this decision process. If this format is tested and appears to be too complex, it may be wise to limit the number of attributes. If only two attributes seem feasible, a matrix survey design could be used. One should be certain, however, that the complexity is the result of the number of attributes and not due to imprecise wording or an excess of levels for certain attributes.

2.3 Summary.

DUA is a laboratory-type simulation demand modeling technique, using data obtained from survey experiments. The most commonly used technique, revealed preference modeling, uses data describing actual travel choices made by individuals. In addition, there are other simulation techniques which rank prepared alternatives according to preference, and are generally termed conjoint analysis.

CHAPTER 3

DESIGN OF EXPERIMENTS AND SURVEY

3.1 Steps in Survey Design.

A DUA experiment consists of a set of realistic but hypothetical situations defined by factors that most strongly influence actual trip choice. At least one of the situations closely resembles the current travel environment to allow the validation of the resulting model. The pattern of situations is based on an experimental design, which ensures that all the factors influencing the trip choice are uncorrelated. Thus, we can isolate the influence each factor has on a person's decision to use one mode or another.

The design of a set of survey instruments for direct utility analysis requires the following steps:

1. Identify the scope of travel choices and issues to be taken into consideration.
2. Prepare initial versions of the experiments and incorporate into draft surveys.
3. Conduct focus group meetings. A focus group is a collection of six to twelve individuals asked to describe what factors most influence their travel choices and the process for making those choices. Focus group participants can also fill out the draft surveys and suggest improvements.

4. Evaluate the results of the focus groups.
5. Redraft the survey instruments.
6. Pretest the surveys by distributing them to a sample.
7. Evaluate the pretest results and make final changes before public distribution.

This section describes the procedure for designing the experiments and the surveys and preparing them for distribution to the public.

Many quick-response studies do not follow all these steps in survey development. A shorter set of steps may be all that is necessary:

1a. Identify the scope of travel choices and issues to be taken into consideration.

2a. Prepare initial versions of the experiments and incorporate into draft surveys.

3a. Pretest the surveys informally.

4a. Evaluate the pretest results and make final changes before public distribution.

The development of such surveys rests more on the experience and judgment of the analyst, but is appropriate in many of the short-run planning projects for which DUA is well-suited.

3.2 Development of the Experiments.

The design of a DUA experiment begins with general considerations of the scope of travel choices, the range of issues, and the general form of the ultimate model to be prepared. The first consideration is the set of travel choices to be addressed. In some demand studies only mode choice needs to be considered; urban work travel is such an example because trip generation is fixed, and trip origins and destinations are fixed (in the short run) by home and workplace locations.

In other cases, trip generation, distribution and mode choice must be modeled to accurately assess the impacts of certain policies. For example, rising energy costs may affect total intercity travel (or its destinations) more than modal composition. Similarly, broad frameworks may be needed for nonwork urban travel, elderly travel, and other specialized markets. DUA models are capable of addressing all these levels of travel demand, although the examples in this chapter concentrate on mode choice. Chapter 7 describes the analysis of multiple levels of travel demand with DUA. At the stage of survey development, however, the levels of travel choice to be considered must be specified.

The issues that are to be examined also influence the survey design, and should be identified at this stage. Some DUA surveys are aimed at operational issues (such as Figure 1.1) and can concentrate on only a few variables and a single choice set. Many short-range transit service changes and TSM actions are well treated in this way. Broad issues such as energy policy, parking regulation, or substantial pricing or service shifts will require many variables and perhaps multiple levels of demand. Thus, the focus of the study must be defined at this stage, and a list of key issues and variables prepared to guide the decisions in preparing the survey.

In many studies, there are only two alternatives that are relevant to the problem (e.g. transit and auto in simple mode choice studies). In other cases, there is a larger set of alternatives (e.g. local bus, express bus, auto driver, auto passenger in mode choice studies), which pose some further issues in the design of a DUA experiment. In the case of multiple (more than two) alternatives, there are three further considerations. The first concerns whether subjects of the experiment will choose among all the available travel choices or only two at a time. A second and related consideration is whether the experiment will be administered to a small but representative group in a carefully structured environment, or whether the experiments will be mailed out to a large number of people to be filled out in a less controlled setting. If the decision is to administer the experiments through a mass mailing, it may be impractical to have subjects consider more than two alternatives (such as modes) at a time. In this case, a third consideration arises -- the choice of the base alternative.

The goal of DUA is to predict people's travel behavior in settings that resemble as closely as possible trip choices they either currently face or may face in the future. Ideally, a DUA experiment should allow the subject to choose from all the alternatives available. However, there may be many factors to consider. To choose among five work travel modes in an experiment, one might have to weigh so many variables that most people are unable to do it without considerable time and assistance. If one wishes to conduct a DUA experiment in which all travel choices are simultaneously available to the subject, it is necessary to do so in a carefully controlled and structured way. One must explain to each person the meaning of the variables and provide detailed directions on how to take the experiment. Audio-visual aids can greatly assist the subject in understanding the choice, especially if the person has never used a certain mode of transportation.

One procedure used by market analysts and psychologists is to administer the experiment in such a controlled environment. However, such a procedure is expensive and time-consuming. This necessarily limits the sample size and may introduce substantial errors if the sample is excessively small.

To reduce the complexity of a DUA forecasting effort, one can devise a set of experiments where an individual considers only two choices at a time. Ideally, an individual should then participate in an experiment concerning every possible choice, but to exhaust all the pairwise combinations may be extremely time-consuming. A compromise is to select a base mode and ask the subject to make pairwise choices between the base mode and the other options. Thus, if there are five modes available and one is the base mode, there need to be only four pairwise choices. This procedure is still sufficiently complicated so that the experiments must be administered individually or in relatively small groups.

Further simplification is possible by having each subject participate in only one pairwise choice with respect to the base mode. Experience with DUA models has shown that individuals in similar situations behave similarly. If we accept this finding, then we ought to believe that people in similar situations would respond to each pairwise choice similarly. In this way, one can reduce the complexity of conducting an experiment to such a degree that it is possible to distribute the experiments in a mass mailing or onboard distribution with only simple instructions written to the interviewee. The main drawback of this approach is that there is no control over the response rate. However, this can be an extremely efficient, cost-effective technique. The experiments described in the following sections are framed in terms of binary (pairwise) choice, although they can be adapted for multiple choice, as discussed in Chapter 7.

3.3 Experimental Designs.

3.3.1 Definitions.

Once the broad outlines of the experiment are established, the process of selecting a specific design can begin. A sense of the key variables, preferably no more than 10 for each pairwise choice, and at least a preliminary decision on the levels of travel demand should be made before proceeding with the steps in this section. This section describes how actual values are determined for variables in the survey, how they can be arranged into experimental designs, and the assumptions inherent in the design options available.

A multi-variable experiment contains a series of independent variables which are to be related to some dependent variable such as mode choice or trip rate. The independent variables may be either expressed on a continuous scale, such as travel time, or they may be discrete, such as type of service. Each independent variable is considered at two or more conditions or levels, as designated by the experimental plan. For example, in a mode choice experiment, gas price may have four levels, \$1.20, \$1.60, \$1.90, and \$2.60 per gallon. Another factor, fuel availability, may have only two levels, rationing and ample supply (defined in the utility function by two discrete values, 0 and 1). Suppose an experiment takes into consideration five factors and each has only two levels. We call this experiment a 2^5 factorial design. Suppose instead all five factors have four levels. Then the experiment would be a 4^5 factorial design. If there were three "two-level" factors and two "four-level" factors, then we speak of a $2^3 \cdot 4^2$ factorial design. In general, if a, b and c are different numbers of levels and there are x a-level factors, y b-level factors and z c-level factors, then the experiment is called an $a^x \cdot b^y \cdot c^z$ factorial design.

Tables have been constructed by statisticians laying out the patterns of most experimental designs in which one might be interested. Appendix A contains many such designs, commonly referred to as experimental plans.

3.3.2 Main and Interaction Effects. The experimental results will be analyzed to evaluate the statistical significance of the independent variables, estimate their effects, establish functional relationships, and measure experimental error (as described in Chapter 5). In conducting such analyses, one is interested in the main effect of each variable, that is, the effect on the experimental response of going from one level of the variable to the next given that the remaining variables do not change. In many situations the effect of two independent variables is not additive, and the variables are said to <u>interact</u>, i.e., the effect of one variable upon the response depends upon the value of some other variable.

Two-factor interactions can be demonstrated as shown in 3.1 In Figure 3.1a the effect on mode share of a ten-minute change in headway is constant, regardless of fare level. Likewise, the effect of fare is independent of headway. A model with additive, main-effect terms only describes this situation fully:

$$\text{Mode Share} = .50 - .01\ \text{Headway} - .004\ \text{Fare}$$

In Figure 3.1b the effect of headway depends on the fare level; thus a model including an interaction term is required to correctly represent behavior:

$$\text{Mode Share} = 1.10 - .04\ \text{Headway} - .02\ \text{Fare} + .0008\ (\text{Headway} \times \text{Fare})$$

Interactions between three or more variables are interpreted in a similar manner. Thus, in a given experiment, one might be interested in estimating two-factor (or higher) interactions among a designated group of variables. The specification of the interactions of interest, as well as the variables and their levels, will determine which experimental plan is appropriate.

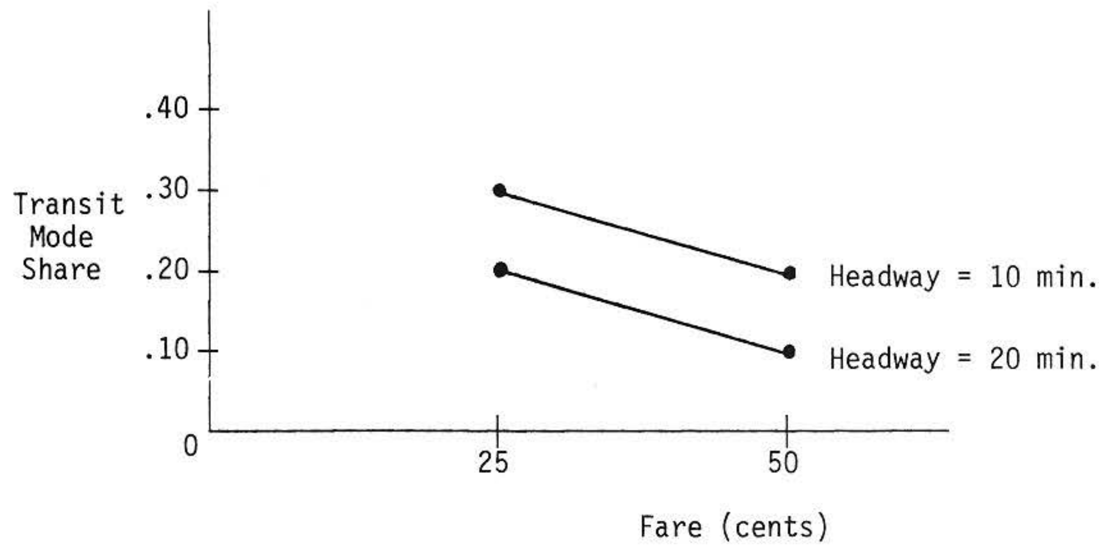
Suppose we are trying to measure the effect on mode split of three variables, gas price, fuel availability, and bus fares. These variables can appear as main or interaction effects.

Main Effects	Two-Way Interactions	Three-Way Interactions
Price	Price x Availability	Price x Availability x Fare
Availability	Price x Fare	
Fare	Availability x Fare	

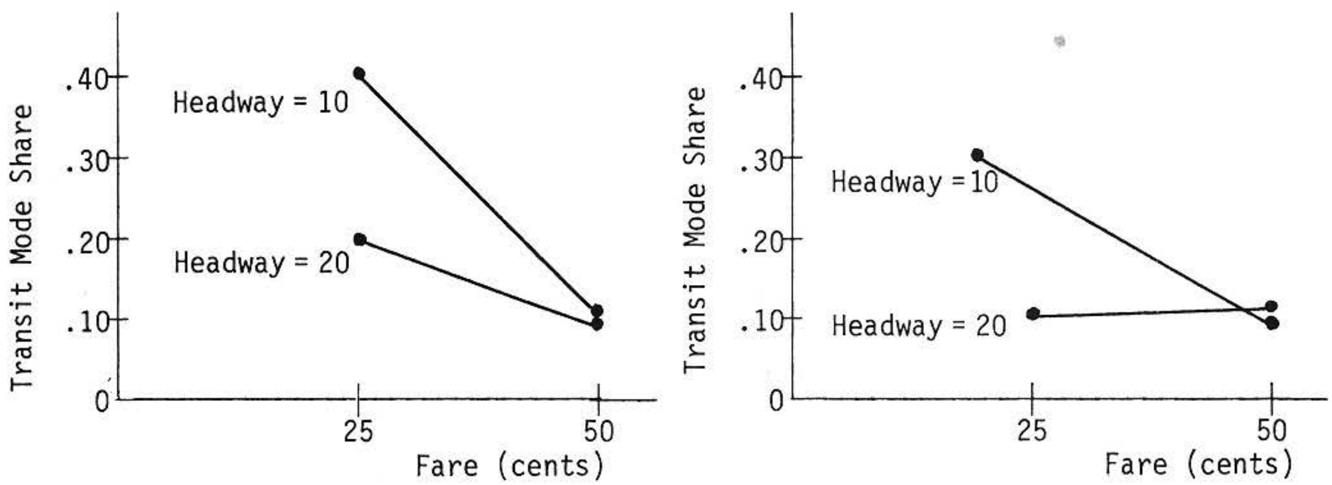
In an experiment with more than three variables there is a much

FIGURE 3.1

Examples of Two-Factor Interactions



a. Situation with No Interaction



b., c. Situations with Interactions

larger number of interactions.

A simple multi-variable experimental plan is called a full factorial experiment. This requires that one create a situation for every possible combination of levels for each of the variables. Say, for example, that one is interested in four variables, two at two levels, and one each at three and four levels. A full factorial experiment requires running all the $2^2 \times 3 \times 4$ possible combinations or a total of 48 situations to which a respondent must react. Such a plan is denoted a $2^2 \times 3 \times 4$ full factorial experiment.

A full factorial experiment permits one to obtain estimates of the effect of all possible interactions among the variables. For example, in a four variable full factorial experiment, there are six two-factor interactions, four three-factor interactions, and one four-factor interaction.

A limitation of the full factorial plan is that for a moderate number of variables and levels, an unreasonable number of situations is required. For example, for an experiment with six variables, with two variables <u>each</u> at two, three and four levels, an impractically large total of 576 experimental points would be necessary[1].

To cope with this problem, a family of experimental plans known as fractional factorial designs have been developed. A fractional factorial plan is one which requires only a fraction of

---

[1] The following discussion is drawn from Hahn and Shapiro (1966).

the number of experimental points needed for the full factorial plan. The specific points are selected to evaluate interactions considered to be important. All other interactions are assumed to be negligible. Consider a situation with five variables, with two at two levels and three at three levels, requiring a total of 108 tests for a full factorial experiment. If some of the interactions are assumed negligible, a fractional factorial plan could be used to estimate the importance of the remaining terms. The exact nature of the plan and the required number of situations depends upon the number of interactions which need be estimated. For example,

a. To estimate the main effects and all two-factor interactions, assuming all higher order interactions negligible, a total of 81 situations are required. (Plan 45d from Appendix A).

b. To estimate only the main effects and those two-factor interactions involving one of the five variables <u>with each of the other factors</u>, assuming all other interactions negligible, a total of 27 situations are required. If these five variables are designated A, B, D and E, such a plan (45c in Appendix A) permits estimation of the two-factor interactions between:

   i. A and B

   ii. A and C

   iii. A and D

   iv. A and E

c. To estimate only main effects and those two-factor interactions involving <u>all combinations</u> of three of the five variables, assuming all other interactions negligible, a total of 27 situations are required.[2] Using the previous designation of variables, the following two-factor interactions can be estimated from this plan (45b in Appendix A):

i. A and B

ii. A and C

iii. B and C

d. To estimate only main effects, assuming all interactions to be negligible, a total of 16 situations would be required (Plan 45a in Appendix A).

The above illustrates four of the five types of fractional factorial plans contained in Appendix A. A fifth type which is similar to d) above is one in which only the main effects can be estimated but they are estimated independently of two-factor interactions. Thus, if two-factor interactions in fact are not negligible, their effects are not combined (or confounded) with the main effects.

It is a matter of judgment to assess the type of experimental plan to use in a survey. It is an almost universal practice to assume all three-way and higher interactions are negligible, but the treatment of two-way interactions must be decided on a case-by-case basis. Experiments that assume all interactions are

---

[2] The 27 test points for this plan are <u>not</u> the same as in b) above.

negligible require the smallest number of situations, produce the best response rate, but yield the least precise models. As interactions are included, model precision improves but survey length also increases markedly. If the response to some variables is non-monotonic (e.g. high and low numbers of pedestrians on a street are bad, but moderate levels are good for perceived neighborhood safety), interaction effects _must_ be included for them. For monotonic variables, the need for interaction terms is less, but they may still be important. (Sometimes different designs can be administered across individuals to form a larger overall design, which meets the criteria both for including necessary interactions and keeping the survey length reasonable. This is discussed in Chapter 7.)

Appendix A includes designs with variables at differing numbers of levels. No design involving more than 32 situations has been included, though designs for such experiments do exist.

3.3.3 Orthogonality. _All_ the designs in the appendix are _orthogonal_, meaning all variables are statistically _independent_ of one another. This means that those effects and interactions which can be found from a given design can be estimated without correlation with other main effects or with those interactions which are _not_ assumed negligible. There are other types of fractional factorial designs which permit "near orthogonal" estimation. Such plans might on occasion have advantages in terms of sample size, but they are more difficult to analyze and interpret.

Let us consider a simple experiment. An individual is asked to choose between driving alone or carpooling to work under four situations defined by three factors, fuel availability, gas price, and parking costs. Each factor has two levels. The four-situation experiment shown below is a 2^3 fractional factorial design, which allows main effects only to be estimated, assuming all interactions are negligible.[3]

Consider you are going to work.
Say how likely you are to drive alone or car pool to work in each of the following situations.

				Circle One Likelihood of Driving Alone				
	Gas Availability	Gas Price	Parking Cost	Always Drive Alone		Indif-ferent		Always Car Pool
Situation 1	Rationing	\$1.30	Free	1	2	3	4	5
Situation 2	Ample Supply	\$2.60	Free	1	2	3	4	5
Situation 3	Ample Supply	\$1.30	\$30/mo.	1	2	3	4	5
Situation 4	Rationing	\$2.60	\$30/mo.	1	2	3	4	5

[3] A full factorial could be constructed using 2^3 or 8 situations, which would allow all interactions to be estimated.

The pattern of levels in the experiment can be represented using a number for each level. If there are only two levels, we need only two numbers. The experimental plans found in Appendix A are presented in this manner. If one looked up this example experiment, design 2a, the layout would be described as follows:

A 2^3 Fractional Factorial Design - Main Effects Only

	Factor A	Factor B	Factor C
Situation 1	0	0	0
Situation 2	1	1	0
Situation 3	1	0	1
Situation 4	0	1	1

(The columns are in reverse order from those shown in design 2a.) To determine whether or not the factors are independent of one another, we can transform the 0's to 1's so they are equidistant from zero, that is, use +1/2 and -1/2 instead. Then the pattern of the experiment appears as follows:

A 2^3 Fractional Factorial Design - Main Effects Only

	Factor A	Factor B	Factor C
Situation 1	$-\frac{1}{2}$	$-\frac{1}{2}$	$-\frac{1}{2}$
Situation 2	$+\frac{1}{2}$	$+\frac{1}{2}$	$-\frac{1}{2}$
Situation 3	$+\frac{1}{2}$	$-\frac{1}{2}$	$+\frac{1}{2}$
Situation 4	$-\frac{1}{2}$	$+\frac{1}{2}$	$+\frac{1}{2}$

Two factors are independent if and only if the sum of the products of their transformed values (+1/2 or -1/2 in this case) is equal to 0. For example, Factor A and Factor B are independent because:

(-1/2 x -1/2) + (+1/2 x +1/2) + (+1/2 x -1/2) + (-1/2 x +1/2) = 0.
(Situation 1) (Situation 2) (Situation 3) (Situation 4)

An equivalent way of saying that two factors are independent is to say they are <u>orthogonal</u>. It is useful to understand this concept for two reasons. First, a person can invent orthogonal experimental designs by trial-and-error if a suitable one cannot be found in a cookbook set of plans. Second, it is crucial to be able to check the pattern of the experiment to ensure independence. The development of a survey containing a DUA experiment normally requires revisions. Once one settles on an experimental design, it may be necessary to shift the rows and columns around and use different factors. One may lose track of the original plan and so it is necessary to be able to check for orthogonality. If an error occurs and orthogonality no longer holds, the experiment will usually produce incorrect results. The easiest way to check for orthogonality is to make sure each level of one factor occurs an equal number of times for each level of any other factor.[4]

<u>3.3.4 Ordering of the Situations</u>. The sections above, treating basic main effects, interactions, and orthogonality, summarize the main technical issues in developing DUA experiments. The reader is urged to examine Appendix A at this point to review the examples of design selection it contains. There is an additional set of less technical issues which must also be resolved in survey design; they are covered in the next three sections.

---

[4] An excellent summary of the steps in building an experiment is contained in Green, Carroll and Carmone (1978). This reference should be consulted for creating and checking experiments with interactions.

The order of the situations in an experiment can bias the responses. For instance, if the subject felt the first half of the situations in an experiment were grossly unrealistic, or imposed severe penalties, he or she might overreact to those and underreact to the remaining ones. There are two remedies to minimize a bias of this sort. One is to allow the first situation to closely resemble current conditions and the order of the remaining situations be set at random. Another is to use "stretchers" as the first two situations, which are defined to be "best" and "worst" cases, by which a respondent can then scale his or her responses. The responses to these "stretchers" are generally thrown out, so their use increases the total number of situations by two. If either of these simple procedures is used, the order of the remaining situations is less likely to affect the result. The order of the remaining situations is then determined randomly by any convenient technique.

3.3.5 Further Considerations in the Choice of an Experimental Design. The choice of a specific design requires three steps, each involving technical and non-technical issues:

1) The choice of a set of factors (variables)
2) Specification of levels for each factor
3) Selection of a design from Appendix A

The technical issues relating to these steps have already been discussed, and must be considered along with the broader issues discussed below. The selection of the set of variables to define each travel alternative is based on previous knowledge and information gained from the focus group. Certain factors, such as travel time and travel cost, are usually included. Other possibilities are convenience, safety, accessibility, fuel availability, reliability, parking cost, gasoline cost, and various out-of-vehicle times and costs. The focus group discussion (see Section 3.4) is a good method for translating the qualitative factors into verbal descriptions. For example, reliability could be described as "bus runs on schedule", and "bus runs within ten minutes of schedule". The sample surveys in Appendix B contain pretested scenario designs for a number of different mode choice experiments.

The number of situations that must be included in the experimental design is dependent on the number of attributes, the number of levels for each attribute, and the number of interactions considered. The eight situations in Figure 2.1 (plan 91) were designed to estimate the effects of five independent factors (three for auto, two for carpooling). If three more factors were included, each with two levels, twelve situations would be required for estimation. The respondent's ease of completing the survey experiment declines with each additional situation included, and there is a trade-off between the number of factors considered in the experiment and the difficulty in obtaining a complete response.

The focus group will usually identify more variables than can be reasonably included in the DUA experiments. In narrowing down this group of attributes, the following points should be considered:

- Factors that can be changed by policy decisions (or are frequently changed by other forces) should be included for future forecasting.
- Factors that are included for both choices in an experiment can be described in a single "generic" factor as a difference between choices.
- It is best to include variables whose real current values can be obtained from supplementary survey questions for use in validating the results.

When a set of attributes has been selected, a range of values, or levels, should be specified for each. The extreme values, as seen by the public, can be identified through the focus group. DUA estimates the effect of each factor over the range encompassed by the extremes. Extrapolation to values outside this range results in a higher level of uncertainty. Therefore, if a major change in one of the variables is expected, the endpoint should be adjusted to accommodate the change. The gas price of $2.60/gallon in Figure 2.1 is an example. If such adjustments are anticipated before the focus group discussion, perceptions of likely future levels can be used to specify reasonable endpoints.

If there is one variable of particular interest, or if it appears that people react differently to values of an attribute at different ends of the specified range, then intermediate levels can be included in the design. The effect of the attribute can then be estimated between each pair of levels. For example, a gas price of $2.00 was included in Figure 2.1, and the estimated reaction may be different for values between $1.30 and $2.00 than for prices in the \$2.00 - \$2.60 range. Again, the trade-off between completeness and complexity exists. If one of the factors in Figure 2.1 had three levels instead of two, the experiment would require responses to sixteen different situations (plan 111). Experience has shown that people find the experiment more difficult as the number of variables, the number of levels of each variable, and the number of situations increase. Although there is some uncertainty as to the maximum number of situations that individuals can manage, it is thought to be between 10 and 30. The challenge is to include all of the most important factors in the choice process while keeping the experimental design to a manageable size.

3.3.6 Background Questions. The experimental design is the key element in DUA surveys, but attention must also be given to the remainder of the survey, which is used to collect socio-economic information for use in the DUA model and to validate the estimated model system. Each survey instrument should contain a limited number of background questions in addition to the DUA experiment. As in the experimental designs, the number of background questions should be kept as low as possible to encourage complete responses. These questions should be simple to understand, and should provide information concerning socio-economic variables, current travel patterns, and the base level of any factor in the experiment for which it may be difficult to collect data to validate the DUA models. A forecasting model estimated from DUA data describes what people say they would do under various situations. To compare what people say they would do with what they actually do means that we need to know for each respondent the level of each factor in the experiment under today's conditions. To determine the base case for a variable like gas price is relatively easy. In summer, 1980, virtually everybody was paying about $1.20 per gallon for gasoline. However, the base case for other variables in the experiment such as parking costs and bus travel time vary widely from traveler to traveler. To be able to validate the influence of the variables on a person's travel choice, it is necessary to ask each subject the current level of each variable. It is also necessary to ascertain each subject's current travel choices.

Socio-economic variables are used to extend the DUA model by incorporating the effects on the responses of such variables as age, sex, income, vehicles owned. These background questions can also be used to check the representativeness of the survey data by comparison with census data (see Chapter 4). Other commonly used variables include household size, number of children, housing type and occupation. In practice, it is necessary to make trade-offs between collecting all the socio-economic data one might want, keeping the form as simple as possible, and collecting sufficient data to validate all the factors in the experiment. To ensure a good response rate, it is necessary to include in the background section only those questions which would provide data concerning the most important socio-economic characteristics, and the most important variables to validate.

3.3.7 General Design of the Survey Document. A final concern in the survey design phase is the overall layout and wording of the instrument, especially in the case of a mailback survey. The most critical element is the experiment itself. Figure 2.1 is an example of a survey form used by the State of Wisconsin DOT. The modes and situations are briefly described in terms of number of passengers, number of choices, length of trip, and purpose of trip.

The last instruction requires the respondent to answer "how likely" he or she is to choose a particular mode. The answers are recorded on a scale from one to five, corresponding to the terms "always", "probably", and "indifferent". The focus group interview may be useful in determining the wording of the response scale. Often, the respondent is asked to choose from a scale of one to twenty, or to choose a point on a line segment between two extremes. Such detail, however, may add to the difficulty of completing the experiment. It appears that a five point scale is generally adequate. See Appendix D for a discussion of trade-offs in scale definitions and complexity.

The layout of the survey itself is very important, especially in mailout surveys. The matrix of situations and attributes can appear formidable to a potential respondent. A block layout with large type will make the survey less difficult to fill out. The instructions and the scenarios should all appear on one page. Limiting the entire survey form to one sheet of paper is another way to increase response rate. The experiment shown in Figure 2 appears as the inside portion of a single, folded survey sheet. On the front is a cover letter explaining the reason for the experiment, the confidentiality of the results, and their eventual use. The background questions appear on the back (fourth) page of the survey.

These considerations complete the survey design phase, which must be done in the same way for regular and "quick-response" DUA studies. A draft survey instrument is shown in Figure 3.2 which was the predecessor to the final survey given in Figure 2.1. It uses a 2^7 fractional factorial design in a binary choice between walking and driving alone. Mode choice only is considered, and a 5-point response scale is used. Instructions are brief, with considerable effort expended to make the variables and their levels self-explanatory. Lengthy written instructions preceding the experiments appeared to have a significant depressing effect on the response rate.

The next phase in the survey development process is generally to conduct focus groups as described below. Although many market researchers hold the focus group sessions as the first step in survey development, we feel that some preliminary design work is useful in setting the agenda for the focus groups, as specific issues or questions in survey design may be apparent prior to the group sessions. In quick-response studies, however, focus groups can be dispensed with, and the pretest step conducted next.

3.4 Focus Groups.

An integral part of DUA model development is the convening of a series of focus groups. The primary purpose of a focus group is to have a small group of six to twelve people representative of the general public discuss the issues and factors that influence

FIGURE 3.2

DUA Walk/Auto Survey (Initial Draft)

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR WALK?

Consider a trip short enough so that walking or driving alone are realistic choices, for example one half to two miles. Below are seven factors (listed across the top) describing eight different situations where you are faced with choosing whether to drive alone in an automobile or walk to make this trip. Look at each situation across the entire line and answer in the last column to the right how likely you are to drive alone or walk.

SITUATIONS	GAS AVAILABILITY	GAS PRICE	AVERAGE WAIT TIME AT STATION TO BUY GAS	LENGTH OF TRIP	AMOUNT OF SIDEWALKS ON THE WAY	WALK SIGNALS AT BUSY INTERSECTIONS	SEASON	ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE ALONE IN AN AUTO OR WALK TO WORK (CIRCLE A NUMBER) Probably Auto … Probably Walk
1	Ample Supply	$1.30/gallon	5 minutes	½ mile	All the way	Walk Signals	Winter	1 2 3 4 5
2	Ration of 10 gallons/week	$2.60/gallon	5 minutes	½ mile	Part way	Walk Signals	Rest of Year	1 2 3 4 5
3	Ration of 10 gallons/week	$1.30/gallon	20 minutes	½ mile	Part way	None	Winter	1 2 3 4 5
4	Ample Supply	$2.60/gallon	20 minutes	1 mile	Part way	Walk Signals	Winter	1 2 3 4 5
5	Ration of 10 gallons/week	$1.30/gallon	20 minutes	1 mile	All the way	Walk Signals	Rest of Year	1 2 3 4 5
6	Ample Supply	$1.30/gallon	5 minutes	1 mile	Part way	None	Rest of Year	1 2 3 4 5
7	Ample Supply	$2.60/gallon	20 minutes	½ mile	All the way	None	Rest of Year	1 2 3 4 5
8	Ration of 10 gallons/week	$2.60/gallon	5 minutes	1 mile	All the way	None	Winter	1 2 3 4 5

*Under rationing each registered vehicle gets 10 gallons per week.

If your car gets [10 / 20 / 30] miles per gallon, you can travel [100 / 200 / 300] miles per week.

OVER →

their travel choices. A secondary purpose is to have the members of the group fill out the preliminary draft of a DUA experiment and critique it.

The people in the focus group should be free to say anything at all which concerns their travel choice. The person who conducts the focus group should scrupulously avoid asking leading questions. In a typical focus group session, the organizer begins by explaining the purpose of the session. He or she might explain that the agency is developing models to forecast the mode of travel people use for work trips, and that they want to know what various people typically consider in deciding how to get to work. Ideally the person who conducts the focus group should say no more, and with luck, people will volunteer much useful information regarding the factors that influence their trip choice. If the group does not spontaneously provide useful information, then the organizer should begin to ask questions without leading to specific answers. A focus group should reveal what the public thinks is important in making travel choices, not what the leader of the group thinks. A secretary, remaining discreetly in the background, may record the conversation at each session.

When the conversation languishes, the following types of questions may be asked of the participants in a mode choice study, for example:

1) What factors do you consider in deciding how to go to work?
2) What components of cost do you think about?
3) What might prompt you to use a mode you do not

customarily take to work?

4) Do you take the fuel efficiency of your vehicle into account when determining cost to go to work?

The main reason for holding focus groups is that those who develop the forecasting models cannot think of every variable that has a strong influence on people's choices. Participants in the focus groups are likely to suggest factors the modelers have not considered. Also, each person who develops a model has personal biases concerning which factors are important. Information obtained from the focus groups can correct or at least temper the biases.

Focus groups conducted in a study of urban mode choice in Wisconsin (WisDOT, 1981) revealed a number of interesting things which significantly influenced which factors were included in the DUA experiment or as variables in the validated models. Among these were:

1. Individuals could respond to changes in pump gas price far more readily than to changes in gas cost per mile, indicating that their responses in actual situations may also follow this pattern. Thus, it appears that most individuals either consider fuel efficiency only implicitly or do not consider it at all when reacting to a change in gas price.
2. Participants in the bicycle focus group were able to quantify several issues that bear on the issue of safety. In particular, pavement surface, traffic levels and the existence of a marked bike lane seemed to capture the

"safety" measure adequately. As in other studies, these safety-related variables were more important than monetary issues such as gas price or parking costs. This experience is indicative of the way many "soft" issues can be represented in DUA surveys.

3. Insights into the socio-economic variables to include in the background questions can also be obtained. For example, many women said they had to drive to work because they had children to transport to day care centers or schools. The number of times this comment was made indicated that a socio-economic variable representing the traveler's sex and the number of children in the household should be significant in explaining mode choice.

4. There was such strong antipathy toward a policy of imposing parking charges of $30/month on persons who drive alone to work (while retaining free parking for carpoolers) that this variable was dropped from the carpool survey. Such insights may aid decisionmaking as well as survey design.

In addition to revealing what people feel are the important factors in their travel choice, members of the focus groups can fill out the survey forms containing the DUA experiment, and recommend changes. Participants can offer suggestions concerning the factors in the experiment, the levels of each factor, the number of factors, and the visual appearance of the layout. In addition, they may suggest changes to the cover letter and the backup questions. A particularly useful exercise is to ask each participant what he or she found to be the three most important and unimportant factors in the draft experiment and to indicate if any important factor was not taken into account.

3.5 Evaluation of Focus Group Responses to Draft Surveys.

3.5.1 Evaluation Steps.

The focus group participants may fill out the draft survey form at the end of the session; 10 to 20 minutes should be given to allow time to discuss the instrument briefly. In quick-response surveys, no focus group is conducted; an informal pretest of the survey is used instead. Both approaches produce a set of responses to the draft survey, and this section describes a simple technique for analyzing them. In some quick-response studies, this level of analysis may be sufficient. In general though, an intensive evaluation of the focus group responses is made prior to redrafting the survey instruments.

The evaluation steps are:

- Review the notes and transcripts of the focus group sessions and make an inventory of all suggested changes.
- Estimate by hand, or with a calculator, the utility functions for each choice, using data from the DUA experiments.
- Evaluate the implied value of travel time, determine the rates at which people trade off various factors, and assess the reasonableness of these trade-off rates.
- Calculate elasticities of demand and determine their reasonableness by comparing them with elasticity data

available from the travel demand literature. (Optional)

-Estimate how changes in discontinuous factors in the experiment (which become dummy variables in the utility function) influence choice. (Optional)

The first of these steps is self-explanatory. The remainder are described below.

3.5.2 Calculation of Utility Functions. Figure 3.2 shows a draft walk-auto mode choice experiment which was completed by a focus group participant. We can calculate how a factor in the experiment influences that person's choice by taking the difference between the mean scores a person gives to each level of that factor. Consider the factor, fuel availability, in the experiment. Fuel availability takes on two levels, ample supply and rationing. The total scores for each level are calculated as follows:

Level	Situations	Number of Situations	Scores	Total	Mean Score	Difference in Mean Score
Ample Supply	1,4,6,7	4	1+3+1+3	8	2.00	1.75
Rationing	2,3,5,8	4	4+3+4+4	15	3.75	

The calculations say if there is a switch from ample supply of fuel to rationing, the rating the individual gives on the utility scale of 1 (Always Drive Alone) to 5 (Always Walk) will shift by 1.75 away from the direction of Always Drive Alone.

We can perform the same exercise for each of the other factors in the experiment:

Variable	Levels	Situations	Number of Situations	Scores	Total Score	Mean Score	Difference
Gas Price	$1.30/gal.	1,3,5,6	4	1+3+4+1	9	2.25	1.25
	$2.60/gal.	2,4,7,8	4	4+3+3+4	14	3.50	
Wait Time for Gas	5 min.	1,2,6,8	4	1+4+1+4	10	2.50	0.75
	20 min.	3,4,5,7	4	3+3+4+3	13	3.25	
Length of Trip	½ mile	1,2,3,7	4	1+4+3+3	11	2.75	0.25
	1 mile	4,5,6,8	4	3+4+1+4	12	3.00	
Sidewalks	All the way	1,5,7,8	4	1+4+3+4	12	3.00	0.25
	Part way	2,3,4,6	4	4+3+3+1	11	2.75	
Walk Signals	Walk Signals	1,2,4,5	4	1+4+3+4	12	3.00	0.25
	None	3,6,7,8	4	3+1+3+4	11	2.75	
Season	Rest of year	1,3,4,8	4	1+3+3+4	11	2.75	0.25
	Winter	2,5,6,7	4	4+4+1+3	12	3.00	

Many insights can be obtained from this analysis. First, given changes within the range of values in the experiment, gas availability is the most important variable to this individual. A change in availability would cause the rating on this person's utility scale to shift by 1.75 in the direction of walking. Gas price is next in importance. Then comes wait time; the other variables matter little to this person.

All of the surveys filled out by members of the focus groups are analyzed in this fashion. They may be analyzed individually, or pooled into groups pertaining to each mode that competes with auto. In the latter case, the <u>average</u> response to each situation is used in the analysis described above.

This type of analysis can suggest many changes to the experiment.

- If there is no change in travel choice as a result of a change in the level of a factor, either the levels are not sufficiently different to be a concern to the respondent, or the factor should be dropped from the experiment.
- If too many people give an illogical response to a factor, it should be redefined or reexamined.
- If one factor seems to have a disproportionate influence on people's choices, the levels of the other factors should be reviewed. No factor should completely dominate the others. In a well-designed experiment, the average subject should be making trade-offs among the factors, not ignoring most of them. Obviously, each person will consider only a few variables to be really important and ignore the rest. But in the aggregate, the respondents of a large sample should be making trade-offs among most of the variables.

The difference in the mean scores a group of respondents gives to two levels of a factor in an experiment is the coefficient of the factor when treated as a variable in that group's utility function of the individual who must choose between walking and driving alone. We can write the person's utility function as follows:

$$R = \text{Constant} + 1.75GA + \frac{1.25}{(2.60-1.30)}GP + \frac{0.75}{(20-5)}WT + \frac{0.25}{(1-0.5)}TL + 0.25SW + 0.25CR - 0.25SN$$

where

R = response on the 1-5 scale to walk/auto experiments

GA = 0 if ample supply

1 if rationing

GP = gas price, in \$/gallon

WT = wait time to buy gas, in minutes per fillup at gas station

TL = trip length from home to work, in miles

SW = 0 if sidewalks part of the way from home to work

1 if sidewalks all the way

CR = 0 if there are no crossing signals

1 if crossing signals at every busy intersection

SN = 1 winter

0 rest of year

The coefficient of a variable describes the change in utility with respect to that variable, holding everything else constant. In other words,

$$\text{Coefficient} = \frac{\Delta R}{\Delta \text{ Variable}}$$

Δ R is drawn from the responses to the survey; Δ Variable depends on the levels in the experiment. For example, gas price varies from \$1.30 to \$2.60 so Δ Variable = \$1.30. The constant is derived in the following equation:

$$\text{Constant} = AR - \sum_i a_i \bar{x}_i$$

where AR = average response to all situations

a_i = coefficient of variable i

$\bar{x}_i$ = average value of variable i in the experiment

In our example,

$AR = 2.875 (=23/8)$

$$\text{Constant} = 2.875-1.75\cdot 0.5-0.962\cdot 1.95-0.05\cdot 12.5$$
$$-0.5\cdot 0.75-0.25\cdot 0.5-0.25\cdot 0.5+0.25\ .5$$
$$=-1.0$$

Thus, the complete utility function can be written as:

$$R = -1.0+1.75GA+0.962GP+0.05WT+0.5TL+0.25SW+0.25CR-0.25SN$$

This equation fully describes the survey responses of the individual respondent shown in Figure 3.2. This equation (based on a group of individual responses) can be used directly in quick-response studies to evaluate policy options. For example, it can be seen that sidewalk construction and crossing signalization have comparable but small effects on walking to work. Each raises the response by 0.25; both together raise the response by 0.5, or half a point on the 5 point scale. The auto-related variables have a far greater impact, changing the response by between 0.75 and 1.75. This individual's choices are not affected by trip length in the one-half to one mile range used on the survey; in fact, the coefficient has an intuitively incorrect sign. Over a larger group such individual anomalies are balanced by other responses.

These responses on the 5 point scale can be interpreted as probabilities of choice as well; this issue is discussed in Chapter 5. Quick response studies can accept a standard assumption to derive probabilities, while other studies follow a formal validation procedure.

3.5.3 Travel Time and Trade-off Analysis. One of the purposes of conducting a DUA experiment is to measure the rates that people trade off one factor against another in trying to decide whether to use one of two alternatives. The rate at which a person trades off two factors can be derived directly from that person's utility function. In the experiment shown in Figure 3.1 an individual must determine the relative value of a change in wait time and gas price. The trade off rate between these two variables to maintain a constant level of utility is:

$$\Delta R = 0 = \frac{1.25}{(260-130)} \Delta GP + \frac{0.75}{(20-5)} \Delta WT$$

$$\frac{\Delta GP}{\Delta WT} = \frac{-0.75\cdot(260-130)}{(20-5)\cdot 1.25} = 5.2 \text{ cents/min.} = \$3.12/\text{hour}$$

which is the imputed value of wait time in dollars per hour. (The sign is ignored.) Evaluate the value of time whenever it appears in the focus groups' utility functions, and assess its reasonableness. If the value of time is excessive or negligible, find the reason for it in the experiment and make changes accordingly.[5] In experiments with interactions, trade-off rates should be computed at several values of the variables.

3.5.4 Elasticities and Dummy Variable Analysis. Additional insights into people's responses to the experiment are analyzed by calculating elasticities and cross elasticities of demand for continuous variables such as gas price and wait time. An elasticity is defined as the percentage change in travel demand,

---

[5] Note that the standard error of the estimate of value of time may be quite high even though the individual coefficients of time and cost have low standard errors. Thus, seeming anomalies may appear but may be statistically insignificant. This test is used only as an approximate check on the model.

measured in units of person trips, which results from a 1% change in the variable of interest with all other variables held constant. One can compare the elasticity of demand estimated from the utility function with information on elasticities available in the travel demand literature. If the elasticities are the wrong order of magnitude, or have the wrong sign, it is likely the experiment requires revision. A similar type of analysis can be performed with discontinuous variables, which normally appear as dummy variables (0-1) in the utility function. Chapter 9 explains how to calculate elasticities and the effect of dummy variables on the utility of choice. These analyses are optional; they are different ways of representing the response data beyond those already shown.

3.6 Pretest.

The final stage of survey preparation is to pretest the instrument developed through the focus group and pre-analysis just described. A small sample is generally used (30 respondents or less). The same analysis of responses is done as for the focus groups.

The pretest survey can include additional questions, such as:

-Are the instructions clear?

-Is the experiment too complicated? How so?

-Is the response scale appropriate?

-Do the attribute levels seem reasonable?

-Are the final questions answerable? Objectionable?

-What might be done to stimulate more interest in the experiment?

3.7 Summary.

This chapter has presented the steps in designing a DUA survey for both standard and quick-response studies. A structured set of decisions must be made at the outset of the study to determine the issues addressed, levels of demand to be studied, and survey administration technique. Preliminary decisions on the number of variables, their levels, and the need to estimate interactions must then be made to be able to select an initial experimental plan from Appendix A. Trade-offs between model accuracy and survey complexity must also be assessed. In quick-response studies, the draft survey is pretested informally and then administered to the public. In other studies, a set of focus groups is held to explore the issues being addressed in depth, the survey is revised, and then the revised instrument is pretested.

A series of simple analysis steps are used to assess the results of the surveys. Utility functions describing the factors influencing the survey responses are computed by hand or using a calculator. Tradeoff rates between key variables are also computed. Based on these results and other feedback from focus groups and pretests, a final survey design is prepared for public distribution.

As discussed in Chapter 5, analysis is straightforward in DUA models compared to revealed preference (e.g. logit) models, because the variables and the functional form of the model are already specified in the design. Because of this feature, however, errors or shortcomings in the survey are reflected in the final model quite directly; therefore, it is useful to devote substantial effort to the survey design, as outlined in this chapter. Chapter 7 returns briefly to survey design to treat some advanced topics.

CHAPTER 4

SURVEY ADMINISTRATION

4.1 Introduction.

After the final revision of the survey forms, based on feedback from the focus groups and the pretests, the survey is administered to a sample of respondents. This chapter describes the sampling plan used to determine how many surveys to distribute, the response rates to the surveys, the handling and preparation of the surveys for data processing, and representativeness checking of the response samples.

4.2 Sampling Plan.

4.2.1 Determining Sample Size. The number of surveys to be administered is determined based on (1) the sampling error we wish to have in the responses, and (2) the expected usable response rate. The first step in developing a sampling plan for administering a survey is to decide what level of statistical accuracy and confidence we need in our responses. In much research, it is customary to obtain estimates based on a sample that is accurate within plus or minus ($\pm$) 5% or 10%, with 95% confidence, of the actual population being studied. In other words, if we were to take twenty different samples, the results from nineteen of them would include the true population value within their confidence limits of $\pm$5% or $\pm$10%.

Once the desired confidence interval and accuracy have been decided on, the required sample size can be determined using the following formula (see Blalock, 1979, pp. 214-218):

$$N = \left[\frac{z_{1-\alpha/2} \cdot s}{d} \right]^2$$

Where:

N = the sample size

$z_{1-\alpha/2}$ = the z-level of the standard normal curve[1] at significance α

s = the standard deviation for the variable being considered[2]

d = the desired accuracy or confidence interval (e.g., $\pm 5\%$, or $\pm 10\%$, expressed as .05 or .10)

In DUA, we are concerned primarily with categorical variables, such as the likelihood of using a mode of transportation (measured on a scale of 1 to 5), current mode used to work (drive alone, shared ride, bus, walk, bike or some other mode), sex, and income range. In determining the required sample size from the above formula, the following example values can be used: s = 0.5, d = 0.1, and z = 1.96. Substituting these values into the sample size formula indicates a sample size of N = 96. If d = 0.05, then N = 384. Note that these sample sizes are based only on sampling error, or the uncertainty in measuring the average response of a population to

---

[1]At the 95% confidence level, for example, the significance level α is .05 and 1-.05 /2 is .9750. Locating .9750 in a table showing the distribution of areas under the standard normal curve (found in Appendix E) leads to a z-level of 1.96 in this case.

[2]Estimated by expert knowledge or the results of previous studies for continuous data, and conservatively estimated by .5 for categorical data. Since $s^2 = p(1-p)$ for categorical data and the product p(1-p) reaches a maximum value when p = .5, the maximum $s^2 = .25$ and s = .5. Thus, since we normally desire a small confidence interval, we are being conservative using .5 as an estimate of s since .5 produces the widest possible confidence interval.

a situation. If 40% of our sample responds "3" to a situation, and our sample size is 384 (±5% accuracy), all we know (with 95% confidence) is that between 35% and 45% of the total population would respond "3". We cannot determine in advance the sample size needed to attain any level of model "fit", as measured by t-statistics or R^2 (see Chapter 5 for definitions). However, these sample sizes in the 96 to 384 range do yield satisfactory models, based on past experience. Successful models have in fact been built with as few as 30 respondents. (Since each respondent reacts to many situations in the experiment, the size of the data set is in fact much larger than 30.)

4.2.2 Sample Type. One must also choose between a strict probability sample, a quota sample, or other quasi-random approaches to sampling the population of interest. A strict probability sample is one in which every member of the population being surveyed (e.g. residents of a city) has an equal chance of being chosen. It is generally a very expensive proposition to construct such a sample, which is based on randomly sampling Census units to the block level, and then sampling residences. Strict probability samples are generally not used for DUA surveys, because DUA models relate the survey responses to causal factors (in the experiment and in socio-economic data). Slight departures from a strict probability sample do not impair our ability to estimate these causal connections, although these departures do affect simple attitude or opinion surveys which simply record average responses.

Quota samples are quasi-random samples in which categories of demographic variables are monitored to ensure that the demographic profile of respondents matches a predetermined target, often drawn from Census data. This approach requires telephone screening, or deletion of certain responses after all are received, to meet the quotas. An example is shown in Appendix B.

Other quasi-random samples result from mailout, onboard or other survey administration techniques with limited control of response rates. Checks for representativeness must be made on the data received to ensure correspondence with the population being modeled. This is discussed in Section 4.3.

In general, DUA surveys will produce representative models as long as the sample data set contains no major biases. Potential areas of difficulty in many cases include undersampling of low income, handicapped, student, minority and elderly groups. Attention should be given to designing surveys that can be successfully administered to and completed by these groups. Often, areas with concentrations of these groups can be oversampled; in other survey formats (e.g. central interview) screening questions can be asked to identify members of these groups, and quotas can then be established to ensure minimum levels of representation.

4.2.3 Survey Techniques and Expected Response Rate. Once an appropriate sample size has been determined that provides results with a desired level of sampling error, the next step is to estimate the usable response rate that can be expected from the survey. This should be a conservative estimate of the proportion of the total surveys administered that one can confidently expect to be completed.

There are four techniques of survey administration commonly used for DUA studies: mailout/mailback, onboard (transit vehicles), central group interview, and home interview. Mailout surveys are often used because a large sample can be obtained at relatively low cost. Addressing and postage costs can be minimized (and the response rate increased) by mailing the survey with another form which is widely distributed. Examples are tax forms, newsletters, municipal or utility bills, and drivers' license or vehicle registration renewal forms.

The experience in DUA studies has been that a 50% "raw" response rate to a mailout survey is as high as one can expect. We emphasize "raw" response rate here because often many surveys are returned incompletely filled out and cannot be used in many types of statistical analyses (such as regression analysis, for example, which requires complete records for all variables and cases used). Typically the usable response rate is less than 50%, especially for DUA surveys, since the DUA part of the survey is much more purpose-specific and complex than a simple attitude or opinion survey which asks easy "agree or disagree" type questions. A conservative estimate of the usable response rate on a well-designed DUA survey is 20%, although rates of up to 46% have been obtained.

Transit onboard surveys can also include DUA experiments. It will be difficult to insist that they be completed onboard the vehicle, so most of the forms will be mailed back. This will result in a response rate lower than if the surveys were completed on the vehicle, but the overall response rate will generally be higher than a mailout/mailback survey. Onboard surveys, if used for general mode choice models, present some special statistical issues; refer to Lerman and Manski (1979) for the techniques of weighting responses as required in this case. For operational studies (such as shown in Figure 1.1) these special techniques are not required.

The central group technique involves administering the survey in person to groups of eight to fifteen people. Appointments can be made by telephone, or by recruitment in public places, such as shopping centers or municipal buildings. People are usually paid $5 to $10 to participate in a survey of 30 to 45 minutes duration. Audio-visual techniques are often used to present the survey choices. Virutally all respondents attending a central group session will complete the survey, although a few will be meaningless, completing the survey only to receive the monetary reward. These responses can be screened out in the analysis step as having insignificant coefficients resulting from a random response pattern.

The home interview technique is similar to the central group session. The main difference is a one-to-one interaction between administrator and the respondent. The interviewer can make certain that the instructions are clear and that the responses are complete. The close interaction, however, may bias some of the responses, and people may feel nervous in the presence of the interviewer as they complete the DUA task.

Appendix B presents examples of DUA surveys, together with a brief discussion.

4.2.4 Example of Mailout Survey Administration Procedure. As the sampling issues for a mailout survey are more complex than for other techniques, a brief example of a Wisconsin urban DUA project's procedures is given here. The quota sampling procedures for central group and home interview surveys are given in Appendix B.

Three basic options existed for mailing out a survey from Wisconsin DOT: (1) include the survey with vehicle registration renewals; (2) include the survey with driver's license renewals; and (3) develop a strict random sample of urban state residents for a special mailing. The first two involve including the survey form with regular Division of Motor Vehicle mailings (an inexpensive option since no additional postage is required) and the third involves a costly special mailing.

Vehicle registrations are renewed on a yearly basis and the sheer numbers involved require continuous mailings by the Department. This option was not chosen because the population is limited only to registered owners of motor vehicles and contains fewer women and lower income people than the statewide population as a whole. The registration population would also contain leasing companies and dealerships which could skew the sample. (However, if one is interested in sampling the opinion of only registered motor vehicle owners, then this would be a reasonable mailout option.)

The second option was to include the survey with driver's license renewals. These are currently renewed every two years and about 30,000 are mailed by the Department biweekly. The population consists of all licensed drivers in Wisconsin. This population closely parallels the statewide population as a whole, sixteen years old and over. The male-female distribution, for example, is almost equal and very close to Census figures for the state (53% male and 47% female among Wisconsin licensed drivers versus 49% male and 51% female in the general population).

The third option for mailing out surveys at WisDOT was to develop a strict random sample of Wisconsin residents, requiring a special mailing. Not only would the time and cost required for this type of sample and mailing be prohibitive, but in the end the resulting sample probably would be no more random than a quasi-random sample or quota sample taken from the slightly different population of licensed drivers.

From these options, Wisconsin chose to include its surveys with driver's license renewals and a quasi-random sample was drawn from the population of licensed drivers. While this sample is not strictly a random sample in the absolute statistical sense -- everyone in the population of licensed drivers does not have an equal chance of being included in the sample -- it does closely approximate a random sample. Driver's licenses are renewed on a person's birthday -- which are somewhat randomly distributed in the population -- so that any given month's renewals represent a quasi-random subpopulation of the entire population. Further, it is even safer to assume that socio-economic characteristics are randomly distributed with regard to birthdates.

Having decided (1) the number of surveys of each type to mail out to each urban area, and (2) to mail out with driver's license renewals, the mailout plan was further refined to insure the proper sampling of each city or village with a zip code in an urban area. This was deemed necessary because driver's license renewals are mailed out by zip code, beginning with the highest number zip code in the state to the lowest. The survey was added to the mailing machine as the urban area zip codes of interest appeared.

The 17,000 DUA surveys were mailed out the week of August 11, 1980. Surveys returned before the end of October were included in the analysis. Of the 17,000 surveys mailed, 5% (864) were returned with the driver's license renewals unopened because some licensed drivers died, moved out of state, or moved without a forwarding address during the two years since their license was last renewed. Of the remaining total (16,136), the gross response rate was 57% (9,208).

As the surveys were returned, each was checked for completeness before being coded and used in an analysis. Any survey in which the experiment was not completed could not be used. Nineteen percent (1,750) of the returned surveys were dropped because of incomplete information. Discarded surveys were primarily from people who felt the alternatives presented did not apply to them. This was true especially for retired people since the surveys were specifically addressed to work trips.

Only the most unintelligible or wildly illogical completed responses were excluded from analysis. This accounted for less than 1% of the returned surveys. Despite the fact that DUA experiments look excessively complex, experience has shown that few people have difficulty understanding how to respond to the experiment, even in an unaided, uncontrolled mailout setting. Surveys in which the same choice was circled for all eight situations -- such as "1", "always drive alone" -- were retained, even though they provided no variation, because some people probably would always drive alone, for example, despite the different situations presented. Many salespeople, for example, indicated in the space provided for comments that they had little or no choice but to drive alone.

In a few cases, the experiment was completed but no information was provided on the background questions. These surveys could not be used either. In all, 46% (7,400) of the 16,136 delivered surveys were returned filled out and usable for the analysis.

4.3 Coding the Survey Data.

The data from DUA surveys must be manually coded and stored for data processing and computer-assisted analysis. To facilitate the coding processes and minimize coding errors, special coding sheets are usually designed from standard 80-column coding sheets. Much of the data on the coding sheets is self-explanatory. To fully interpret all the data, it is necessary to prepare a codebook, which contains the detailed conventions used in coding the survey data.

Once the surveys are coded and keypunched, a processing program must be written to merge each respondent's data record with the data describing the situation in the experiment (which is constant for all respondents). If there are eight situations in the experiment, this has the effect of multiplying each respondent's data record eight times. Thus, from 500 raw response records, one would end up with a total of 4,000 experiment observation response records from which the utility equations will be estimated. In essence, then, each respondent provided eight observations, corresponding to the eight situations in the experiment. An example processing program is shown in Appendix C.

Once the survey data sets are developed and properly organized, the data sets should be checked for coding, keypunching, or data processing errors before they are analyzed. This can be done using the "Simple Data Description" program (BMDP1D) of the Biomedical Computer Programs, P-Series (BMDP-1979), statistical package (UCLA, 1979), or other tabulation packages. Any coding errors must be corrected before proceeding with the analysis.

4.4 Checking the Samples for Representativeness.

The next step in a DUA study, before proceeding to the analysis of the survey experiment responses, is to check the samples for representativeness. To accomplish this, socio-economic characteristics of the respondents in the samples are compared to the same socio-economic characteristics of the population to ensure that the samples closely reflect (are representative of) the population. This is necessary to guard against potential biases that might otherwise enter into the models.

The socio-economic characteristics or criteria typically examined in checking samples for representativeness are sex, household size, yearly household income, and age.

Census data for the areas in the survey sample are gathered on the selected representative criteria, with income figures factored up to account for inflation, and proportioned according to the categories appearing on the survey. These categorically proportioned distributions of socio-economic characteristics in the population are then compared to the proportional distributions for the same categories in survey samples. The goal is for the categorically proportioned distributions in the samples to be within ±5% to 10% of the proportional distributions for the same categories in the population, depending on the tolerance used to set the original sample size. An example of the results of representativeness checking is shown in Table 4.1.

If the samples are not representative according to some characteristic, then corrective weights can be computed. This can be done by simple dividing the desired number of returns for an under-represented characteristic by the actual number of returns for that characteristic (desired number/actual number). For example, given a sample of 120 responses, 80 from men and 40 from women, and given

TABLE 4.1

Madison Representativeness Checks: An Example

Socio-Economic Characteristic	Categorical Proportions	
	Survey	Census
Household Size		
1 Person Households	0.184	0.212
2 Person Households	0.349	0.306
3 Person Households	0.169	0.167
4 Person Households	0.211	0.150
5 Person Households	0.063	0.086
6 Person Households	0.012	0.044
7+ Person Households	0.012	0.031
Annual Household Income		
Under $5,000	0.036	0.056
$5,000 - $9,999	0.094	0.074
$10,000 - $14,999	0.163	0.092
$15,000 - $19,999	0.181	0.177
$20,000 - $29,999	0.256	0.315
$30,000 and Over	0.265	0.282
Age		
16 - 24	0.235	0.376
25 - 34	0.335	0.221
35 - 44	0.178	0.156
45 - 54	0.125	0.141
55 - 64+	0.115	0.105

that the male-female distribution in the general population is nearly equal, women would be underrepresented in the sample. This could be corrected by calculating weights to correct the difference. In this case, the desired number of returns from both men and women would need to be 60, for a 50/50 split. Therefore, the weight for male respondents would be 60/80 = 0.75 and the weight for female respondents would be 60/40 = 1.5. This would correct an imbalance in the sample which might otherwise lead to biases assuming for this example that men and women respond differently to travel choices. These weights are used by regression and other programs described in Chapter 5.

CHAPTER 5

ANALYSIS OF SURVEY RESPONSES

5.1 Introduction.

The analysis of the survey data requires two distinct steps. First, a model is built that explains the survey responses as a function of the variables in the experiment and the respondent's socio-economic characteristics. This is a model of stated behavior, and is fitted with multiple linear regression. The second step is to test whether individuals' stated preferences correspond to their actual behavior. In this step, current values of all variables are substituted into the model found in the first stage, and then the correspondence between model predictions of current behavior and the actual behavior is tested. This second step is a validation step based on actual behavior and can involve estimating parameters of a multinomial logit model. Because the validation step can be performed in many ways, it is discussed at length in Chapter 6. This chapter describes only the first analysis stage.

5.2 Binary Models.

The simplest form of DUA models is one which represents only two choice alternatives, or a binary choice model. The analysis presented in this section produces exactly the same results as the manual technique of Section 3.5.2, although it uses computer analysis and a more general method. The method is multiple linear regression, described in econometric and statistical textbooks (see, for example, Wonnacott and Wonnacott, 1970). It is a general technique for establishing the relationship between a dependent variable and a series of independent variables. Our simple procedure of Section 3.5.2 is a special case of multiple linear regression, which holds only when the data set (experiment) is orthogonal and balanced.

As an example, we will use the walk survey shown in Figure 5.1, which is the final version of the draft survey shown in Figure 3.1. A multiple linear regression is performed on the data for individuals responding to the walk survey and yields the following equation:

$$R = a_1 + a_2GA + a_3GP + a_4WT + a_5TL + a_6SW + a_7SN$$

where:

R = response on 1-5 "likelihood of use" scale

$a_1, \ldots, a_7$ = coefficients (a_1 is the constant)

GA = gasoline availability (0=ample, 1=rationing)

GP = gasoline price (dollars per gallon)

WT = wait time at station to buy gas (minutes)

TL = one-way trip length (miles)

SW = amount of sidewalk (0=all the way, 1=part way)

SN = season (0=summer, 1=winter)

This equation captures the relationship between the response R and all the independent variables in the experiment which we believe to influence the response or likelihood of walking. This equation is called a utility equation, reflecting the importance or value of each factor in a person's decision.

The multiple linear regression can either be performed for each individual separately, or a single regression can be performed across all individuals. If separate regressions are done for each individual, a very rich description of behavior is obtained but it is relatively cumbersome to use for analysis. Most marketing research

FIGURE 5.1

DUA Walk/Auto Survey (Final Version)

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR WALK?

Consider a trip short enough so that driving alone in an automobile or walking are realistic choices.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or walk to make a one half or one mile trip.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or walk.

	AUTO FACTORS			WALK FACTORS			PLEASE– ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE ALONE IN AN AUTO OR WALK? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Average Wait Time at Station to Buy Gas	Length of Trip	Amount of Sidewalk on the Way	Season	Always Auto	Probably Auto	In-different	Probably Walk	Always Walk
SITUATION 1	Ample Supply	$1.30/gallon	5 minutes	½ mile	All the way	Winter	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	5 minutes	½ mile	Part way	Summer	1	2	3	4	5
SITUATION 3	Ration of 10 gallons/week*	$1.30/gallon	20 minutes	½ mile	Part way	Winter	1	2	3	4	5
SITUATION 4	Ample Supply	$2.60/gallon	20 minutes	1 mile	Part way	Winter	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$1.30/gallon	20 minutes	1 mile	All the way	Summer	1	2	3	4	5
SITUATION 6	Ample Supply	$1.30/gallon	5 minutes	1 mile	Part way	Summer	1	2	3	4	5
SITUATION 7	Ample Supply	$2.60/gallon	20 minutes	½ mile	All the way	Summer	1	2	3	4	5
SITUATION 8	Ration of 10 gallons/week*	$2.60/gallon	5 minutes	1 mile	All the way	Winter	1	2	3	4	5

*If your car gets 15 miles per gallon, you can travel 150 miles per week.

OVER →

T-277E-80

uses this approach, however. In transportation planning the usual approach is to estimate a single model across all respondents. Individual-to-individual variability is captured through the inclusion of socio-economic variables in the model, as described below. The examples in this chapter use the single-model approach, but the individual-model approach can also be used. There is no difference between them in the analysis steps, though the forecasting methods for each are quite different.

To further explain the responses, we can include socio-economic variables in the utility equations. Then the utility equation can be expressed as:

$$\begin{aligned} R = {} & a_1 + a_2GA + a_3GP + a_4WT + a_5TL + a_6SW + a_7SN \\ & + a_8S1 + a_9S2 + a_{10}S3 + \ldots \\ & + a_{11}S1 \cdot GA + a_{12}S2 \cdot GA + a_{13}S3 \cdot GA + \ldots \\ & + a_{14}S1 \cdot GP + a_{15}S2 \cdot GP + a_{16}S3 \cdot GP + \ldots \end{aligned}$$

where S1, S2, S3, ... = socio-economic variables. The terms a_1 through a_7 are the same as in the previous equation. The terms a_8 through a_{10} represent the main effects of socio-economic variables; these shift the effective constant a_1* for each individual:

$$a_1^* = a_1 + a_8S1 + a_9S2 + a_{10}S3$$

but do not affect the coefficients of any of the variables. The terms a_{11} through a_{16} represent interaction effects between socio-economic variables and level of service variables in the experiment. These allow the coefficients for each variable to vary by individual, depending on his or her socio-economic characteristics.

In general, only a few of the terms a_8 through a_{16} will be included in the model, because the socio-economic data are not collected within the experimental design and are thus not orthogonal, may not exhibit much variability, and may be highly collinear. If no terms of the form a_{11} through a_{16} are included, the coefficients a_2 through a_7 will remain the same as various socio-economic main effects (a_8 through a_{10}) are tested. This is due to the orthogonal design of the experiment, and it points out the need for careful survey design and testing. A poorly defined variable can result in a poor coefficient in the model about which little can be done at this stage of analysis.

The only type of term not included in the equation above is interactions among the experimental variables (e.g. $a_{17}GP \cdot GA$) because the design in Figure 5.1 does not allow their estimation.[1] In designs where they can be estimated, they can be included in the final equation. Interactions are discussed in Chapter 7.

Table 5.1 shows an example data set for the walk/auto experiments for three respondents; thus, there are 24 observations in the data set. Since groups of 8 responses come from each individual, the socio-economic data vary in blocks of 8 observations. (This is also an example of the output produced by the processing program mentioned in Section 4.3 and described in Appendix C.)

Figure 5.2 shows the regression results for the data set. A single equation is estimated across all three respondents, but socio-economic main effects (SEX and VEH) are used to reflect some individual variations. The utility equation is:

$$\begin{array}{llllllll} R = 4.99 & - 0.63SEX & - 1.88VEH & + 0.75GA & + 0.58GP & + 0.03WT & - 1.17TL \\ (5.90) & (-1.88) & (-5.64) & (2.76) & (2.76) & (1.54) & (-2.15) \end{array}$$

$$\begin{array}{ll} + 0.08SW & - 0.75SN \\ (0.31) & (-2.76) \end{array}$$

---

[1] Plan 5a is used, which actually could allow one interaction to be estimated. We ignore it here for simplicity.

Table 5.1
Example of Data Set, Walk/Auto Survey

GA	GP	WT	TL	SW	SN	R	SEX	VEH
0	1.30	5	.5	0	1	2	0	1
1	2.60	5	.5	1	0	5	0	1
1	1.30	20	.5	1	1	4	0	1
0	2.60	20	1	1	1	4	0	1
1	1.30	20	1	0	0	5	0	1
0	1.30	5	1	1	0	2	0	1
0	2.60	20	.5	0	0	4	0	1
1	2.60	5	1	0	1	4	0	1
0	1.30	5	.5	0	1	1	0	2
1	2.60	5	.5	1	0	4	0	2
1	1.30	20	.5	1	1	2	0	2
0	2.60	20	1	1	1	1	0	2
1	1.30	20	1	0	0	2	0	2
0	1.30	5	1	1	0	1	0	2
0	2.60	20	.5	0	0	3	0	2
1	2.60	5	1	0	1	1	0	2
0	1.30	5	.5	0	1	1	1	2
1	2.60	5	.5	1	0	2	1	2
1	1.30	20	.5	1	1	1	1	2
0	2.60	20	1	1	1	1	1	2
1	1.30	20	1	0	0	1	1	2
0	1.30	5	1	1	0	1	1	2
0	2.60	20	.5	0	0	2	1	2
1	2.60	5	1	0	1	1	1	2

Figure 5.2

Example of Regression Results, Walk/Auto Survey

Dependent Variable is R

Independent Variable	Estimated Coefficient	Standard Error	T Statistic
GA	0.750000	0.271314	2.76
GP	0.576923	0.208703	2.76
WT	0.027778	0.018088	1.54
TL	-1.166667	0.542627	-2.15
SW	0.083333	0.271314	0.31
SN	-0.750000	0.271314	-2.76
CNST	4.986110	0.844759	5.90
SEX	-0.625000	0.332290	-1.88
VEH	-1.875000	0.332290	-5.64

0.8589 = R-Squared
0.6625E+01 = Sum of Squared Residuals
11.42 = F-Test (8, 15)

0.6646E+00 = Standard Error of Regression
24 = Number of Observations

where all variables in the experiment are as defined earlier, SEX is 0 for male and 1 for female, and VEH is the number of motor vehicles owned by a household. The numbers in parentheses are the t-statistics, or ratios of the coefficient values to their standard errors. An absolute t-value of 2 or more indicates a greater than 95% confidence that the coefficient is statistically different than zero.

The utility equation can be broken into two equations algebraically by assuming:

$$R = U_w - U_a$$

where U_w = utility of walking

U_a = utility of driving alone

This algebraic step is taken merely to put the analysis results in a standard form for policy analysis. Variables describing characteristics of a particular mode are put in that mode's utility equation. Socio-economic variables and constants are assigned arbitrarily to a utility equation, but following the sign convention above. Each utility is assumed to be positively related to the mode's share of travel. Thus:

$$U_w = 4.99 + 0.03WT - 1.17TL + 0.08SW - 0.75SN$$

$$U_a = 0.63SEX + 1.88VEH - 0.75GA - 0.58GP$$

The signs in the U_a equation have been reversed as defined above. As gas price increases, for example, the utility of auto decreases, as expected. The auto mode is most likely to be chosen in the experiment when a "1" response is recorded, and least likely when a "5" is recorded; thus its coefficients must be reversed to produce a utility equation in the usual sense. The walk coefficients are already of the correct sign.

If only a binary choice is being modeled, and no validation is being performed, this completes the analysis. The utility equations can then be used for policy analysis as described in Chapter 9. Certain of the pretested instruments given in Appendix B appear to validate with virtually no adjustment, and thus their results can be used directly, if desired. In many cases, however, validation will be performed, so the steps laid out in Chapter 6 must be followed.

5.3 Multinomial Models.

For many policy or planning decisions, a binary model is sufficient. DUA surveys can be done quickly and cheaply enough that purpose-specific models can be developed as needed. In some cases, however, more general models are required and these will often contain multiple alternatives. (Models with multiple levels of demand, such as trip frequency and mode choice, can still be built using the binary procedure if there are only two alternatives; see Chapter 7.) Multiple alternatives can include varying modes, destinations or trip rates to be included in a single, final model. This section gives an example of modeling the choice among three modes.

We take Figure 5.3 and Table 5.2 as an example. If a three-mode model for short trips (auto, walk, bike) is desired, than both the walk/auto survey shown earlier and the bike/auto survey shown in Figure 5.3 would be administered. In addition to the data collected from the walk/auto survey (Table 5.1), the data shown in Table 5.2 for the bike/walk survey are used.

When considering choices among multiple alternatives, there are consistency constraints which must be addressed. If the bike/auto and walk/auto data sets were analyzed separately (as if they were isolated binary choices) and then the results were to be combined into a single model, the coefficients of the auto-related variables

FIGURE 5.3

DUA Walk/Bike Survey

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR RIDE YOUR BIKE?

Consider a trip short enough so that driving alone in an automobile or riding a bicycle are realistic choices. Assume the weather is nice.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or ride a bike to make a one or three mile trip.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or ride a bike.

	AUTO FACTORS		BIKE FACTORS				PLEASE– ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE ALONE IN YOUR AUTO OR RIDE YOUR BIKE? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Length of Trip	Whether There is a Bike Lane	Street Surface	Level of Auto and Truck Traffic Along Route	Always Auto	Probably Auto	In-different	Probably Bike	Always Bike
SITUATION 1	Ample Supply	$2.60/gallon	3 miles	Marked bike lane in street	Smooth	Quiet	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	1 mile	Marked bike lane in street	Smooth	Busy	1	2	3	4	5
SITUATION 3	Ration of 10 gallons/week*	$1.30/gallon	3 miles	None	Smooth	Busy	1	2	3	4	5
SITUATION 4	Ample Supply	$2.60/gallon	1 mile	None	Rough	Busy	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$1.30/gallon	1 mile	Marked bike lane in street	Rough	Quiet	1	2	3	4	5
SITUATION 6	Ample Supply	$1.30/gallon	1 mile	None	Smooth	Quiet	1	2	3	4	5
SITUATION 7	Ample Supply	$1.30/gallon	3 miles	Marked bike lane in street	Rough	Busy	1	2	3	4	5
SITUATION 8	Ration of 10 gallons/week*	$2.60/gallon	3 miles	None	Rough	Quiet	1	2	3	4	5

*If your car gets 15 miles per gallon, you can travel 150 miles per week.

T-277A-80

OVER →

Table 5.2
Example of Data Set, Bike/Auto Survey

GA	GP	TL2	BL	SS	TR	R	SEX	VEH
0	2.60	3	1	1	1	4	0	1
1	2.60	1	1	1	0	5	0	1
1	1.30	3	0	1	0	5	0	1
0	2.60	1	0	0	0	3	0	1
1	1.30	1	1	0	1	5	0	1
0	1.30	1	0	1	1	4	0	1
0	1.30	3	1	0	0	4	0	1
1	2.60	3	0	0	1	4	0	1
0	2.60	3	1	1	1	1	1	2
1	2.60	1	1	1	0	3	1	2
1	1.30	3	0	1	0	1	1	2
0	2.60	1	0	0	0	1	1	2
1	1.30	1	1	0	1	1	1	2
0	1.30	1	0	1	1	1	1	2
0	1.30	3	1	0	0	1	1	2
1	2.60	3	0	0	1	1	1	2
0	2.60	3	1	1	1	2	0	2
1	2.60	1	1	1	0	5	0	2
1	1.30	3	0	1	0	2	0	2
0	2.60	1	0	0	0	2	0	2
1	1.30	1	1	0	1	4	0	2
0	1.30	1	0	1	1	3	0	2
0	1.30	3	1	0	0	2	0	2
1	2.60	3	0	0	1	2	0	2

(gas availability, gas price, wait time to buy gas) would differ in the two models and we would not be able to write a single utility function for the drive alone mode. To avoid this inconsistency, a simple procedure is used.

The two data sets are combined into a single "grand" data set on which regressions are run. The "grand" data set is shown in Table 5.3. All variables relevant to bike are set to zero for the walk cases, and vice versa. By performing a "grand" regression, we obtain a single coefficient of all auto-related variables (gas availability, gas price, etc.) across both the bike/auto and walk/auto utility equations. In validation and forecasting, the utility equations can then be manipulated to yield separate utility equations for each mode, as in the binary case already shown.

Figure 5.4 shows the bike/auto regression model based on the bike/auto survey only, and Figure 5.5 shows the combined bike/walk/auto regression model. The utility equation for the bike/auto experiment (Figure 5.4) is:

$$\begin{aligned} R = \underset{(7.99)}{5.50} &+ \underset{(3.42)}{0.83GA} + \underset{(0.00)}{0.0GP} - \underset{(-2.74)}{0.33TL2} + \underset{(2.74)}{0.67BL} + \underset{(2.05)}{0.50SS} - \underset{(-0.68)}{0.17TR} \\ &- \underset{(-5.03)}{1.50SEX} - \underset{(-5.03)}{1.50VEH} \end{aligned}$$

where

R = response on 1-5 scale to bike/auto survey

GA = gasoline availability (0=ample, 1=rationing)

GP = gasoline price (dollars per gallon)

TL2 = length of bike trip (miles)

BL = bike lane (0=none, 1=marked lane in street)

SS = street surface (0=rough, 1=smooth)

TABLE 5.3

Data Set for Bike/Auto and Walk/Auto Surveys Combined

R	GA	GP	WT	TL	SW	SN	TL2	BL	SS	TR	SEX	VEH	WCON
2.0	0.0	1.3	5.0	0.5	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
5.0	1.0	2.6	5.0	0.5	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
4.0	1.0	1.3	20.0	0.5	1.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
4.0	0.0	2.6	20.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
5.0	1.0	1.3	20.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
2.0	0.0	1.3	5.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
4.0	0.0	2.6	20.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
4.0	1.0	2.6	5.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0
1.0	0.0	1.3	5.0	0.5	0.0	1.0	0.0	0.0	0.0	0.0	0.0	2.0	1.0
4.0	1.0	2.6	5.0	0.5	1.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	1.0
2.0	1.0	1.3	20.0	0.5	1.0	1.0	0.0	0.0	0.0	0.0	0.0	2.0	1.0
1.0	0.0	2.6	20.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	2.0	1.0
2.0	1.0	1.3	20.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	1.0
1.0	0.0	1.3	5.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	1.0
3.0	0.0	2.6	20.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	1.0
1.0	1.0	2.6	5.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	2.0	1.0
1.0	0.0	1.3	5.0	0.5	0.0	1.0	0.0	0.0	0.0	0.0	1.0	2.0	1.0
2.0	1.0	2.6	5.0	0.5	1.0	0.0	0.0	0.0	0.0	0.0	1.0	2.0	1.0
1.0	0.0	2.6	20.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	2.0	1.0
1.0	1.0	1.3	20.0	0.5	1.0	1.0	0.0	0.0	0.0	0.0	1.0	2.0	1.0
1.0	1.0	1.3	20.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	2.0	1.0
1.0	0.0	1.3	5.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	2.0	1.0
2.0	0.0	2.6	20.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	1.0	2.0	1.0
1.0	1.0	2.6	5.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	2.0	1.0
4.0	0.0	2.6	0.0	0.0	0.0	0.0	3.0	1.0	1.0	1.0	0.0	1.0	0.0
5.0	1.0	2.6	0.0	0.0	0.0	0.0	1.0	1.0	1.0	0.0	0.0	1.0	0.0
5.0	1.0	1.3	0.0	0.0	0.0	0.0	3.0	0.0	1.0	0.0	0.0	1.0	0.0
3.0	0.0	2.6	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0
5.0	1.0	1.3	0.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0
4.0	0.0	1.3	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	0.0	1.0	0.0
4.0	0.0	1.3	0.0	0.0	0.0	0.0	3.0	1.0	0.0	0.0	0.0	1.0	0.0
4.0	1.0	2.6	0.0	0.0	0.0	0.0	3.0	0.0	0.0	1.0	0.0	1.0	0.0
1.0	0.0	2.6	0.0	0.0	0.0	0.0	3.0	1.0	1.0	1.0	1.0	2.0	0.0
3.0	1.0	2.6	0.0	0.0	0.0	0.0	1.0	1.0	1.0	0.0	1.0	2.0	0.0
1.0	1.0	1.3	0.0	0.0	0.0	0.0	3.0	0.0	1.0	0.0	1.0	2.0	0.0
1.0	0.0	2.6	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	2.0	0.0
1.0	1.0	1.3	0.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	1.0	2.0	0.0
1.0	0.0	1.3	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	1.0	2.0	0.0
1.0	0.0	1.3	0.0	0.0	0.0	0.0	3.0	1.0	0.0	0.0	1.0	2.0	0.0
1.0	1.0	2.6	0.0	0.0	0.0	0.0	3.0	0.0	0.0	1.0	1.0	2.0	0.0
2.0	0.0	2.6	0.0	0.0	0.0	0.0	3.0	1.0	1.0	1.0	0.0	2.0	0.0
5.0	1.0	2.6	0.0	0.0	0.0	0.0	1.0	1.0	1.0	0.0	0.0	2.0	0.0
2.0	1.0	1.3	0.0	0.0	0.0	0.0	3.0	0.0	1.0	0.0	0.0	2.0	0.0
2.0	0.0	2.6	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	2.0	0.0
4.0	1.0	1.3	0.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	2.0	0.0
3.0	0.0	1.3	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	0.0	2.0	0.0
2.0	0.0	1.3	0.0	0.0	0.0	0.0	3.0	1.0	0.0	0.0	0.0	2.0	0.0
2.0	1.0	2.6	0.0	0.0	0.0	0.0	3.0	0.0	0.0	1.0	0.0	2.0	0.0

Figure 5.4

Regression Results, Bike/Auto Survey

Dependent Variable is R

Independent Variable	Estimated Coefficient	Standard Error	T Statistic
CNST	5.499998	0.688530	7.99
GA	0.833333	0.243432	3.42
GP	0.000000	0.187256	0.00
TL2	-0.333333	0.121716	-2.74
BL	0.666667	0.243432	2.74
SS	0.500000	0.243432	2.05
TR	-0.166667	0.243432	-0.68
SEX	-1.500000	0.298142	-5.03
VEH	-1.499999	0.298142	-5.03

0.8984 = R-Squared
0.5333E+01 = Sum of Squared Residuals
16.58 = F-Test(8, 15)

0.5963E+00 = Standard Error of Regression
24 = Number of Observations

Figure 5.5

Regression Results, Bike/Walk/Auto Model

Dependent Variable is R

Independent Variable	Estimated Coefficient	Standard Error	T Statistic
CNST	5.124997	0.610535	8.39
WCON	0.236111	0.651555	0.36
GA	0.791667	0.193068	4.10
GP	0.288462	0.148514	1.94
WT	0.027778	0.018203	1.53
TL	-1.166666	0.546079	-2.14
SW	0.083333	0.273040	0.31
SN	-0.750000	0.273040	-2.75
TL2	-0.333333	0.136520	-2.44
BL	0.666667	0.273040	2.44
SS	0.500000	0.273040	1.83
TR	-0.166667	0.273040	-0.61
SEX	-1.062500	0.236459	-4.49
VEH	-1.687499	0.236459	-7.14

0.8509 = R-Squared
0.1521E+02 = Sum of Squared Residuals
14.92 = F-Test(13, 34)

0.6688E+00 = Standard Error of Regression
48 = Number of Observations

TR = traffic level (0=busy, 1=quiet)

SEX = gender (0=male, 1=female)

VEH = number of vehicles owned

Its interpretation is very similar to the walk/auto regression: it gives the effects of each of the explanatory variables on the response.

The utility equation based on both the bike and walk experiments is drawn from Figure 5.5:

$$
\begin{aligned}
R = {} & \underset{(8.39)}{5.12} + \underset{(0.36)}{0.24WCON} - \underset{(-4.49)}{1.06SEX} - \underset{(-7.14)}{1.69VEH} + \underset{(4.10)}{0.79GA} + \underset{(1.94)}{0.29GP} \\
& + \underset{(1.53)}{0.03WT} - \underset{(-2.14)}{1.17TL} + \underset{(0.31)}{0.08SW} - \underset{(-2.75)}{0.75SN} - \underset{(-2.44)}{0.33TL2} + \underset{(2.44)}{0.67BL} \\
& + \underset{(1.83)}{0.50SS} - \underset{(-0.61)}{0.17TR}
\end{aligned}
$$

where all variables are defined previously, except WCON = walk constant (0=bike, 1=walk). The variable WCON essentially allows different constants for the walk and bike responses.

This utility equation is closely related to the individual bike/auto and walk/auto equations. In particular, the bike variables (TL2, BL, SS and TR) and walk variables (TL, SW and SN) have the same coefficients as in their separate models; the auto coefficients (GA, GP and WT) are weighted averages across the two experiments; the socio-economic variables are also weighted averages; and the constants (C and WCON) shift slightly. This equation can be broken into three equations as follows:

$$U_a = 1.06SEX + 1.69VEH - 0.79GA - 0.29GP - 0.03WT$$

$$U_b = 5.12 - 0.33TL2 + 0.67BL + 0.50SS - 0.17TR$$

$$U_w = 5.12 + 0.24 - 1.17TL + 0.08SW - 0.75SN$$

where

U_a = utility of auto

U_b = utility of bike

U_w = utility of walk

This algebraic change is analogous to the one shown for the binary case earlier. Again, the signs for the auto utility are reversed.

5.4 Interpretation of Regression Results.

The regression analyses required for DUA studies can be run with several readily-available packages. Appendix C describes these options briefly and shows the associated data processing steps.

The basic functional form of the multiple linear regression equations that define the utility functions is:

$$R = a_0 + a_1x_1 + a_2x_2 + \ldots + a_nx_n$$

where

R = utility, the dependent variable

a_0 = the constant (the aggregate effect of all other variables not included in the equation on the dependent variable)

$a_1, \ldots, a_n$ = coefficients describing the effects of the various independent variables

$x_1, \ldots, x_n$ = the independent variable

Looking at the models in the previous figures, we can make a number of general observations and comments about the equations and statistics. First, the number of observations reported for each model are from the experiment observation files; each survey respondent provided eight observations. The raw sample size or number of respondents is the number of reported observations divided by eight, in these examples.

Second, the first number in each equation is the constant. This term is sometimes referred to as the bias coefficient and is interpreted as the utility of "bias" people have for one mode of transportation over another, the values of all other variables in the equation being equal for both modes. In most DUA models, however, this interpretation does not hold because most variables are defined for only one of the two alternatives (e.g. street surface, bike lane). Thus, the constant is of limited interest.

Third, the coefficients from the DUA models almost always meet hypothesized expectations about their sign and magnitude. If they do not, there is little that can be done, because of the orthogonality of the experiment. Unlike the usual regression models, adding and deleting variables has little or no effect on remaining variables; only socio-economic characteristics allow any latitude in model formulation at this stage. This re-emphasizes the need for careful survey design and model formulation <u>before</u> data collection in DUA studies.

Fourth, the t-statistics and other goodnes-of-fit statistics such as F-statistics and R^2 are sometimes low in DUA experiments because of the nature of the response scale and other issues discussed in Appendix D. The response scale limits goodness-of-fit because, if a consumer wished to respond "2.5" to some situation, only "2" or "3" is possible. A finer scale lessens this error, but at the cost of making the survey document more formidable.

Another issue affecting the goodness-of-fit statistics is the inclusion of responses with no variation, i.e., the same response is given by an individual to all eight situations, generally "1" (always drive alone) or "5" (always use competing mode). Including responses with no variations lowers the t-statistics for the following reasons: (1) the lack of variation lowers the coefficients -- a person responding the same for all eight situations would have coefficients of <u>zero</u> for all the variables; and (2) the extreme values or outliers (all ones or all fives) increase the standard errors of the coefficient. This has a double effect on lowering the t-statistics; recall that the t-statistic is defined as the ratio of the coefficient to the standard error of the coefficient.

The dilemma caused by people who respond without variation to the DUA experiment can be approached reasonably in three ways. One is to exclude these responses from the sample since they provide no information on the relative importance of the independent variables anyway. This is commonly done and it obviously improves the regression goodness-of-fit statistics significantly. For purposes of forecasting, this does no harm provided the forecasts are segmented. That is, the mode choices for those segments of the market who responded all ones or all fives are determined separately and proportioned to drive alone or the respective competing mode. Then the mode choices for the remaining segment of the market, represented in the sample, are arrived at by the DUA model.

A second approach to the predicament caused by invariant responses is to weight the responses according to the amount of information (variability) they provide. This would have the effect of pulling in the outliers and reducing the standard errors of the coefficients, thus notably improving the regression statistics. This second approach is similar to throwing out responses without variation.

The third approach is to include all responses, regardless of variation, in estimating the models and to accept the fact that the resulting regression statistics will be significantly lower. The advantage of this approach is that is avoids the added complexity of segmented forecasts. The choice among these options may vary from study to study, depending on the complexity of the forecasting method that is feasible and on the number of invariant responses.

This concludes the analysis of the survey responses, and the following chapter turns to validation of the models on actual behavior. In some quick-response studies, validation is not necessary and the utility equations from the regression models can be used directly in policy analysis. The beginning sections of the next chapter describe the assumptions required in lieu of formal validation.

CHAPTER 6

MODEL VALIDATION

6.1 Introduction.

Validation is the process of comparing a statistically estimated demand model (such as DUA or logit) against a different sample than was used to fit the model, to test the model's ability to represent behavior in varying situations. This, after all, is the purpose for which the model will be used. DUA surveys contain their own built-in validation data set. DUA models are built only on the stated responses to the experimental situations; people's actual behavior is not used at all in this stage. Therefore, the portion of the DUA survey that records actual behavior and current travel conditions makes a good validation data set.

There are two basic approaches to validating demand models. One is to validate them based upon disaggregate data, data pertaining to actual travel choices of individuals. The other is to validate based upon aggregate data which refers to a collection of individuals. The current modal split in a city or corridor is an example of aggregate data. We also distinguish between two types of disaggregate validation, binary and multinomial. The binary validation concerns choices between only two alternatives. The multinomial validation refers to choices among three or more alternatives.

DUA measures how people respond to hypothetical (though realistic) situations, not to actual ones. Other demand forecasting models are developed from what is called revealed preference data. When individuals have actually made a choice among several options, they have revealed their preferences. The attributes of each alternative and a person's actual choice form the data set to estimate a revealed preference model.

In validation we combine DUA analysis with revealed preference modeling. Subsequent to estimating a DUA utility function for some choice, we validate it by estimating adjustment parameters to the utility function based on people's actual behavior and the attributes of each available choice. If there is perfect correspondence between what people say they would do and what people actually do, then coefficients of the utility function remain unchanged. Ignoring the constant in the utility function for a moment, one can represent a perfect fit between what people say they would do and what they actually do by the multiplicative factor, one. If the utility function is multiplied by one it remains unchanged. Thus, if the validation procedure produces one as the validation coefficient, there is no discrepancy between stated and actual behavior. If the multiplicative factor is less than one, then what people say they would do under various situations overstates what they actually do; and if the multiplicative facotr is greater than one, the reverse is the case. The approach described in this Chapter is only one of several possible means of validating DUA models. Alternative approaches are outlined in Chapter 7, which may be more appropriate in some cases.

6.2 Assumptions in Validation Procedure.

Before we can proceed with the validation step (or its omission), we need to state several assumptions. Figure 6.1 illustrates the most crucial of these. If stated behavior (linear model) corresponds to actual behavior (logit model), then we expect the utility equations drawn from the linear regressions to perform well in the logit model. We switch to the logit model at this stage of the analysis for three reasons:

- It is able to handle multinomial choices, while a linear model is generally limited to binary choices.
- It always produces probabilities between zero and one. While the linear model can be used and truncated to remain between zero and one, this is cumbersome to check in forecasting programs.
- The logit model has a convenient incremental form for policy analysis which allows rapid calculation of the impacts of many policies.

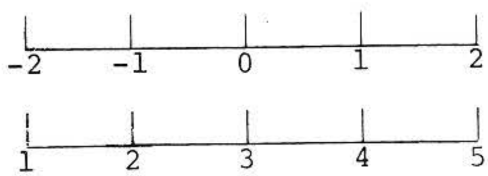
We could also have initially assumed that the experimental responses followed the logit curve, and fit the models of stated behavior using logit instead of multiple linear regression. We chose not to do this for three reasons:

- To use a logit model in the first stage requires assuming that the points of the response scale correspond to actual probabilities (e.g., a "1" equals a probability of 0.1 of using bike, a "2" equals 0.3, etc.). The relationship assumed is necessarily arbitrary at this stage, however, and it can affect the results strongly. An alternative assumption (e.g. "1" equals a probability of .05, "2" equals .275, etc.) changes not only the constant and overall magnitude of the coefficients, it also changes the ratios or trade-off rates among the coefficients. In some cases, though, this may be a reasonable approach (see Chapter 7).
- The linear model produces coefficients whose trade-off rates are invariant with shifts in the relationship between the 5-point scale and actual choice probabilities. Thus, if the validation step uncovers systematic differences between stated and actual behavior, the trade-off rates among the variables in the

utility function (which remain unchanged through the validation) are not affected by wrong relationships assumed in the first step.

- The linear regression is simpler than the logit procedure.

The linear regression on the "stated behavior" responses is thus assumed to provide an approximation to the utility functions of a logit model used to assess actual behavior. In particular, <u>if</u> the responses to the experiment match actual behavior closely, then the relationship shown in Figure 6.1 will hold. A linear approximation tangent to the logit function at probability p=.5 (as drawn) has a slope of .25, and thus intersects the p=0 and p=1 axes at U=-2 and U=+2, respectively. This scale, from -2 to +2, is simply our 1 to 5 scale shifted downward three units:



Linear Scale

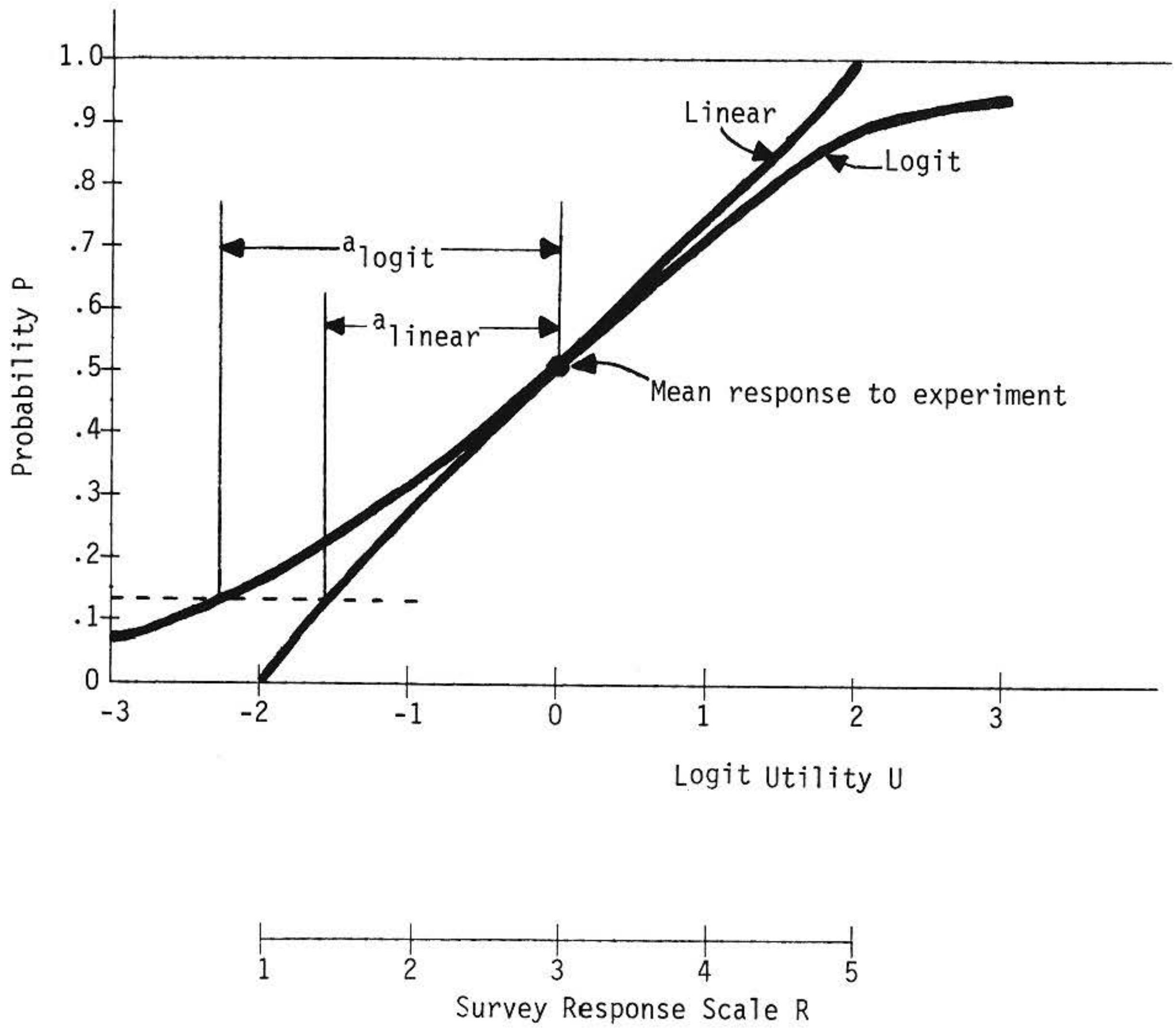
Survey Response Scale

In the case shown in Figure 6.1 the linear coefficients from the regression step will be good estimates of the coefficients of the utilities in the logit function tested in the validation.

If individuals have not responded to the experiment in a way that reflects their actual behavior, the situation illustrated in Figure 6.2 occurs. In this example, when an individual scores a particular situation as "5", indicating that he or she would always bicycle, he or she would actually bicycle with a probability of only .3. The actual probability of bicycling is thus overstated by this example individual, who also overstates his or her sensitivity to the

FIGURE 6.1

Comparison of Linear and Logit Model Forms



The a_{logit} and a_{linear} denote equivalent coefficients in the two model forms to produce equal changes in probability p. As can be seen, the linear coefficients are generally underestimates of the logit coefficients.

to the variables on the survey, as seen by the steep slope of the linear model relative to the logit model. In the case illustrated in Figure 6.2, the utility equations from the linear model must be modified to make them correspond with the true utilities influencing actual behavior. The necessary adjustment to align the linear model based on stated behavior with the logit model that describes actual behavior is to multiply the slope of the linear model by an appropriate factor: in this example, some number less than 1.

The above arguments are developed for binary experiments, and they also apply to a series of binary experiments combined to form a multinomial model. Less exact relationships bewteen the linear and logit forms can be postulated if multinomial experiments are used, as described in Chapter 7.

6.3 Quick Response Validation.

6.3.1 Single-Point Check.

In quick response studies a full validation exercise is often not needed. There are several short-cut checks on model validity which may be used instead. The first of these is the single point check. The average response to the situation closest to the status quo can be computed from the survey responses and plotted against current choice behavior as shown on Figure 6.3. In the case shown, the current proportion of travellers choosing transit, for example, is 20%, and the average response to the situation on the survey closest to the status quo is 1.5. This is a good match, and could support direct use of the DUA model in forecasting.

If the average response in this case had been 3.5, however, then the model would have to be adjusted. With only one validation

FIGURE 6.2

Comparison of Logit and Linear Model Forms
When Stated Preferences Do Not Correspond to Actual Behavior

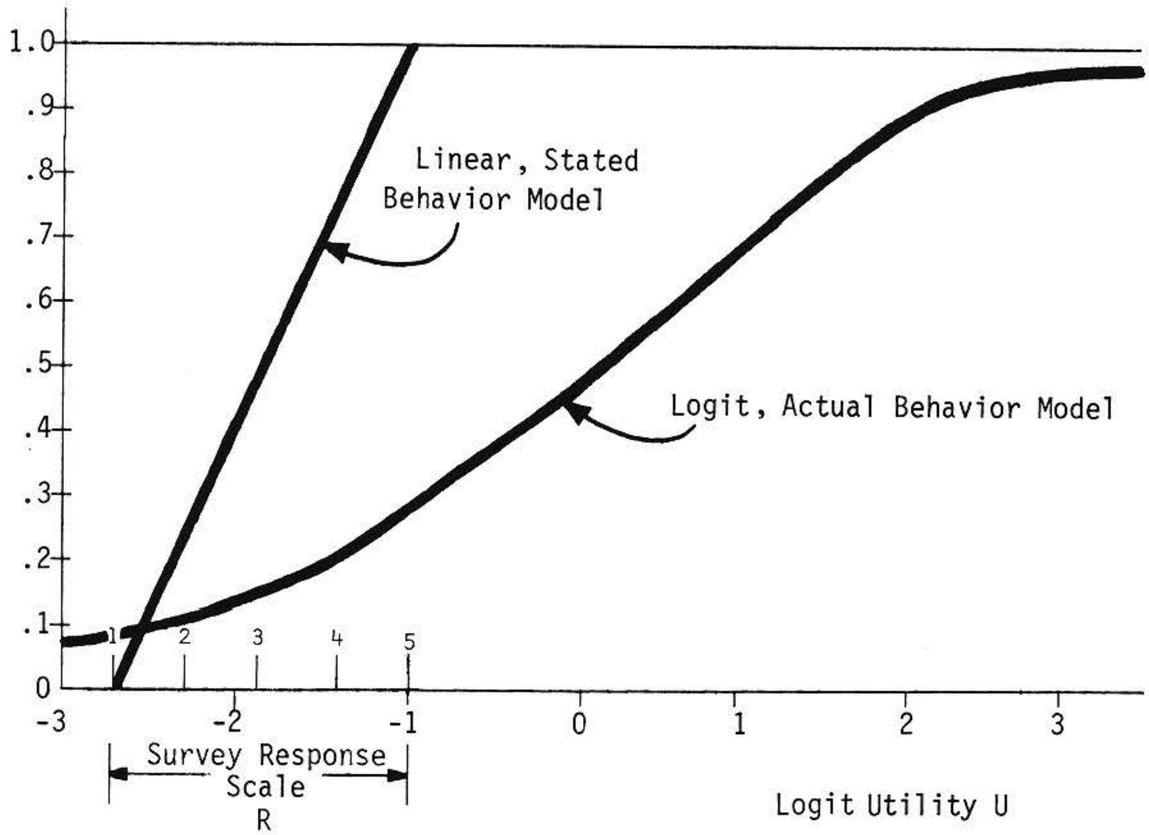
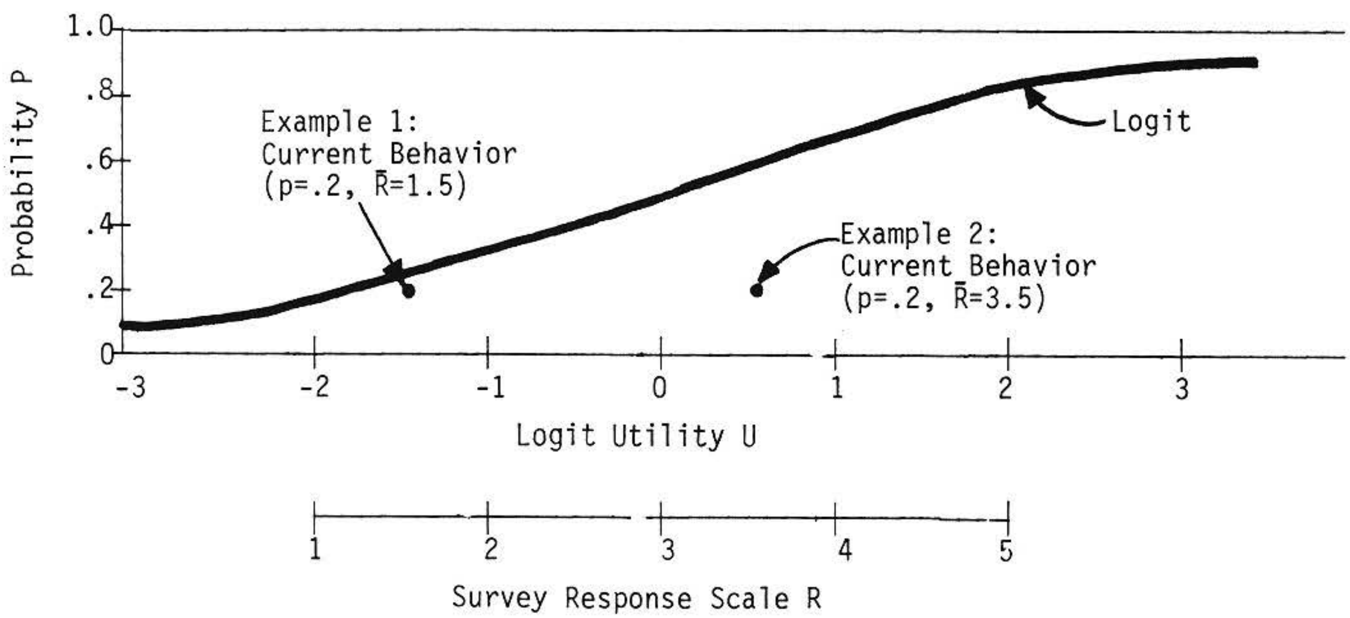


FIGURE 6.3

Quick Response Validation, Single Point



point, one can either change the constant or the slope in the stated utility equation, but there is insufficient information to change both. The simplest course in this case would be to adjust the stated utility equation by subtracting 2 from its constants, before using the model for forecasting.

In cases where none of the situations in the survey correspond closely to the status quo, the predicted utility obtained from substituting current values of the independent variables into the utility equation can be used instead. Note that the actual choices plotted in Figure 6.3 must be based on binary comparisons (e.g., transit and auto only, ignoring all other modes). In a four-mode model (e.g., auto, transit, bike, walk), three graphs like Figure 6.3 would be required: transit/auto, bike/auto and walk/auto). Constants for transit, bike and walk are adjusted based on these analyses; the base mode, auto, is left unchanged. This procedure produces a multimodal model with correct current mode shares.

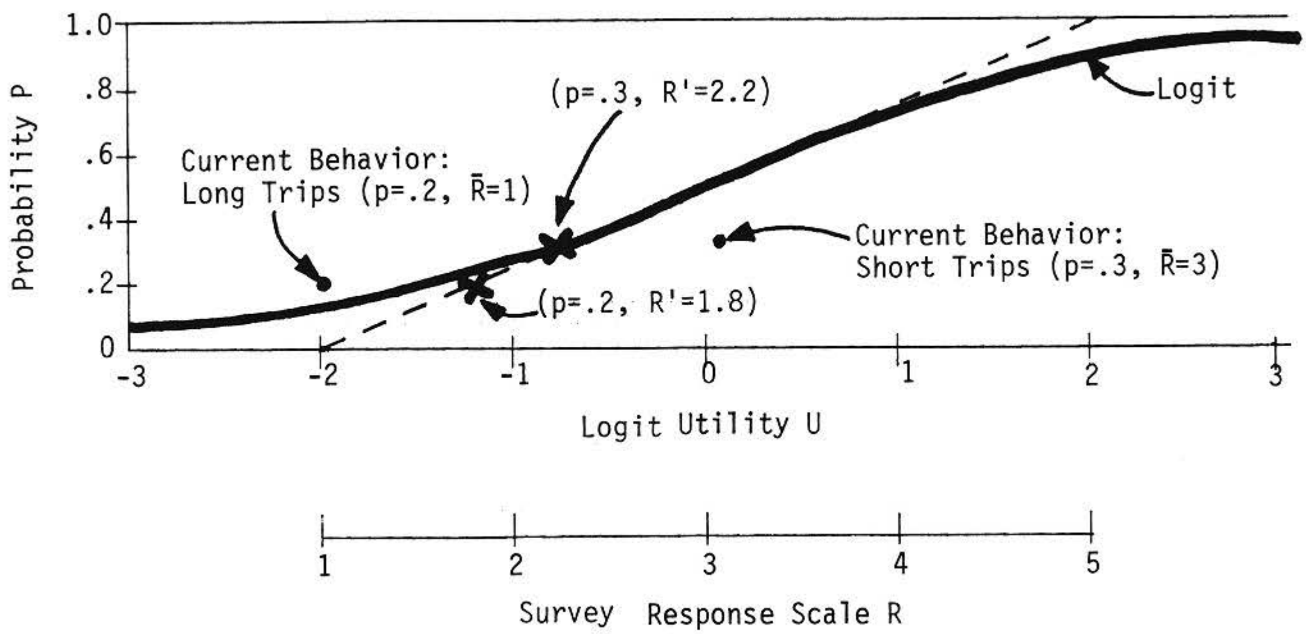
6.3.2 Two-Point Check.

Sometimes two points of validation will be easily available. For example, in a bicycle/auto mode choice survey, data may be available on current mode splits at two trip lengths: 0-3 miles and over 3 miles. By substituting the average trip length in these categories into the utility equation, the average responses can be found for both trip lengths, providing two points of validation as shown in Figure 6.4.

In this example the two validation points are ($p=.2$, $\bar{R}=1$) and ($p=.3$, $\bar{R}=3$). As can be seen, the respondents overstate their sensitivity to trip length. The stated response changes from 1

FIGURE 6.4

Quick Response Validation - Two Points



(always auto) to 3 (indifferent) while actual bike mode share only increases from $p=.2$ to $p=.3$. Some algebra can be used to correct this response bias; the linear approximation to the logit curve is used as the curve to match because the computations are easier. We know that the response R from the survey overstates actual behavior, so we wish to adjust it to match the two points in Figure 6.4. We allow both the slope and the constant of the adjusted response R' to shift from the original response R:

$$R' = a + bR$$

where a and be are adjustment coefficients. The linear relationship between the corrected response R' and probability p shown as the dashed line in Figure 6.4 is:

$$p = .25R' - .25 = .25(a + bR) - .25$$

When $R'=1$, $p=0$; $R'=2$, $p=.25$, and so on.

The two validation points to be matched provide two equations to determine a and b:

$$.2 = .25(a + b\cdot 1) - .25$$

$$.3 = .25(a + b\cdot 3) - .25$$

Solving them algebraically, we obtain:

$$a = 1.6$$

$$b = 0.2$$

Thus, if the original utility equation had been:

$$R = 5.50 - 0.33TL2 + 0.83GA + \ldots$$

the revised utility equation is:

$$R' = 1.6 + 0.2(5.50 - 0.33TL2 + 0.83GA + \ldots)$$

$$= 2.70 - .0\,66TL2 + 0.166GA + \ldots$$

This revised utility equation should be used in policy analysis in place of the original equation.

6.3.3 Comparison With Previous Models.

The last simple validation check possible is to compare the coefficients from the experiment with coefficients of the same variables obtained in earlier studies. If the coefficients common to the two models exhibit a consistent pattern (e.g. DUA coefficients are always lower than corresponding coefficients from a previous logit model), then the DUA coefficients can be adjusted. The constant in the DUA model can be checked (after the coefficients are adjusted) using the single-point method described above.

This type of check is useful when the DUA experiment is being used to find coefficients for variables that do not exist in other models (e.g. shelters, seat availability, reliability). If the DUA experiment also includes common variables such as wait time or fare whose coefficients are relatively better known, they can be used to adjust the coefficients for which no comparisons exist.

6.3.4 No Validation.

In some cases no validation is done. The justification for this can be:

- The survey was previously validated and found to require little or no adjustment in validation.
- Only a ranking of the effects of policy options is desired and actual probability estimates are either unimportant or not desired.
- The survey focuses exclusively on alternatives or levels of variables that differ markedly from the status quo. In this case, informal comparisons to previous models and reasonableness checks may be all that is possible.

DUA is still a useful technique in these cases; indeed, its usefulness may be greatest in such instances because of its ability to assess new issues and alternatives. The accuracy of its forecasts will necessarily be lower than in more common situations, however.

6.4 Disaggregate Validation Using Logit Analysis.

6.4.1 Binary Validation.

The logit validation step addresses the issue of the correspondence between stated and actual behavior by formally validating the experimentally derived utility functions on current, actual data (found by asking survey respondents their current travel choices). We substitute the levels of independent variables closest to the status quo into the experimentally derived utility equations, and use them in a logit model to see if they explain current choices of the survey respondents. This approach differs from those described in the previous section because it is a formal statistical method with goodness-of-fit measures.

Binary validation compares the actual and stated choice between two alternatives:

$$p_i = \frac{1}{1 + e^{-(a + b\bar{R}_i)}}$$

where p_i = probability of choosing alternative i in the status quo (equal to zero or one in actual data)

e = base of natural logarithms (2.71828...)

a, b = validation coefficients to be found through logit estimation

$\bar{R}_i$ = value of the utility (response) function evaluated at current values of variables

The equation above is the definition of the binary logit model; it produces the S-shaped curves drawn in Figures 6.1 - 6.4.

In this binary case,

$$R_i = U_i - U_b$$

where U_i = utility of alternative i (e.g., walk)

U_b = utility of base alternative (e.g., auto)

It is not necessary to separate R_i into its two components as in multinomial models.

As in the quick response case, we can define the adjusted (validated) utility function as:

$$R_i' = a + bR_i$$

In the validation, the value $\bar{R}_i$ is used as the independent variable to explain the dependent variable p_i. This step is performed using a logit estimation package such as ULOGIT in UTPS or other available programs described in Appendix C.

Table 6.1 shows an example data set used in binary validation, drawn from the walk/auto survey. The data set contains 12 individuals, half of whom walked and half of whom drove. The column $\bar{R}$ denotes the computed value of each individual's response to the status quo choice between walking and driving, and the "actual choice" denotes their current behavior. A correspondence can be seen between the ratings and choices, as expected.

If the stated behavior is close to actual behavior, we expect that a=-3 (to shift the indifference point from "3" on the 1-5 response scale to zero for the logit model) and that b=1. In the example of Table 6.1 the result of a logit estimation is:

$$R' = \underset{(-1.28)}{-2.135} + \underset{(1.38)}{0.7461}R$$

The numbers in parentheses are t-statistics, analogous to those in multiple linear regression. These results suggest that stated and actual behavior in this case are quite close; the parameters a and b are not significantly different than -3 and 1.

The data set for Table 6.1 is drawn from all respondents who either chose auto or walk as their actual choice; if another mode is used, the observation is dropped. The validated model that emerges is likewise useful only for walk/auto choices. The final model combines both the initial and validation steps as follows:

$$\begin{aligned} R' &= -2.135 + 0.7461R \\ &= -2.135 + 0.7461\ (4.99 - 0.63SEX - 1.88VEH + 0.75GA \\ &\quad + 0.58GP + 0.03WT - 1.17TL + 0.08SW - 0.75SN) \\ &= 1.588 - 0.47SEX - 1.40VEH + 0.56GA + 0.43GP \\ &\quad + 0.02WT - 0.87TL + 0.06SW - 0.43SN \end{aligned}$$

where the initial equation for R is drawn from Figure 5.2.

6.4.2 Multinomial Validation.

Multinomial validation compares the actual and stated choices across three or more alternatives:

$$p_i = \frac{e^{(a_i + b_i \bar{U}_i)}}{\sum_{\text{all } j} e^{(a_j + b_j \bar{U}_j)}}$$

where p_i = probability of choosing mode i in the status quo

e = base of natural logarithms (2.71828...)

a_j, b_j = validation coefficients for mode j (one a_j must be set equal to a constant, generally zero

$\bar{U}_j$ = value of the relative utility function evaluated at the "status quo" (current) values of variables

TABLE 6.1

Validation Data - Walk/Auto Only

Individual	$\overline{R}$	Actual Choice
1	1.1	0
2	1.3	1
3	1.6	0
4	2.0	1
5	2.2	0
6	2.3	0
7	3.0	0
8	3.5	1
9	3.9	0
10	4.1	1
11	4.7	1
12	4.8	1

Actual Choice: 0 = auto, 1 = walk

$\overline{R}$: computed utility at status quo

As in the binary case, adjusted utility equations are found in the validation step of the form:

$$U'_j = a_j + b_j U_j$$

Note that the multinomial validation must use the individual modes' utility equations, broken out from the original response equation R ($R = \sum_j U_j$) as described in Section 5.3. (It does not matter whether R or U is used in the binary case.) The utility values $\bar{U}_j$ in the status quo are the independent variables, and the probabilities p_j are the dependent variables. This step is also performed using a logit estimation package such as the ULOGIT program in UTPS.

One further assumption is made in the multinomial validation step: linking all the binary models from the individual surveys together into a single n-dimensional model for validation. This step is based on the Axiom of the Independence from Irrelevant Alternatives (IIA). The logit model is a share model in which the market share or probability of choosing a particular alternative can be represented by the ratio of its utility to the sum of utilities of every alternative under consideration. (In the logit model, exponentiated utilities e^{U_i} are used to compute market shares.)

For example, suppose we had two binary experiments: walk/auto and transit/auto. We have pooled their data into a "grand" data set, and have fitted a regression giving U_w (walk), U_t (transit) and U_a (auto). We then find the status quo values of these functions, $\bar{U}_w$, $\bar{U}_t$ and $\bar{U}_a$. Assume that $e^{\bar{U}_w} = 2$, $e^{\bar{U}_t} = 3$ and $e^{\bar{U}_a} = 7$. In the two binary models:

walk/auto

$$\left\{\begin{aligned} p_w &= \frac{e^{\bar{U}_w}}{e^{\bar{U}_w} + e^{\bar{U}_a}} = \frac{2}{2 + 7} = .22 \\ p_a &= \frac{e^{\bar{U}_a}}{e^{\bar{U}_w} + e^{\bar{U}_a}} = \frac{7}{2 + 7} = .78 \end{aligned}\right.$$

transit/auto

$$\left\{\begin{aligned} p_t &= \frac{e^{\bar{U}_t}}{e^{\bar{U}_t} + e^{\bar{U}_a}} = \frac{3}{3 + 7} = .30 \\ p_a &= \frac{e^{\bar{U}_a}}{e^{\bar{U}_t} + e^{\bar{U}_a}} = \frac{7}{3 + 7} = .70 \end{aligned}\right.$$

The ratios of these market shares are:

$$p_w/p_a = 2/7$$

$$p_t/p_a = 3/7$$

If we now combine these two binary models into a single model:

$$p_w = \frac{e^{\bar{U}_w}}{e^{\bar{U}_w} + e^{\bar{U}_t} + e^{\bar{U}_a}} = \frac{2}{2 + 3 + 7} = .17$$

$$p_t = \frac{e^{\bar{U}_t}}{e^{\bar{U}_t} + e^{\bar{U}_w} + e^{\bar{U}_a}} = \frac{3}{3 + 2 + 7} = .25$$

$$p_a = \frac{e^{\bar{U}_a}}{e^{\bar{U}_t} + e^{\bar{U}_w} + e^{\bar{U}_a}} = \frac{7}{3 + 2 + 7} = .58$$

The ratio of the market shares is still:

$$p_w/p_a = 2/7$$

$$p_t/p_a = 3/7$$

Thus, the logit model preserves the market share relationships among pairs of alternatives when they are grouped into larger models, allowing us to perform this operation.

The IIA property is used to build up a multi-choice model from individual, binary surveys. This can be done through the use of a common base alternative (the drive alone mode in our examples) across all the binary surveys distributed. All the surveys involving the common base alternative are analyzed together using multiple linear regression, as described in Section 5.3, to produce a set of utility equations, one for each alternative. The current value of these utility functions is computed and used in the validation step.

The expected values of a_j and b_j for all the alternatives differ slightly from the binary case. One a_j must be set arbitrarily to identify the model; generally the a_j of some non-base alternative is set to zero. We expect all non-base alternatives to have the same constant, so all their $a_j=0$. If the base mode is represented, as in our examples, as being preferred when the responses are low (e.g. "1" or "2"), its a_j is expected to be +3 because of its reversed position on the response scale.[1] Optionally, if the base alternative a_j is set to zero, then we expect all other $a_j=-3$. In all cases, we expect all $b_j=1$ if stated and actual behavior correspond.

Table 6.2 shows the data set for a multinomial validation on walk, bike and auto mode choices. A different set of 12 individuals

---

[1]This $a_j=+3$ applies to U_a in our example, which has already been broken out from the R equation <u>and had its sign reversed</u>.

TABLE 6.2

Validation Data - Walk, Bike and Auto

Individual	$\bar{U}_w$	$\bar{U}_b$	$\bar{U}_a$	Actual Choice
1	0.5	0.8	-0.6	auto
2	1.0	1.5	-0.3	auto
3	1.3	1.7	0.0	auto
4	2.0	1.4	-1.0	walk
5	1.5	2.2	-0.7	bike
6	1.6	1.5	-0.7	auto
7	2.1	2.3	-0.9	auto
8	3.3	3.5	-0.2	bike
9	3.9	3.0	0.0	walk
10	3.8	1.4	-0.3	auto
11	4.4	3.0	-0.3	walk
12	3.7	1.8	-1.1	walk

is used, of which two choose bike as the mode to work. The values of U_w, U_b and U_a are computed from the DUA regression equations fitted to the walk/auto and bike/auto experimental data, as described in Section 5.3. Status quo values for all variables are again used.

The results of validating the data in Table 6.2 are:

$$U^*_a = \underset{(1.26)}{4.384}U_a$$

$$U^*_b = \underset{(-1.71)}{-12.336} + \underset{(1.69)}{3.885}U_b$$

$$U^*_w = \underset{(-1.73)}{-9.2047} + \underset{(1.88)}{2.415}U_w$$

This example is one in which considerable adjustment occurs to bring the stated preferences into line with actual preferences. The multiplicative factors are all greater than one, indicating respondents systematically understated their sensitivity to the factors in the experiment.

The final models, based on both the original regressions and the validation results, are:

$$\begin{aligned} U^*_a &= 4.384\ (1.06SEX + 1.69VEH - 0.79GA - 0.29GP - 0.03WT) \\ &= 4.65SEX + 7.41VEH - 3.46GA - 1.27GP - 0.13WT \end{aligned}$$

$$\begin{aligned} U^*_b &= -12.336 + 3.885\ (5.12 - 0.33TL2 + 0.67BL + 0.50SS - 0.17TR) \\ &= 7.555 - 1.28TL2 + 2.60BL + 1.94SS - 0.66TR \end{aligned}$$

$$\begin{aligned} U^*_w &= -9.2047 + 2.415\ (5.12 + 0.24 - 1.17TL + 0.08SW - 0.75SN) \\ &= 3.740 - 2.83TL + 0.19SW - 1.81SN \end{aligned}$$

where the original expressions for U_a, U_b and U_w are drawn from Section 5.3. The adjusted utility equations should be the ones used for forecasting and analysis.

6.5 Disaggregate Validation Data.

Sources of data used to describe actual travel choices are background questions on each of the survey forms (see Appendix B) and level of service data available from urban transportation planning studies. Background data should be collected on the survey whenever it is possible to learn from each respondent the current levels of the experimental variables, without being confusing, exceeding one page of background questions or cramping the questions.

Figure 6.5 shows all the background questions asked on the six Wisconsin urban surveys described in Chapter 8; they provided the bulk of the validation data. Although the data are self-reported, we find them generally to be accurate. If background questions cannot be used to collect validation data for every variable in an experiment, it will be necessary to construct a supplementary validation data set. Whenever validation data are unavailable, either because they are not requested or the respondent fails to furnish it, the missing data must be drawn from the level of service data for each travel choice available to the respondent.

A computer program to create the validation data set for a binary case is given in Appendix C; its extension to the multinomial case is straightforward. Figure 6.6 provides a brief summary of the general design of validation data processing. In general, a customized program along these lines will be required for each study.

The flow chart shows that responses to background questions are combined with planning data on level of service to compute base case utilities for each respondent. These computed utilities are placed in a data set along with actual travel choice (drawn from background questions) to be used by the logit step.

FIGURE 6.5
Example Background Questions for the Experiments

PLEASE ALSO ANSWER THE FOLLOWING QUESTIONS:

1. How do you usually get to work? *(check one)*:

- ☐ 1. Drive alone
- ☐ 2. Bus
- ☐ 3. Carpool (with _____ people).
- ☐ 4. Vanpool (with _____ people)
- ☐ 5. Share a ride with family member.
- ☐ 6. Bicycle
- ☐ 7. Motorcycle
- ☐ 8. Walk
- ☐ 9. Taxi
- ☐ 10. Do not work outside home
- ☐ 11. Other *(please specify)*: ____________

2. Where do you live? City ____________ Zip code ________

3. Where do you work? City ____________ Zip code ________ ☐ Not applicable

4. About how far is it from your home to work in miles?

_____ miles ☐ Not applicable

5. How many miles per gallon does the motor vehicle you drive most often get?

_____ miles per gallon *(city driving)* ☐ Not applicable

6. How old are you ? _______ years

7. What is your sex?

☐ Male ☐ Female

8. Do you have any disabilities that prevent you from riding a bike?

☐ Yes ☐ No

9. How many people are in your household?

_____ adults *(16 and over)* _____ children *(under 16)*

10. How many motor vehicles does your household own?

_____ vehicles

11. What is your work scehdule?

- ☐ fixed shift
- ☐ flexitime *(can vary daily)*
- ☐ flexitime *(same hours daily)*
- ☐ other *(specify)* ____________
- ☐ not applicable

12. How many bicycles does your household own?

_____ Bicycles

13. What types of trips would you consider making by bike?

☐ Work ☐ shop ☐ visit friends ☐ recreation ☐ school

14. How much must you pay to park at work? $ ________ /month ☐ Do not work

15. About how far from your home is the nearest bus route or park and ride stop where you can pick up a bus to work? _____ Blocks ☐ Not applicable

What is the name of the bus route? ____________

16. About how far from your work place is the nearest bus stop? _____ Blocks ☐ Not applicable

17. Must you transfer buses between home and work? ☐ Yes ☐ No ☐ Not applicable

18. How often does the nearest bus come during rush hour? Every _______ minutes ☐ Not applicable

19. How long does the nearest bus take to go to work compared to driving alone?

_______ minutes slower ☐ the same amount of time
_______ minutes faster ☐ Not applicable

20. What is your total household income before taxes? *(optional)*

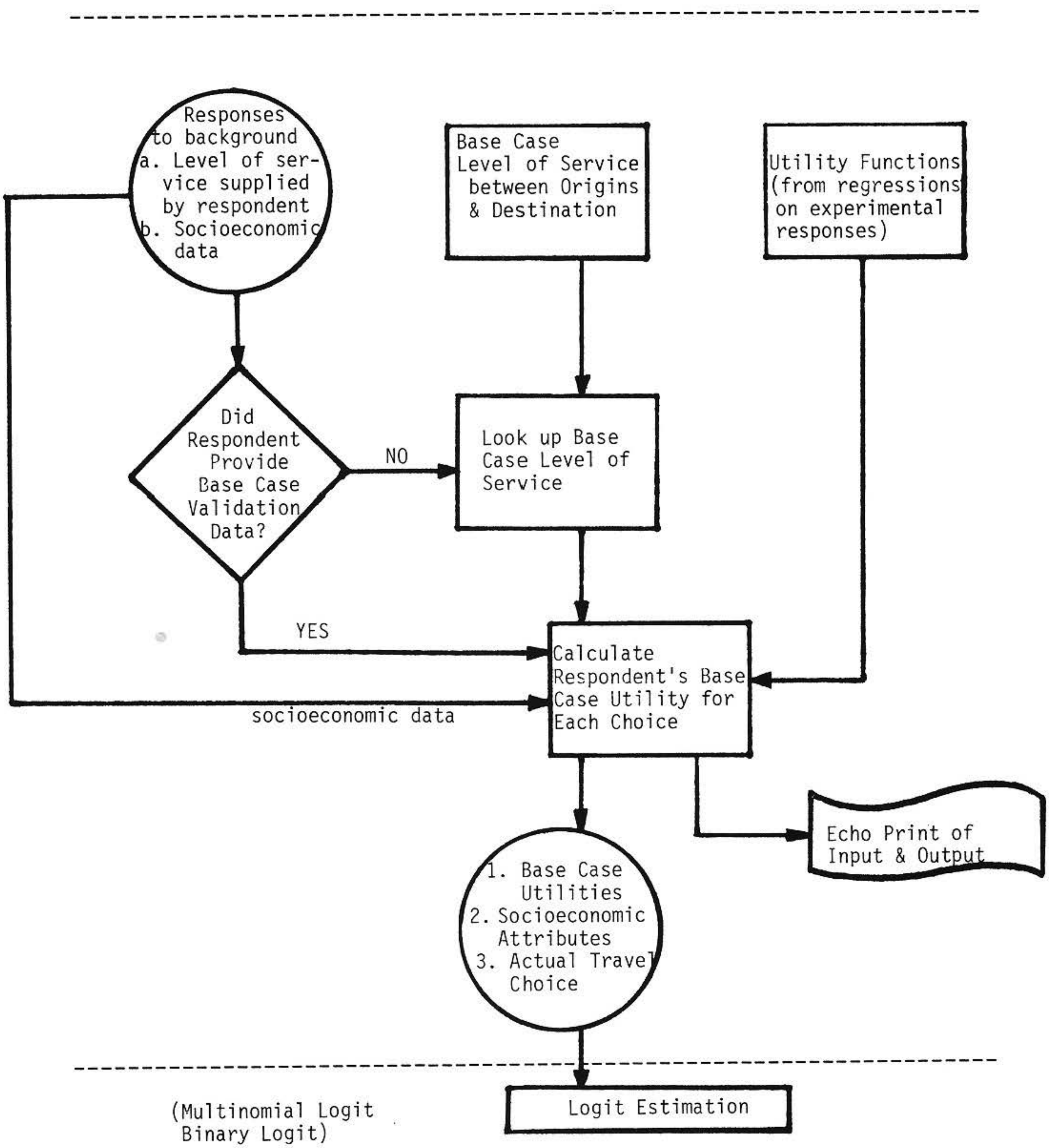
- ☐ Under $5,000
- ☐ $5,000-$9,999
- ☐ $10,000-$14,999
- ☐ $15,000-$19,999
- ☐ $20,000 -$24,999
- ☐ $25,000-$29,999
- ☐ $30,000-$39,999
- ☐ $40,000- and over

COMMENTS: *(optional)*:

Questions 1-10 and 20 appeared with all experiments; Question 11 is specific to ridesharing; Questions 12 and 13 are specific to bicycling; Question 14 is specific to ridesharing and bus; and Questions 15-19 are specific to the bus experiment.

FIGURE 6.6

Validation Data Processing



6.6 Aggregate Validation.

Sometimes it is desired to validate the experimentally-derived utilities directly on aggregate data. This can occur in cases when actual choices are not asked in the survey, or when they are not useful as validation data. For example, intercity travel is relatively infrequent, and asking about actual travel from a small sample for even a one-week period could produce very few trips.

The procedure for aggregate validation is similar to disaggregate validation. Both binary and multinomial options exist. The major difference is that data from zone pairs, corridors or cities are used as the current travel choices, and average utility values corresponding to these units of observation are used as the independent variables. The observed choice probabilities in aggregate data rarely equal zero or one (as they always do in individual-level data), so slightly different statistical techniques can be used.

In the binary case, the validation step compares actual and stated behavior as before:

$$p_i = \frac{1}{1 + e^{-(a + b\bar{R})}}$$

where all variables are previously defined. However, since p_i can be assumed never to equal zero or one, the binary logit model can be transformed as follows. By the definition of a share model:

$$p_j = 1 - p_i = \frac{e^{-(a + b\bar{R})}}{1 + e^{-(a + b\bar{R})}}$$

Dividing the expression for p_i by p_j and simplifying:

$$\frac{p_i}{p_j} = \frac{p_i}{1 - p_i} = \frac{1}{e^{-(a + b\bar{R})}} = e^{(a + b\bar{R})}$$

Taking the natural (base e) logarithm of both sides yields:

$$y = \ln\left(\frac{p_i}{1 - p_i}\right) = a + b\bar{R}$$

This transformation is impossible with individual level cross-sectional (probability 0 or 1) data, for it leads to division by zero. With aggregate data, however, this transformation can be used to estimate the parameters a and b of the logit function using multiple linear regression.

The new variable y is computed and used as the dependent variable, and $\bar{R}$ is used as the independent variable. The interpretation of the coefficients a and b is the same as in the disaggregate case.

This transformation may be used in multinomial aggregate validation also, in modified form. In this case a base mode denoted j must be chosen. The variable y is then computed using every mode in competition with mode j:

$$y = \ln\left(\frac{p_i}{p_j}\right) = a_i + b_i\bar{U}_i + b_j\bar{U}_j$$

where U_i and U_j are the separate utilities of modes i and j. All observations are placed in a single data set, and all a_i, b_i and the b_j are found in a grand regression. The base a_j is implicitly set equal to zero, so we expect all other a_i=-3 in our example, and we expect all b_i to equal one and the base b_j to equal minus one. Weighted least squares, a variant of multiple linear regression (Wonnacott and Wonnacott, 1970) is theoretically preferred here, but ordinary multiple regression will generally suffice for validation.

6.7 Additional Validation Checks.

In some studies an additional validation step may be useful. This is to accept the original utility equations drawn from the regression results (adjusting the sign and constant on the base mode) as valid, simulate (forecast) current behavior based on actual variable values, and then compare the results to current market shares. This validation step is the same as common practice in validating revealed preference models.

One may wish to omit the statistical validation steps of Sections 6.4 and 6.5 and simply do this check in some cases. The drawback is that, if validation is not satisfactory, little guidance is offered by the results on how to adjust the model. The advantage is that this check gives a clear idea of the market shares implied by the original model.

In studies where the subject alternatives have low market shares, this additional check is likely to be quite useful. In such cases the model may, for example, predict a market share of 1% when the actual share is 2%. This would produce a large statistical validation adjustment (the estimate is 100% off!), but in fact the original model may be quite acceptable.

6.8 Summary.

This chapter has presented a variety of validation approaches ranging from informal comparisons to formal multinomial logit estimation. The user should select a level of validation appropriate to the objectives and resources of his or her study. In general, though, the less formal techniques will suffice in many studies.

In most actual studies, obtaining good validation results will be difficult for the same reasons that DUA would have been chosen over revealed preference techniques in the first place: alternatives which don't exist, very low usage of other alternatives (which makes demand forecasting difficult), levels of variables or issues that do not currently exist, lack of variability, multicollinearity, and so on. Although the validation exercise is important, its results will often be ambiguous for these reasons and some judgment will likely be required to determine the best final model. The leading issue will generally be whether to apply the validation adjustments to the original utility equations or not, since the validation coefficients will often be based on poor data and have low statistical reliability. This judgment can be aided by comparing the elasticities and sensitivities (see Chapter 9) of the two possible models, and choosing the one with the more reasonable values. Comparisons with other DUA and revealed preference models can sometimes be helpful also. In the end, it must be realized that no absolute validation of a model dealing with new situations or choices is possible based on current data. DUA's power is to extend some reasonable concepts of analysis to these situations, but some level of uncertainty must be accepted.

CHAPTER 7

ADVANCED DESIGN AND ANALYSIS PROCEDURES

7.1 Introduction.

The basic DUA experiment, as described in the previous chapters, can be modified in several ways. The experiment can be expanded in the design stage to provide more information about certain variables or about interactions of variables. The response scale can be designed to include a choice among several alternatives, and to predict multiple levels of demand (e.g. frequency, destination). Experiments can also be administered across a group of individuals, with each individual responding to only a subset of the situations in the whole experiment; these responses are then combined in the analysis step to yield a richer model. This chapter describes these extensions to the basic method.

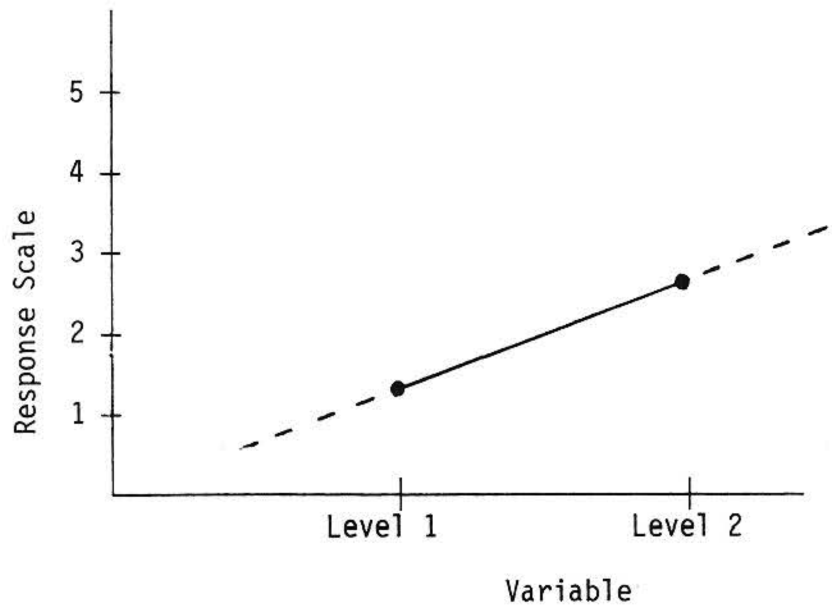
7.2 Design of Experiments With Nonlinearities.

The experimental designs used in the previous chapters have utilized two-level factors, for which only a single, linear utility coefficient can be found. Graphically, as shown in Figure 7.1, this corresponds to a straight line segment connecting the two levels and their responses. The slope of this line is the coefficient of the variable in the utility function, and the dashed lines indicate that we linearly extrapolate the effect of this variable beyond the levels in the DUA experiment, if necessary.

However, we know that the response to many variables is not linear. To capture these effects, we must use variables with 3 or more levels

FIGURE 7.1

Two-Level Factors With Linear Coefficients



in the DUA design. Figure 7.2 shows the alternative forms of the coefficients that can be estimated for three-level coefficients. The piecewise linear function is estimated as:

$$R = 1 + 4F \quad , \quad 0 \leq F \leq 0.50$$

$$R = 3 + 8(F-.50) \quad , \quad F > 0.50$$

The two slopes are designated β_1 and β_2 in the figure. The piecewise linear function is extrapolated linearly as shown by the dashed line in Figure 7.2a.

Alternatively, a quadratic function can be fit to a three-level variable, as shown in Figure 7.2b. The quadratic function is estimated as:

$$R = a_0 + a_1 F + a_2 F^2$$

where a_0, a_1 and a_2 are coefficients. The extrapolation beyond the endpoints uses the same function.

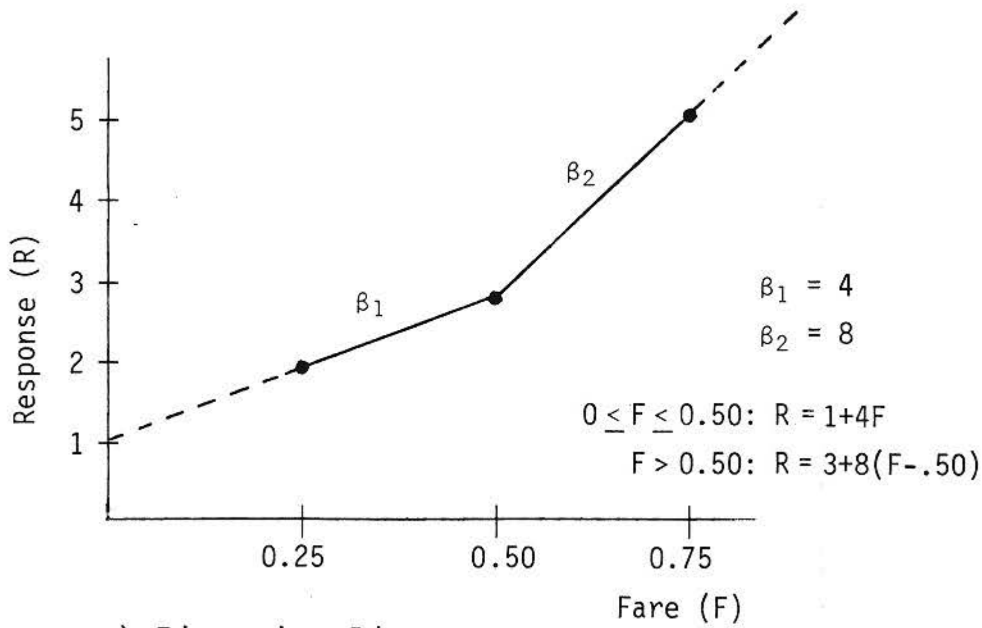
Although these examples are presented for only a single variable, they apply to all variables in a model. Thus, a 4^3 design with four three-level variables could be used to estimate either piecewise linear or quadratic coefficients for each of the four variables.

Figure 7.3 is a graphic representation of alternative forms of four-level coefficients, and similar relationships hold for even higher levels. Variables with four levels are often used if the analyst believes there are threshold effects such as shown in Figure 7.3. These are impossible to find with two-level variables, and are difficult to assess with three-level variables. Variables with more than four levels are rarely used.

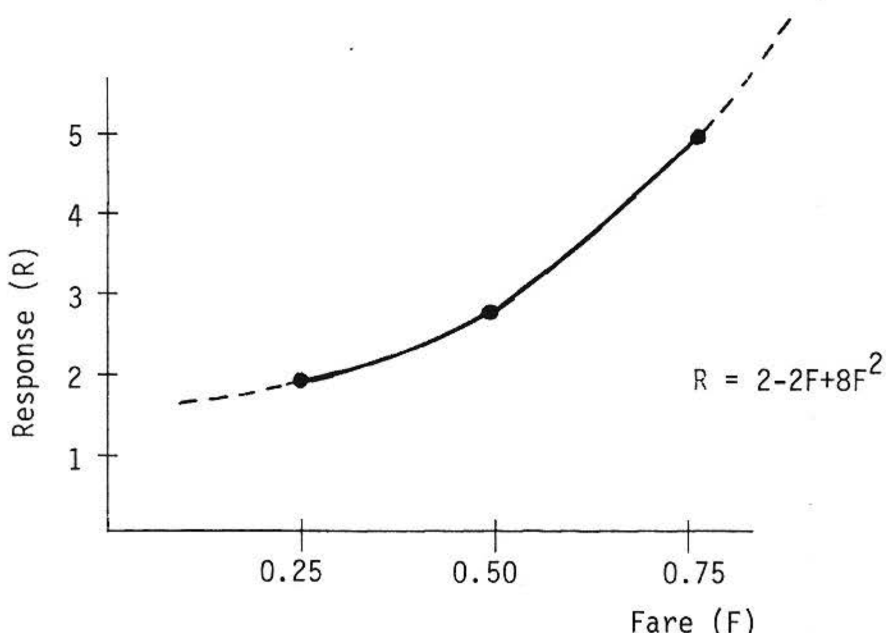
As can be seen in Figure 7.3, the quadratic or cubic models are not always superior to the piecewise linear model. When a threshold

FIGURE 7.2

Alternative Forms of Three-Level Coefficients



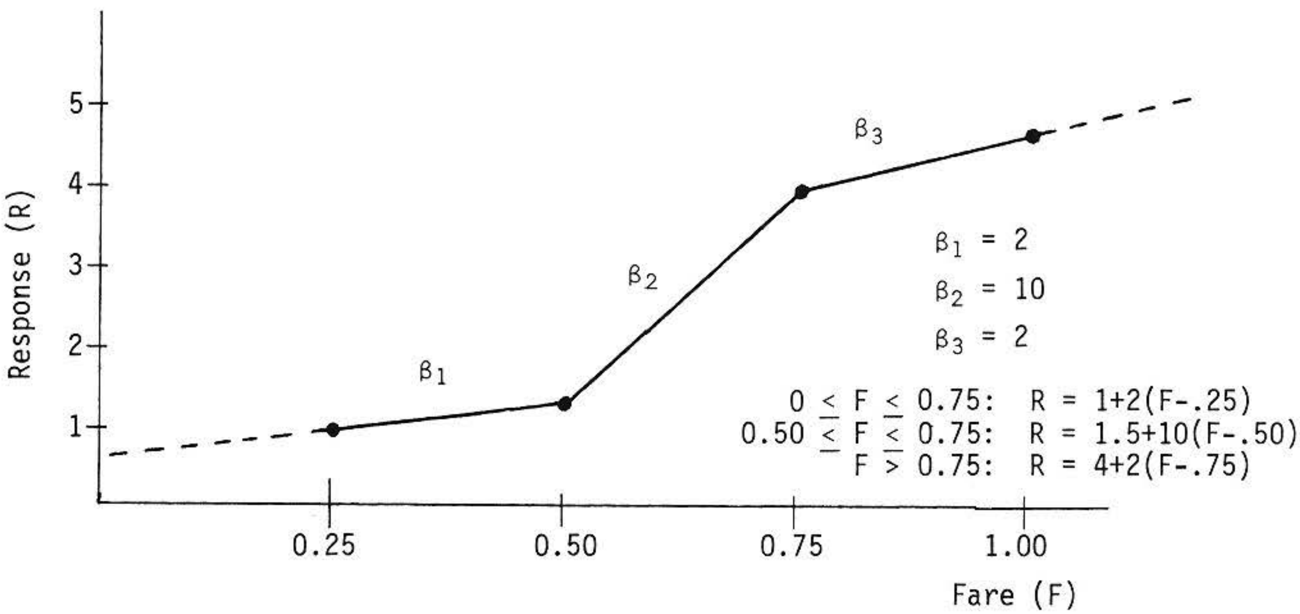
a) Piecewise Linear



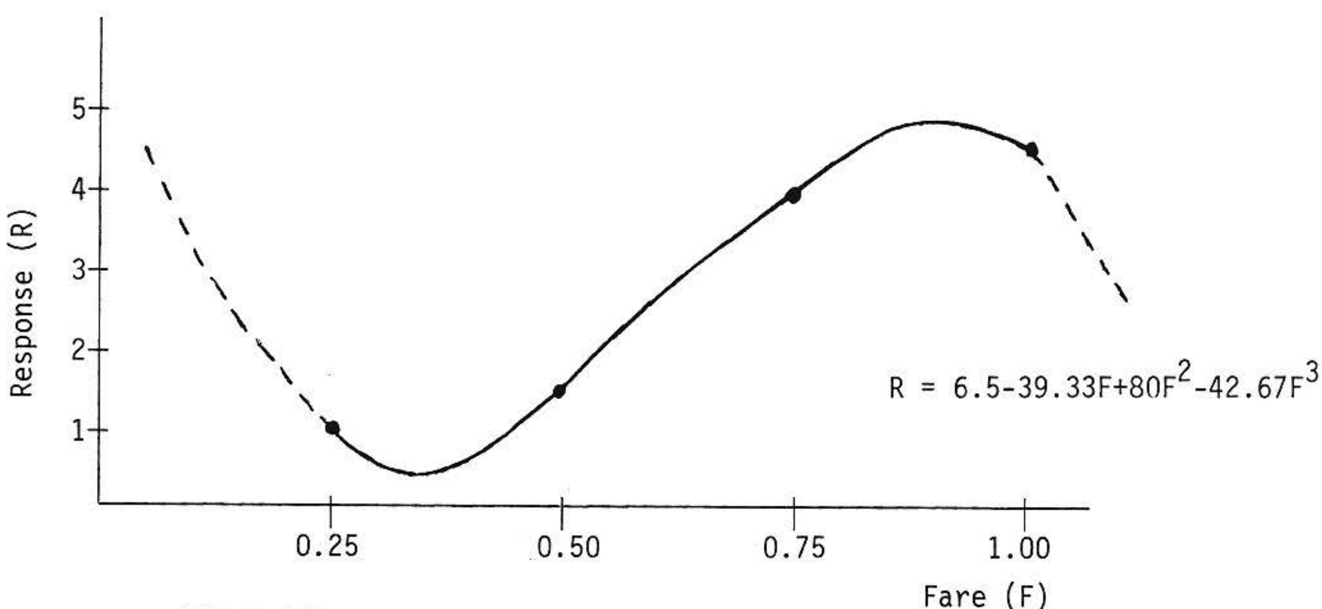
b) Quadratic

FIGURE 7.3

Alternative Forms of Four-Level Coefficients



a) Piecewise Linear



b) Cubic

exists (as shown in Figure 7.3, where fares below 0.50 make little difference, from 0.50 to 0.75 produce a major change, and then matter little above 0.75), the piecewise linear function will generally capture the effect better. If the response to the variable is more uniform (as shown in Figure 7.2), then the quadratic or cubic form may be better.

The catalog of experimental designs in Appendix A contains many plans with three and four levels for selected variables. They are selected and used just as the plans described in previous chapters. The quadratic and cubic forms are readily introduced into all regression packages. The treatment of piecewise linear models varies among statistical packages; their manuals should be consulted to set up such analyses.

7.3 Design of Experiments With Interactions.

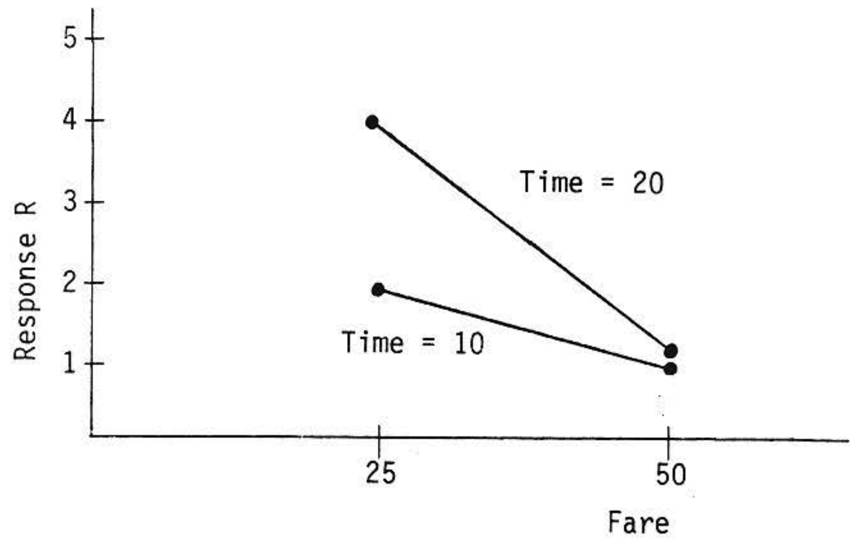
Another key element in many travel decision processes is the interaction among variables in influencing behavior. For example, transit ridership may often depend on both fare and travel time being in an acceptable range. If either is at an unacceptable level, the level of the other matters little; ridership will be low. In this case, travel time and fare interact strongly.

Graphical techniques can represent the effects of interactions. Figure 7.4a illustrates the interaction described above. If fare is 25 cents (an acceptable level) then decreasing travel time increases ridership (increases the response R). If fare is 50 cents (an unacceptable level), then no improvement in travel time can offset it. At this point, time and fare are not traded off.

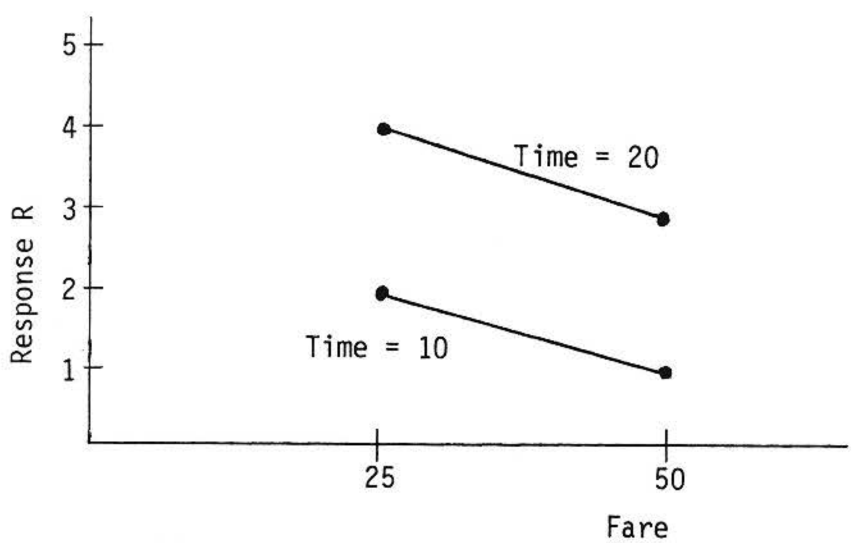
Figure 7.4b illustrates a relationship between the same two

FIGURE 7.4

Illustration of Interactions



a) Interaction



b) No Interaction

variables without interaction. The two lines in the graph are parallel, indicating that the difference between a 10- and 20-minute travel time is constant, regardless of fare level. A similar graph can be drawn for fare, again yielding parallel lines.

In many DUA studies, the interactions among variables will be of major interest. The set of significant main effects and interactions establishes the functional form or shape of the utility equation; this shape can indicate much about the effectiveness of policies or services which involve a series of attributes. Almost all potential functional forms of interest can be transformed (at least through series approximations) to a linear, additive form (in the coefficients), which forms the basis for analysis in this section:

$$R = a_0 + a_1x_1 + a_2x_1^2 + a_3x_2 + a_4x_1x_2 + a_5x_1x_2^3 + a_6x_1x_2x_3 + a_7x_3 + \ldots$$

where $a_0, \ldots a_6, \ldots$ = coefficients

x_1, x_2, x_3 = variables

This function involves linear terms (a_1x_1, a_3x_2 and a_7x_3), nonlinear terms ($a_2x_1^2$), interactions among linear effects ($a_4x_1x_2$ and $a_6x_1x_2x_3$) and general interactions ($a_5x_1x_2^2$).

In most practical work, higher-order interactions are assumed to be negligible; only two-way interactions between linear effects are generally estimated (e.g. $a_4x_1x_2$). Three-way interactions among linear effects (e.g. $a_6x_1x_2x_3$) are ignored, as are any interactions involving nonlinear effects (e.g. $a_5x_1x_2^2$). These simplifications result in major reductions in the number of situations required in an experiment. The designs in Appendix A assume all higher-order interactions are negligible in all cases; in some cases, certain or all two-way interactions are assumed negligible also.

When interactions are to be estimated in a design, the linear/quadratic/cubic representation must be used for three- and four-level variables, rather than the piecewise linear representation described in the previous section. The same cautions apply in using the quadratic and especially the cubic representations as before: unreasonable results may occur with extrapolation.

The analysis of designs with interactions is the same as in main-effects-only designs: a linear multiple regression is run to determine the coefficients of the utility function. The simplified manual approach described in Chapter 3 is <u>not</u> valid for estimating nonlinear and interaction effects.[1] The concept of <u>orthogonal polynomials</u> can be used to modify the manual approach to treat all types of designs (Montgomery, 1976), but it is not discussed in this report.

Table 7.1 gives a simple example of a case with both nonlinear and interaction effects. This is a $2^1 \cdot 3^1$ full factorial, containing all possible interactions between time and fare, and both linear and quadratic effects of time, the three-level variable. The following regression would be run to analyze this experiment:

$$R = a_0 + a_1 t + a_2 f + a_3 t^2 + a_4 tf + a_5 t^2 f$$

The following results would be obtained:

$$R = 4.0 + 0.35t + 0 \cdot f - 0.015t^2 - .006tf + .0002t^2 f$$

where t = travel time (min.)

f = fare (cents)

In this case the nonlinear and interaction effects are dominant, with the main effect of fare being zero and the main effect of time being small and of the "wrong" sign. It's not really a wrong sign because the other terms ensure that R (the stated likelihood of using transit) decreases if transit travel time increases.

---

[1] It is still valid for assessing main effects in such plans.

TABLE 7.1

Experiment With Nonlinearities and Interactions

Travel Time (min.)	Fare (cents)	Response (1-5 scale)
10	25	5
20	25	4
30	25	1
10	50	4
20	50	3
30	50	1

If this example were graphed as in Figure 7.5, it would appear that a travel time of 30 minutes is unacceptable, but at times below that, time and fare are traded off.

7.4 Design of Experiments Across Individuals.

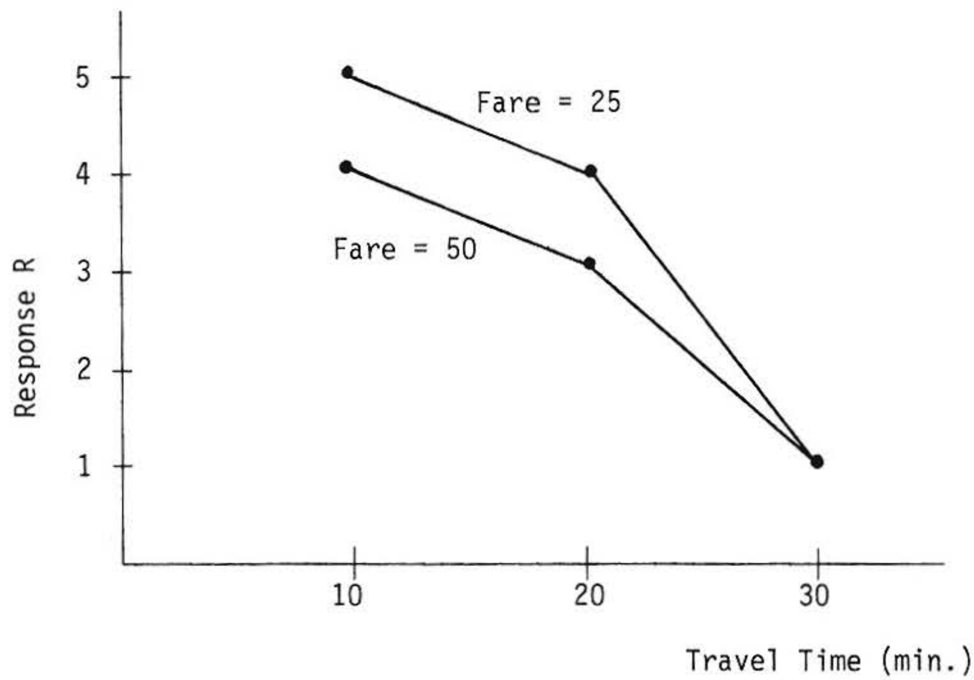
In some situations, it may be impossible to consider all of the important variables and interactions in the experimental design while keeping the survey to a reasonable length. For an experiment containing seven two-level variables, a design to estimate all main effects and two-variable interactions would require sixty-four situations, an experiment eight times as long as those shown in Chapter 3.

By dividing up the situations into separate sub-experiments, or "flats", a large experimental design can be given, in two or more parts, to separate samples. For example, the sixty-four situations required above could be divided into eight separate designs of the same length as the original design. When the results of all of the separate designs are analyzed together, they may be interpreted as the responses to the total composite design. Thus, when the responses from the eight "flats" are grouped together, the interaction effects for each combination of the seven variables can be estimated. The same approach can be used to measure the effects of just a few interactions, requiring only two or three sub-experiments, depending on the situation.

The design of a large experiment over two or more samples involves two potential drawbacks. First, the procedure rests on the assumption that different random samples will respond in a similar way. In reality, there may be significant biases between the groups due to different socio-economic or demographic makeup, or due to

FIGURE 7.5

Graph of Experiment of Table 7.1



random sampling error. To ensure that the responses from the separate groups are compatible, each sample should be of sufficient size to ensure representativeness in socio-economic characteristics. A minimum of 30 responses per flat is suggested.

To construct such a design, one simply takes the full experiment and breaks it into the requisite sections. It is generally possible to construct such designs so that all main effects can be estimated for each "flat" or section, but this requires topics beyond those covered in this report.

Standard statistical texts treat this topic, as well as orthogonal polynomials, nested situations and other advanced areas. Hahn (1980) provides an excellent review and assessment of current statistics texts, from which a book appropriate to the background and needs of the analyst may be selected. In many cases, faculty from the statistics, mathematics or industrial engineering departments of local universities would be able to produce experimental designs for specific problems very quickly. The planning agency must be familiar with basic concepts, however, and must be able to define its needs realistically.

7.5 Multiple Levels of Travel Demand.

Most travel demand forecasts require estimates of trip generation and trip distribution as well as mode choice. For work trips, the frequency and destination of trips are more or less fixed. For other types of trips (shopping, social, recreational, etc.) these may be important factors of travel demand. Including multiple levels of travel demand in the experiment is relatively straightforward. Experiments for estimating frequency and destination require no more variables or situations than the simple mode choice design. All responses can be obtained on a single survey form from a single sample. One key point in the design of a multiple level experiment is to determine the order of the response scales. Do people choose a mode before deciding whether to make a trip, or vice versa? Do people decide on a destination before making other travel decisions, or do the other factors affect the final destination? Though the true decision process may be simultaneous or iterative, the survey must give the questions separately and in a definite order.

The Wisconsin DOT issued a set of surveys for intercity travel, designed to estimate both mode choice and trip frequency. These pretested forms are included in Appendix B. The likelihood of traveling was estimated conditionally on the mode choice (i.e., the mode choice question was given first). This approach assumes that people consider the characteristics of the best available mode before deciding to make a trip. The same argument could be made for destination choice.

Destination choice can also be included in the experimental demand model. It is possible to offer choices between generic destination types, such as the downtown business district, a suburban shopping mall, or a city playground versus a state park. Such a decision would probably be made after considering the mode of the trip.

In general, the inclusion and order of response for multiple levels of demand is a matter of judgment and the context of the survey. If such additional levels seem appropriate to the type of trip under consideration, the additional behavioral information will provide a more complete demand forecasting model.

The analysis of experiments with multiple levels of travel demand is closely related to the previous discussions. Assume that an additional scale had been provided on the auto/bike survey (Figure 5.1) asking whether the individual would make the trip at all, and the responses shown in Figure 7.6 emerged.

Linear regressions on the data yield:

$$R_m = 1.5 + 0.5GA + 0.38GP - 0.5TL + 0.5BL + 0.0SS + 0.5TR$$

$$R_f = 5.75 - 2.25GA - 0.57GP - 0.125TL + 0.25BL - 0.25SS + 0.25TR$$

where R_m = response on mode choice scale

R_f = response on trip frequency

The same procedure is used to validate the trip frequency model using a logit formulation as for mode choice models. The resulting model is:

$$p_1 = \frac{1}{1 + e^{-(a + bR_f)}}$$

where p_1 = probability of making a trip

a, b = coefficients

The identity $p_0 + p_1 = 1$ holds, where p_0 is the probability of making no trip.

There are consistency conditions on linked trip generation, distribution, and mode choice models which are dealt with using "logsum" variables in the logit literature (see Hensher and Johnson, 1981). Approximations are required to put DUA results in this framework which are beyond the scope of this manual.

7.6 Alternative Response Scales.

Advanced DUA studies have the option of using different response scales than discussed so far. One option is to ask respondents to make discrete choices, as shown in Figure 7.7. This experiment requires logit estimation both for analysis of the experiments and

FIGURE 7.6
Bike/Auto Trip Frequency and Mode Choice Experiment

Gas Availability	Gas Price (per gallon)	Trip Length (miles)	Bike Lane?	Street Surface	Traffic Level	Responses Mode	Responses Frequency
Ample	$2.60	3	yes	smooth	quiet	2	4
Ration	2.60	1	yes	smooth	busy	3	2
Ration	1.30	3	no	smooth	busy	1	2
Ample	2.60	1	no	rough	busy	2	4
Ration	1.30	1	yes	rough	quiet	3	3
Ample	1.30	1	no	smooth	quiet	2	5
Ample	1.30	3	yes	rough	busy	1	5
Ration	2.60	3	no	rough	quiet	2	2

	Scale	Mode	Frequency
Response scales:	1	always auto	always won't go
	2	probably auto	probably won't go
	3	indifferent	indifferent
	4	probably bike	probably would go
	5	always bike	always would go

FIGURE 7.7

Example of Discrete Response Scale

Choice Situation Number	BIKE			AUTO			I WOULD CHOOSE		
	Time	Fare	Walk	Gas	Parking (per hr.)	Time	Bus	Auto	Other
1	15 m.	25¢	5 bl	$1.35	20¢	20 m.	X		
2	15 m.	25¢	5 bl	$1.35	50¢	10 m.	X		
3	15 m.	25¢	5 bl	$1.75	20¢	10 m.	X		
4	15 m.	25¢	5 bl	$1.75	50¢	20 m.	X		
5	15 m.	50¢	1 bl	$1.35	20¢	20 m.	X		
6	15 m.	50¢	1 bl	$1.35	50¢	10 m.	X		
7	15 m.	50¢	1 bl	$1.75	20¢	10 m.	X		
8	15 m.	50¢	1 bl	$1.75	50¢	20 m.	X		
9	15 m.	25¢	1 bl	$1.35	20¢	20 m.		X	
10	15 m.	25¢	1 bl	$1.35	50¢	10 m.	X		
11	15 m.	25¢	1 bl	$1.75	20¢	10 m.		X	
12	15 m.	25¢	1 bl	$1.75	50¢	20 m.	X		
13	15 m.	50¢	5 bl	$1.35	20¢	20 m.		X	
14	15 m.	50¢	5 bl	$1.35	50¢	10 m.		X	
15	15 m.	50¢	5 bl	$1.75	20¢	10 m.		X	
16	15 m.	50¢	5 bl	$1.75	50¢	20 m.	X		

m. = minutes

bl = blocks

Source: Louviere et al., 1981.

validation. It may be possible to use weighted logit estimation to jointly analyze and validate the experiment in a single run by including data on actual choices together with the experimental responses. This approach can be used with the logit "logsum" theory to create linked trip frequency, distribution and mode choice models.

Figure 7.8 shows an alternative method of obtaining discrete responses. This is sometimes a compact means of assessing a large number of alternatives, each described by only a few attributes. The experimental responses are discrete choices and must be modeled using a logit formulation. This survey format might be useful to examine destination shifts; the attributes could be time and cost data for one or two available modes. A frequency response could also be asked, either as the number of trips to the chosen destination over some time period or a go/don't go discrete discussion.

7.7 Alternative Forecasting Approaches.

The previous sections of the report have described analysis techniques based on obtaining a single equation to characterize all individuals' responses. This single equation is then used in forecasting as described in Chapter 9. Marketing research in non-transportation areas often uses the alternative approach of estimating a unique equation for every individual in the sample. In forecasting, the variable values for each alternative are substituted into each individual's equation, and the utility values for each alternative for each individual are computed. Each individual is then assumed to choose the alternative with the highest utility.

FIGURE 7.8
Example of Multiple Alternative Survey

	Attributes/Alt's	A	B	C	D	E	F	C	Choice
	Cost/Person/Month	$ 90	$100	$110	$140	$ 60	$100	$100	(write in letter)
1	Miles from Campus	3-1/4	1/4	2	1-3/4	1-1/2	1-3/4	2	
	No. of Bedrooms	2	6	4	3	1	5	4	
	Attributes/Alt's	A	B	C	D	E	F	G	Choice
	Cost/Person/Month	$ 90	$100	$110	$110	$100	$ 90	$100	(write in letter)
2	Miles from Campus	1-3/4	1-3/4	1-3/4	1-1/2	2	2	1-1/2	
	No. of Bedrooms	4	3	2	3	2	3	4	
	Attributes/Alt's	A	B	C	D	E	F	G	Choice
	Cost/Person/Month	$100	$110	$ 90	$100	$ 90	$100	$110	(write in letter)
3	Miles from Campus	1-3/4	1-3/4	2	2	1-3/4	1-1/2	1-1/2	
	No. of Bedrooms	3	1	3	1	6	6	3	
	Attributes/Alt's	A	B	C	D	E	F	G	Choice
	Cost/Person/Month	$ 90	$ 90	$100	$100	$100	$110	$110	(write in letter)
4	Miles from Campus	1-3/4	3-1/4	1/4	1-3/4	3-1/4	1/4	1-3/4	
	No. of Bedrooms	4	3	4	3	2	3	2	
	Attributes/Alt's	A	B	C	D	E	F	G	Choice
	Cost/Person/Month	$110	$110	$100	$100	$100	$ 90	$ 90	(write in letter)
5	Miles from Campus	1-3/4	1/4	3-1/4	1-3/4	1/4	3-1/4	1-3/4	
	No. of Bedrooms	1	3	1	3	6	3	6	
	Attributes/Alt's	A	B	C	D	E	F	G	Choice
	Cost/Person/Month	$ 60	$140	$100	$100	$100	$140	$ 60	(write in letter)
6	Miles from Campus	1-3/4	1-1/2	1-3/4	1-1/2	2	1-3/4	2	
	No. of Bedrooms	4	3	3	4	2	2	3	
	Attributes/Alt's	A	B	C	D	E	F	G	Choice
	Cost/Person/Month	$140	$100	$100	$ 60	$140	$100	$ 60	(write in letter)
7	Miles from Campus	1-3/4	2	1-1/2	1-3/4	1-1/2	1-3/4	2	
	No. of Bedrooms	1	1	6	6	3	3	3	
	Attributes/Alt's	A	B	C	D	E	F	G	Choice
	Cost/Person/Month	$100	$ 60	$140	$100	$ 60	$140	$100	(write in letter)
8	Miles from Campus	1-3/4	3-1/4	1/4	3-1/4	1-3/4	1-3/4	1/4	
	No. of Bedrooms	3	3	3	2	4	2	4	
	Attributes/Alt's	A	B	C	D	E	F	G	Choice
	Cost/Person/Month	$100	$100	$100	$140	$ 60	$ 60	$140	(write in letter)
9	Miles from Campus	1/4	3-1/4	1-3/4	1/4	3-1/4	1-3/4	1-3/4	
	No. of Bedrooms	6	1	3	3	3	6	1	

Source: Louviere et al (1981).

The advantage of this approach is that it recognizes individual-level variations in responses (coefficients) to different attributes. The disadvantage is that, if a sample of 400 individuals was collected, for example, the forecasting system must evaluate 400 separate equations to yield aggregate forecasts. This approach can be used in transportation studies, and may be particularly useful in cases where large individual-level variations in response may be expected (e.g., transit service in areas with combined elderly, student and high-income populations, etc.). This approach can also be used in validation instead of those outlined in Chapter 6.

CHAPTER 8
SELECTED DUA TRAVEL DEMAND MODELS

8.1 Introduction.

This chapter presents a summary of three previous travel demand model systems estimated by the authors of this report, using the techniques described in previous chapters. This is obviously not an exhaustive survey of the literature, but is intended primarily to indicate the types of surveys used, the degree of success of their design, and the model parameters that resulted. These model parameters can be used as "default" parameters in sketch planning or other preliminary analysis, although care should be taken in "transferring" these models among geographical locations.

These models are useful for examining the effects of variables not usually contained in travel demand models, such as fuel availability and price, existence of public transportation modes in low-volume markets, bicycle or walk facilities, and hard-to-measure effects such as seat availability, mode or vehicle size in public transit modes. In these areas they give initial guidance, which may either be sufficient to address the issues, or may lead to a new DUA or other travel demand model to explore the issues further.

The following sections describe three sets of DUA travel demand models. The first is a set of binary mode choice models (auto versus transit) estimated for two trip purposes (work and nonwork) and two destination types (downtown and suburban centers). These models were estimated in Atlanta, Georgia, and contain a large set of transit-related variables.

The second set is a group of work mode choice models estimated in four groups of cities in Wisconsin: Milwaukee, Madison, Fox River Valley (Green Bay and nearby cities), and four small cities grouped together (Jonesville, Beloit, Eau Claire and La Crosse). These models include a large set of travel modes: drive alone, carpool, local bus, walk, bicycle, express bus and commuter rail. They also include variables relating to fuel availability, fuel price, queuing time to purchase fuel, bike lanes, ridesharing programs and transit service improvements.

The third is a set of intercity trip generation and mode choice models also developed in Wisconsin. Four modes are included (air, auto, bus and rail) for three trip purposes (business, personal and recreation). These models also contain a series of variables relating to energy policy and transit service levels. All three groups of models are described in more detail below. The reader is referred to the original reports for more details.

8.2 Urban Binary Mode Choice Models (Auto versus Transit) for Work and Shopping Trips to Downtown and Suburban Centers.

This study is described in National Analysts (1980) and was performed as part of the Automated Guideway Transit Socio-Economic Research Program of UMTA. The city of Atlanta was used as the study site. The survey was administered in a central group interview format to 550 individuals selected through a quota sampling procedure described in Appendix B. Only persons with an auto available for their use are included in the sample. Four mode choice models were developed as shown in Tables 8.1 and 8.2.

The survey had an objective of exploring the issues of seat availability, vehicle size and the overall perception of different public transit modes in competition with auto. The survey consisted

TABLE 8.1

Binary Urban Mode Choice Model Coefficients

Variable		Work Mode Choice		Nonwork Mode Choice	
		CBD	Non-CBD	CBD	Non-CBD
Constant	C	2.68	2.77	2.84	2.83
Headway	H	-.0129	.00581	-.0264	-.0189
	H^2	-.0000611	-.000779	.000654	.000322
	H^3	-.00000278	.00000544	-.0000112	-.00000778
Vehicle Size	V	.0830	.0489	.0408	.0614
	V^2	-.00314	-.00192	-.00126	-.00242
	V^3	.0000346	.0000221	.0000125	.0000280
Travel Time	T	-.0109	-.0156	-.0144	-.0161
	T^2	.0000667	-.000178	-.000222	-.000378
	T^3	-.0000123	.000000988	.00000198	.00000790
Price	P	-.597	-.433	-.633	-.567
	P^2	-.220	-.500	-.160	-.580
	P^3	-.0533	-.467	.0533	-.413
Mode	E	.110	.120	.210	.230
	R	.220	.140	.090	.230
Walk Distance	B	-.100	-.113	-.0867	-.107
Seat Availability	S	.480	.380	.560	.480

TABLE 8.2

Variable Definitions for Binary Mode Choice Model

Variable	Definition	Units
C	constant	-
H	headway of transit service	min.
V	vehicle size	seats
T	travel time difference, transit minus auto	min.
P	price difference, transit minus auto; auto includes perceived operating plus parking costs	dollars
E	dummy variable, equals 1 if transit service is by express bus, 0 otherwise (baseline is local bus)	-
R	dummy variable, equals 1 if transit service is by rail transit, 0 otherwise (baseline is local bus)	-
B	walking distance to and from transit	blocks
S	probability of finding a seat (0 - 1)	-

of 32 situations and was a $4^5 \cdot 2^3$ main-effects-only plan. The model is reported here in polynomial form; the implied piecewise form used in the original report is cumbersome to write out.

After subtracting 3 from the constant, the equations in Table 8.1 can be used in a binary logit function for sketch planning:

$$p_t = 1/(1 + e^{-(R-3)})$$

where p_t = transit mode share

R = response equation (Table 8.1)

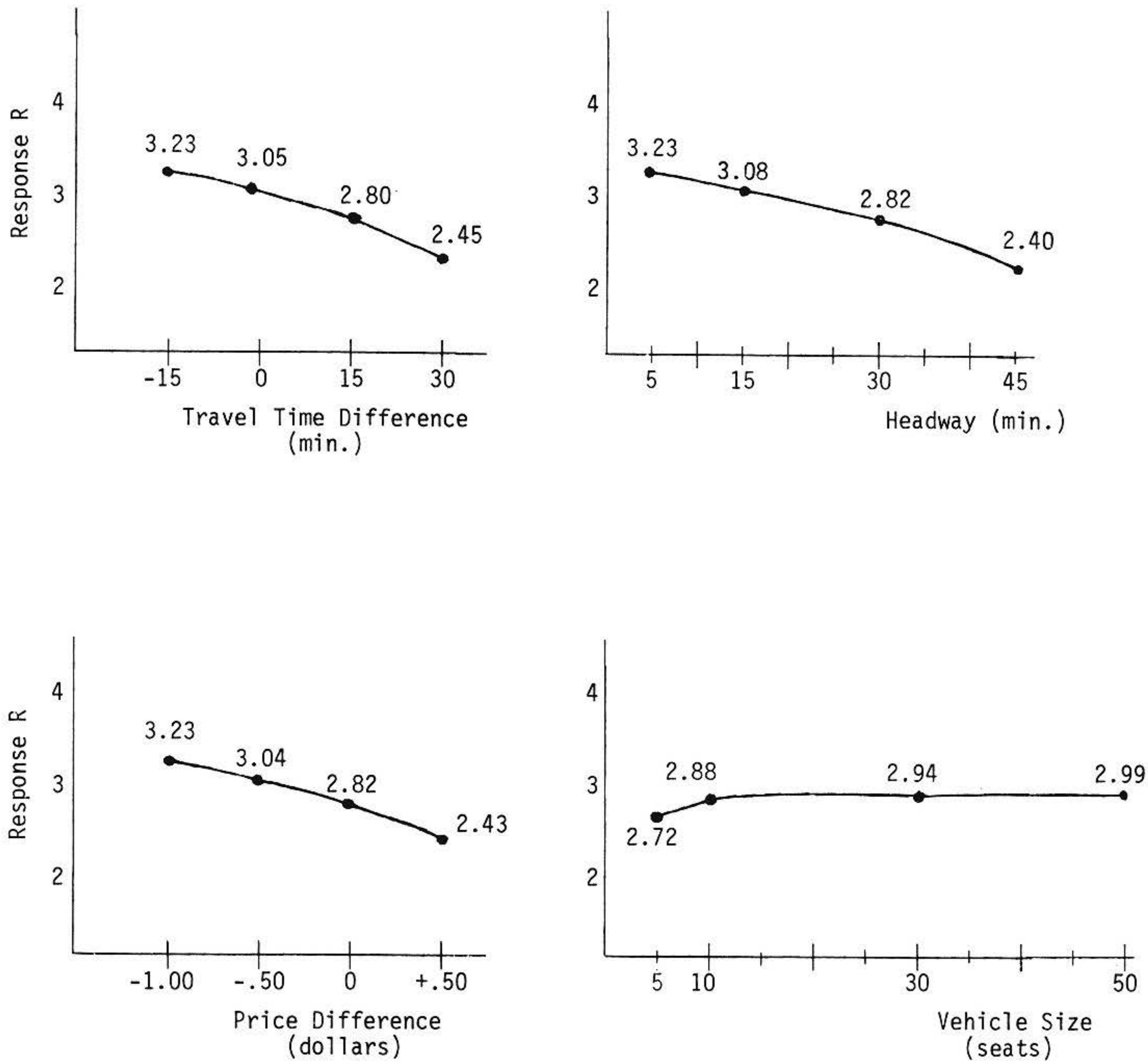
Informal validation indicated good agreement between this model and other logit work mode choice models, although no formal validation was done.

Figure 8.1 shows the functional forms with a data set pooled across all four models; each individual model follows the same general form. Travel time, headway and fare all show the same behavior: the curves are convex, indicating that ridership is lost at an increasing rate as service declines. Also, these curves (since they are not straight lines) indicate a varying trade-off rate among these variables, depending on their level. Larger vehicles are preferred to smaller vehicles; all vehicles are "shared occupancy", even the 5-passenger type.

Other variables in Table 8.1 are modal constants for local bus, express bus and rail transit. The overall constant (e.g. 2.68 for CBD work trips) applies to local bus; the express bus and rail dummy variables adjust the constant upwards, reflecting a user preference for these modes above and beyond that captured through faster running times, etc. The seat availability variable is significant, and finally, walk distance is included in the model.

FIGURE 8.1

Functional Forms of Binary Mode Choice Model



8.3 Urban Multimodal Work Mode Choice Models.

This study is described in WisDOT (1981) and in Kocur, Hyman and Aunet (1982). It was performed by the Wisconsin Department of Transportation as part of an ongoing policy and planning effort. Four groups of cities are used ranging in size from 1,000,000 (Milwaukee County) to 200,000 (Madison, which has a large college population) to 200,000 (Fox River Valley) to 50,000 (Other Cities). This allows comparisons to be made across city size, since the same surveys were administered in each.

This survey was administered as a mailout-mailback questionnaire. Only licensed drivers were surveyed. Sample sizes are indicated on Table 8.3, which summarizes the models. Validation was performed formally with all except the walk mode choice model meeting the statistical criteria. The walk coefficients should be multiplied by approximately 2.5 to reflect validation adjustments. The walk constants change little.

The designs used in this study are shown in Appendix B. They are main-effects-only designs with 8 situations; some are $4^1 \cdot 2^4$ and the rest are either 2^6 or 2^7 plans. Only linear coefficients are available for virtually all variables. The models include a variety of policy variables including energy, transit service, ridesharing programs and bicycle facilities.

The model coefficients can be used in a multinomial logit framework with two adjustments: the multiplier of 2.5 for walk coefficients mentioned above, and by adjusting the modal constants to match base case mode shares as described in Section 6.3.1. The original constants did not validate properly. This model is used in the policy analysis examples given in the next chapter. It also points out the possibility of model transferability across cities, as seen by the similarity of coefficients across cities in Table 8.3.

TABLE 8.3 Urban Work Trip Mode Choice Model:

Variables, Coefficients, and Goodness-of-Fit Statistics for Regressions on Experimental Responses

Variable Name and Definition	URBAN AREA			
	Madison	Milwaukee County	Fox River Valley Cities	Other Cities
	COEFFICIENTS			
AUTO UTILITY: (U_a)				
CA - auto constant	-5.271 -	-4.697 -	-4.448 -	-5.051 -
GA - gas availability: 0 if ample supply 1 if rationing	-0.320 (-6.30)	-0.377 (-6.57)	-0.318 (-7.93)	-0.315 (-8.99)
GP - gas price ($/gallon)	-.234 (-5.48)	-0.320 (-6.62)	-0.284 (-8.41)	-0.284 (-9.59)
PK - parking costs ($/month)	-0.016 (-6.93)	-0.017 (-6.91)	-0.017 (-8.77)	-0.016 (-9.82)
WT - wait time to buy gas (minutes)	-0.008 (-0.89)	-0.004 (-0.38)	-0.013 (-2.30)	-0.007 (-1.29)
IN - annual household income (thousands of 1980 $)	+0.012 (6.02)	+0.010 (3.73)	+0.001 (0.59)	+0.008 (5.09)
VP - vehicles per person 16 yrs. old and over in household	+0.178 (3.12)	+0.078 (1.19)	+0.096 (2.48)	+0.004 (0.13)
TT - travel time (minutes)	-0.030 (-2.77)	-0.025 (-2.27)	-0.019 (-1.89)	-0.033 (-3.70)
SHARED RIDE UTILITY: (U_s)				
CR - shared ride constant	0.216 (3.08)	-0.090 (-1.21)	0.360 (5.91)	0.085 (1.61)
RD - ridesharing partner: 0 if general public matching, 1 if coworker/neighbor	+0.222 (2.58)	+0.216 (2.21)	+0.138 (2.00)	+0.081 (1.41)
WS - work schedule: 0 if flexitime 1 if fixed 8-hr. day	+0.401 (4.66)	+0.384 (3.94)	+0.581 (8.46)	+0.399 (6.93)
TT - travel time (minutes)	-0.030 (-2.77)	-0.025 (-2.27)	-0.019 (-1.89)	-0.033 (-3.70)

TABLE 8.3, continued

Variable Name and Definition	Madison	Milwaukee County	Fox River Valley Cities	Other Cities
	URBAN AREA — COEFFICIENTS			
WALK UTILITY: (U_w)				
CW - walk constant	0.386 (4.46)	0.268 (2.820)	0.151 (2.30)	0.119 (2.01)
WD - walk distance to work (miles)	-0.897 (-3.36)	-0.936 (-3.08)	-0.925 (-5.48)	-0.784 (-5.03)
SW - sidewalks: 0 if all the way, 1 if partway	0 (*)	0 (*)	0 (*)	-0.053 (-0.68)
SN - season: 0 if summer, 1 if winter	-0.756 (-5.66)	-0.750 (-4.93)	-0.868 (-10.29)	-0.848 (-10.83)
BIKE UTILITY: (U_b)				
CB - bike constant	-0.275 (-3.81)	-0.130 (-1.610)	-0.225 (-3.56)	-0.418 (-7.49)
BD - bike distance to work (miles)	-0.245 (-5.24)	-0.213 (-3.67)	-0.259 (-6.69)	-0.276 (-8.19)
BL - bike lane: 0 if marked lane in street, 1 if no lane	-0.356 (-3.81)	-0.216 (-1.87)	-0.330 (4.27)	-0.296 (-4.40)
SS - street surface: 0 if smooth, 1 if rough	-0.383 (-4.11)	-0.470 (-4.05)	-0.431 (5.57)	-0.400 (-5.93)
TR - traffic: 0 if quiet, 1 if busy	-0.517 (-5.53)	-0.500 (-4.31)	-0.417 (5.39)	-0.378 (-5.61)
BUS UTILITY: (U_t)				
BT - bus transfer time (minutes)	-0.044 (-2.00)	-0.035 (-1.58)	-0.019 (-0.96)	0 (*)
BF - bus fare (dollars)	-0.221 (-0.81)	-0.443 (-1.58)	-0.240 (-0.96)	-0.195 (-0.88)
HW - bus headway (minutes)	0 (*)	0 (*)	-0.006 (-0.84)	-0.007 (-1.14)
TT - travel time (minutes)	-0.030 (-2.77)	-0.025 (-2.27)	-0.019 (-1.89)	-0.033 (-3.70)
R^2 =	0.151	0.116	0.139	0.131
F =	21.44	14.24	32.56	38.73
No. of Respondents =	305	273	534	679
Data Points =	2440	2184	4272	5432

The t-statistics are in parentheses; * indicates coefficient was set to zero because the t-value was less than 0.3 and the wrong sign occurred.

8.4 Intercity Trip Generation and Mode Choice Models.

This study is described in WisDOT (1980) and Kocur (1981). It was performed as part of the State Highway Plan. A statewide mailout-mailback sample of drivers was drawn. The final models are based on 494 responses out of 3,000 questionnaires sent out. The survey form is described in Appendix B; it could use many of the improvements that were incorporated afterward in the urban Wisconsin surveys also given in the appendix. Aggregate validation was performed and appeared to be quite satisfactory, although gaps in the validation data prevented a definitive statistical test. The designs use either 8 or 16 situations and reflect $4^1 \cdot 2^4$ and $4^3 \cdot 2^4$ main-effects-only plans respectively. Tables 8.4 and 8.5 show the results.

The mode choice model in Table 8.4 is already validated (only the bus business trip constant was changed) and can be used in the multinomial logit model:

$$p_i = e^{U_i} / \sum_{\text{all } j} e^{U_j}$$

where p_i is the mode share of mode i. There are several coefficients relating to energy and transit policy in the model.

Table 8.5 shows the trip generation model, which is based on the mode choice utilities to a great extent. This model lacks a value of U_0, the utility of making no intercity trip, since it is dependent on the time interval being studied. The model is generally used in policy analysis with the pivot point technique described in the following chapter, so no value for U_0 is required. If a value of U_0 is required, it is a constant and can be found using the approach of Section 6.3.1.

TABLE 8.4
Intercity Mode Choice Model Coefficients

Recreation:

Bus: $U_b = -1.27 - .170\ c_b/d - .85\ t_b/d - .58/f_b - .14RC$

Rail: $U_r = -0.10 - .170\ c_r/d - .85\ t_t/d - .58/f_r - .14RC$

Air: $U_a = -0.66 - .158\ c_a/d - .094\ t_a/d - .010/f_a - .14RC$

Auto: $U_h = -.40AD - .71CW - .89RA - .041g$

Personal:

Bus: $U_b = -.73 - .170\ c_b/d - .93\ t_b/d - .93/f_b - .40RC$

Rail: $U_r = -.18 - .170\ c_r/d - .93\ t_r/d - .93/f_r - .40RC$

Air: $U_a = -.86 - .057\ c_a/d - .16\ t_a/d - .064/f_a - .40RC$

Auto: $U_h = -.27AD - .46CW - .86RA - .059g$

Business:

Bus: $U_b = -2.11 - .110\ c_b/d - 1.25\ t_b/d - 1.86/f_b - .41RC$

Rail: $U_r = 0.30 - .110\ c_r/d - 1.25\ t_r/d - 1.86/f_r - .41RC$

Air: $U_a = -0.57 - .027\ c_a/d - .72\ t_a/d - .26/f_a - .41RC$

Auto: $U_h = -.37AD + 0.0CW - .73RA - .037g$

where

c_i = one-way cost of mode i (cents)

d = one-way auto distance (miles)

t_i = time difference between mode i and auto, including terminal time (min.)

f_i = daily frequency or number of scheduled trips on mode i

AD = 1 if gasoline is available alternate days; 0 otherwise

CW = 1 if gasoline stations are closed weekends; 0 otherwise

RA = 1 if gasoline if rationed at 12 gallons per auto per week; 0 otherwise

TABLE 8.4 (cont.)

g = gasoline price (cents/mile)

RC = 1 if rental car is the only public access mode available at the destination; 0 otherwise (if taxi or local bus are available)

U_i = utility of mode i

TABLE 8.5

Intercity Trip Frequency Model Coefficients

$$P_1 = \frac{e^{U_1}}{e^{U_0} + e^{U_1}}$$

Recreation:

$$U_1 = \underset{(*)}{.754} \ln(e^{U_b} + e^{U_r} + e^{U_a} + e^{U_h})$$

Personal:

$$U_1 = \underset{(*)}{.717} \ln(e^{U_b} + e^{U_r} + e^{U_a} + e^{U_h})$$

Business:

$$U_1 = \underset{(*)}{.760} \ln(e^{U_b} + e^{U_r} + e^{U_a}) + \underset{(*)}{.427} \cdot U_h$$

P_i = probability of choosing mode i, conditional on making a trip

P_1 = probability of making an intercity trip

U_i = utility of mode i

U_0 = utility of not making an intercity trip

U_1 = utility of making an intercity trip

(...) = t-statistic; "*" indicates computed coefficient for which no t-statistic is available

ln = natural logarithm (base e)

CHAPTER 9

QUICK POLICY ANALYSIS

9.1 Introduction

A major reason for undertaking the development of DUA forecasting models is to provide a new tool for policy analysis. In many respects such issues as transportation energy policy and intermodal relationships are best addressed from the standpoint of travel demand. Travel demand models, like those developed with DUA, incorporate many important relationships among the modes. Furthermore, they capture the sensitivity of demand to a change in one or more variables of interest. These variables may be policy instruments an agency can control directly or indirectly.

The forecasting models presented in this chapter are an attractive tool for policy analysis because they can be applied quickly to many problems. With about ten minutes of work, one can examine how changes in one or more variables will affect the mode split or other travel choices in a city. Thus, these forecasting models can serve as a powerful sketch planning tool that allows an analyst to respond to a policy question quickly and meaningfully. This chapter describes how to use DUA models to perform pivot point analysis, a method of quick policy analysis, and it concludes by examining a number of policy issues.

9.2 Pivot Point Analysis

The pivot point approach is based on the incremental form of the logit model. It predicts the revised mode shares of driving alone, sharing a ride, and other modes based only on knowledge of the existing mode shares and the changes in service levels brought about through the policy being analyzed. An extension described in Section 9.4 treats trip distribution and generation issues. By employing this pivot point approach, data requirements are minimal: no knowledge of existing socioeconomic or level of service data is required (Cambridge Systematics, 1976).

Figure 9.1

Illustration of Pivot Point Analysis

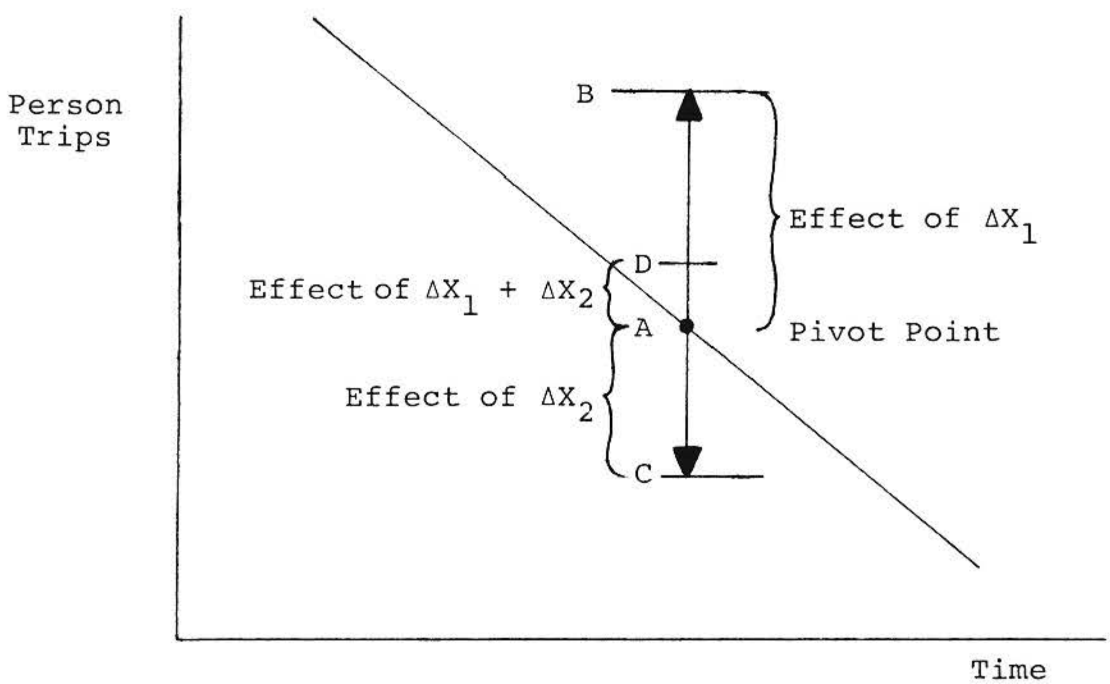


Figure 9.1 shows a demand curve for some mode of transportation that has been experiencing a decline in usage over time. If variable X_1 changes by an amount ΔX_1, then the demand for the mode would shift upward from the pivot point. Similarly, a change in the variable X_2 equal to ΔX_2 would cause the demand to shift down from the pivot point. Suppose the figure represents how transit ridership changes over time, and X_1 is gas price and X_2 is bus fare. An increase in gas price of ΔX_1, everything else remaining constant, would cause transit demand to shift up by the distance AB whereas an increase in bus fare of ΔX_2, everything else constant, would cause demand to shift down by the distance AC. Note that one could simultaneously change X_1 and X_2. Since these variables have an opposite effect on demand, they would partly cancel each other out. The effect of a change in both variables, $\Delta X_1 + \Delta X_2$, is shown by the upward shift in demand from A to D.

Let Q be the total demand in a market measured in units of person trips and let P_i be the market share of mode i. Then $Q_i = P_i Q$ is the total demand for mode i. If Q is a constant, the demand for mode i in units of person trips is a function of only P_i. If P_i changes due to a change in one or more variables, then $P_i'Q$ is the revised demand where the revised mode share, P_i', is determined as follows:

$$P_i' = \frac{P_i e^{\Delta U_i}}{\sum_j P_j e^{\Delta U_j}}$$

Here P_j = the base share for mode j

ΔU_j = the change in the utility function for mode j

e = base of natural logarithms (2.71828. . .)

j = an alternative among the set of available options

The above is the pivot point formula and permits one to perform policy analysis; one needs to know only the changes in the variables that enter a utility function, and the base mode shares for each mode. Derivation of the pivot point formula appears in Appendix F.

Each utility function is a linear function of experimental and in some cases socioeconomic variables:

$$U_i = b_{i1}X_{i1} + b_{i2}X_{i2} + \ldots + b_{in}X_{in}$$

where $X_{i1}, \ldots, X_{in}$ are n variables in the utility function for the ith mode and $b_{i1}, \ldots, b_{in}$ are their corresponding coefficients. The effect of a change in one or more variables on U_i can be written as:

$$\Delta U_i = b_{i1}\Delta X_{i1} + b_{i2}\Delta X_{i2} + \ldots + b_{in}\Delta X_{in}$$

where the ΔX's may be positive, negative or 0. The latter case represents no change in a variable. Thus, if we know the change in utility for each mode, ΔU_i, we can readily calculate the revised mode share using the pivot point formula.

One can gain some intuition for workings of the pivot point formula by noting the following:

1. $e^{\Delta U_j}$ to a first approximation represents a multiplicative factor by which the base share for mode j changes. Thus, if $e^{\Delta U_j} = 1.06$, to a rough approximation, the revised share of mode j, $P_j' = 1.06 \times P_j$. This approximation is quite

accurate provided P_j and U_j are small.

2. Each factor, $e^{\Delta U_j}$, is weighted by its respective base mode share. Thus, a change in a variable influences mode split in proportion to the market share of the mode the variable directly affects. Note that the denominator is a weighted sum of the exponentiated ΔU_j's, and the weights are the respective base mode shares, P_j's.

9.3 Work Sheet for Policy Analysis.

A sample work sheet is shown in Figure 9.2 which can be used to evaluate changes in policy variables using the pviot point formula. This section describes how to perform policy analysis using a work sheet and presents a specific example. One will generally prepare a specific work sheet tailored to each model developed.

With the models developed by DUA, a broad range of policy questions can be addressed. Table 9.1 presents a list of policy variables and socioeconomic factors one can examine with the urban forecasting models given in Section 8.3.

As an example, suppose we wish to evaluate the effect on mode split of two variables:

1. A change in fuel availability from ample supply of gas to rationing; and
2. An increase of ten minutes in the time one must wait at a gas station to purchase gas.

We can evaluate the effects of these changes by filling out the work sheet shown as Figure 9.2 and by following the steps below:

STEP 1: Fill in the heading at the top of the page by writing out

FIGURE 9.2

URBAN AREA: Madison

MODEL SYSTEM:

ESTIMATION OF REVISED WORK TRIP MODAL SHARES

Policy: EFFECT OF RATIONING AND 10 MINUTE WAIT TIME TO BUY GAS

	1	2	3	4	5 = 1 x 2 + 3 x 4	6	7 = e^5	8 = 6 x 7	9 = 8 ÷ Σ	10 = 9 - 6
	VARIABLE 1 Fuel Availability (Rationing)		VARIABLE 2 Wait Time		Total Change in Utility	Base Mode Share	Approximate Factor by Which P Changes	Weighted Change in Factor by Which P Changes	Revised Mode Share	Change in P
MODE	Utility Coefficient	Change in Variable 1	Utility Coefficient	Change in Variable 2	ΔU	P	$e^{\Delta U}$	$P \cdot e^{\Delta U}$	$\frac{P \cdot e^{\Delta U}}{\Sigma} = P'$	P'-P
DRIVE ALONE	-0.320	+1.0	-0.008	+10	-0.400	0.56	0.67	0.375	0.46	-0.10
SHARED RIDE	-	-	-	-	0	0.14	1.0	0.14	0.17	+0.03
BUS	-	-	-	-	0	0.12	1.0	0.12	0.15	+0.03
WALK	-	-	-	-	0	0.07	1.0	0.07	0.09	+0.02
BIKE	-	-	-	-	0	0.11	1.0	0.11	0.13	+0.02

Sum Col 8 = Σ = 0.815

Table 9.1

Policy Issues in Urban Model (Section 8.3)
Which Can be Addressed by Pivot Point Analysis

1. Fuel availability
   (ample supply vs. rationing)
2. Gas price
3. Parking costs at work
4. Type of car pool program
   (general public vs. employment based
   matching programs)
5. Work schedules (fixed shift vs. flexible)
6. Distance
7. Season
8. Sidewalks
9. Presence of bike lanes
10. Street surface on bike routes
    (rough or smooth)
11. Motor vehicle traffic on bike routes
12. Bus transfer
13. Bus fare
14. Difference in auto and bus home
    to work travel time
15. Income
16. Average vehicles per person per family

a. The policy(s) to be evaluated

b. The urban area(s) to which the models apply

Example: We have written in the spaces provided,

Policy: "Effect of rationing and 10-minute increase in wait time to buy gas."

City: "Madison"

STEP 2: Write the name of the first policy variable under the space identifying Columns 1 and 2. If there is a second variable, write its name in the space provided under the heading for Columns 3 and 4.

Example: Under the heading "Variable 1" we have written "Fuel Availability (Rationing)" and under the heading "Variable 2" we have written "Wait Time."

STEP 3: Enter in Column 1 of the work sheet the coefficient(s) of the first policy variable. Refer to Chapter 8 to find the table of coefficients that correspond to a recommended model for the area to which the analysis pertains. In the table corresponding to the recommended model, find the first policy variable to be evaluated and note in which utility function(s) the variable appears.

- If a coefficient appears in only one utility function, enter it in the row of Column 1 to which it corresponds. A coefficient appearing in a shared ride utility equation, for example, goes in the row marked shared ride.
- If more than one utility function has a coefficient for a single policy variable, enter each coefficient in the appropriate row of Column 1. If the gas price

variable has coefficients in the shared ride, walk, bike and bus utility functions, for example, then these coefficients must be written in their corresponding rows of Column 1.

Example: Figure 9.3 shows a table of coefficients drawn from Table 8.3 for Madison, Wisconsin, and all base mode shares. The variable of interest, fuel availability, appears in the left column and has only one coefficient associated with it, -0.320, which appears as a part of the auto utility (U_{AUTO}) under the heading drive alone. This coefficient has been entered in the first row of Column 1. All other rows remain blank.

STEP 4: Enter in Column 3 the coefficient(s) of the second policy variable. Referring to the same table you used in STEP 3, find the second policy variable to be evaluated. Note its coefficient(s); and enter it (them) in the rows of Column 3 following the same procedure described in STEP 3.

Example: The second variable of interest is wait time to buy gas. Figure 9.3 shows the coefficient associated with it is -0.008, which appears in the auto utility function. We have written -0.008 in Row 1 of Column 3 of the work sheet.

STEP 5: Determine the change in each variable and enter their respective changes in Columns 2 and 4 respectively.

Example: The fuel availability variable is a 0-1 dummy, where 0 represents ample supply of fuel and 1 represents rationing. A change to rationing is represented by a

Figure 9.3

Urban Mode Choice Model, Madison, Wisconsin

			COEFFICIENTS				
VARIABLE	UNITS	BASE LEVEL	DRIVE ALONE (U_{auto})	SHARE RIDE (U_{share})	BUS (U_{bus})	BIKE (U_{bike})	WALK (U_{walk})
Constant			-5.271	+0.216		-0.275	+1.754
Fuel Availability	0=Ample Supply 1=Rationing	0	-0.320				
Gas Price	$/Gallon	$1.20	-0.234				
Parking Costs	$/Month	$4.00	-0.016				
Wait Time to Buy Gas	Minutes	5	-0.008				
Household Income	Thousands of 1980 $/Year	$23.4	+0.031				
Vehicles Per Person	Vehicles/ Household Size	0.78	+0.455				
Carpool Rider	0=General Public 1=Co-Worker/Neighbor	1		+0.222			
Employee Schedule	0=Flexi-time 1=Fixed Shift	1		+0.401			
Distance	Miles from Home-to-Work	5				-0.245	-2.144
Bike Lane	0=Marked Lane 1=No Lane	1				-0.356	
Street Surface	0=Smooth 1=Rough	0				-0.383	
Auto Traffic on Bike Route	0=Quiet 1=Heavy	0				-0.517	
Sidewalks	0=Sidewalks 1=No Sidewalks	0					
Season	0=Summer 1=Winter	0				-1.807	-1.807
Bus Transfer	Minutes	5			-0.044		
Bus Fare	$	$.35			-0.221		
Bus Headway	Minutes	15					
Travel Time	Minutes	30	-0.030	-0.030	-0.030		
BASE MODE SHARES:			0.560	0.139	0.119	0.112	0.070

change from 0 to 1, an increase of 1. Thus, Δ Fuel Availability = +1. This has been entered in Row 1 of Column 2. Wait time to buy gas is a continuous variable measured in units of minutes. The change in wait time to buy gas is +10 and has been entered in Row 1 of Column 4.

STEP 6: Calculate the total change in each utility function and enter it in Column 5. In other words, calculate Column 1 x Column 2 + Column 3 x Column 4 and enter the result in Column 5. If for a particular mode there is no coefficient in Columns 1 or 3, write 0 in Column 5 to indicate there is no change in its corresponding utility function.

Example: We enter in the first row of Column 5 the number -0.400 = (-0.320 x 1) + (-0.008 x 10). Thus, the change in the auto utility function, ΔU_{Auto} = -0.400. None of the other utility functions change, so ΔU = 0 for the other modes. So, 0 has been entered in the remaining rows of Column 5.

STEP 7: Enter the base mode share, P_i, corresponding to each mode in Column 6.

Example: The base market share for each mode in Madison is found at the bottom of Figure 9.3. Corresponding data must be developed for each city analyzed. These are entered in their respective rows in Column 6. Thus, we have put 0.56 in the row for drive alone, 0.14 in the row for shared ride, 0.12 in the row for bus, and so forth.

STEP 8: Determine the approximate factor by which the base mode share changes. To do this, calculate $e^{\Delta U}$ for each mode by taking the base of natural logarithms e, and raising it to the power given in Column 5. Enter the result in Column 7. $e^{\Delta U}$ can be calculated using a calculator. Note $e^0 = 1$, since any number raised to the power of zero is always one. Also take care in noting whether ΔU is positive or negative and calculate $e^{\Delta U}$ properly.

Example: For the auto utility function, $\Delta U = -0.400$ and so $e^{\Delta U_{auto}} = e^{-0.400} = +0.67$. For the other modes $\Delta U = 0$, and $e^{\Delta U} = 1$. These numbers have been entered in Column 7 of the work sheet.

STEP 9: Multiply Column 6 by Column 7 and enter the result in Column 8.

Example: We have entered the following numbers in Column 8 on the work sheet beginning with the row labeled drive alone:

Column 8		Column 6		Column 7
0.375	=	0.56	x	0.67
0.140	=	0.14	x	1.0
0.120	=	0.12	x	1.0
0.070	=	0.07	x	1.0
0.110	=	0.11	x	1.0

STEP 10: Sum Column 8 and enter the total in the space provided at the bottom of the page.

Example: The sum of Column 8, 0.375 + 0.140 + 0.120 + 0.070 + 0.110 = 0.815, has been entered at the bottom of the work sheet.

STEP 11: Determine the revised mode share. Divide the number in each row of Column 8 by the sum of Column 8 and enter the results in the corresponding rows of Column 9.

Example: Enter in Column 9 the following:

Column 9

0.46 = 0.375/0.815

0.17 = 0.140/0.815

0.15 = 0.120/0.815

0.09 = 0.070/0.815

0.13 = 0.110/0.815

STEP 12: Calculate and enter in Column 10 the change in the base mode share which is Column 9 minus Column 6.

Example: Enter in Column 10 the results of the following calculations:

Column 10		Column 9		Column 6
-0.10	=	0.46	-	0.56
+0.03	=	0.17	-	0.14
+0.03	=	0.15	-	0.12
+0.02	=	0.09	-	0.07
+0.02	=	0.12	-	0.11

In conclusion, we see it is possible to do pivot point analysis to quickly evaluate how rationing (10 gallons per week) and a ten-minute increase in wait time to buy gas would affect mode split in Madison. The results seem plausible. Drive alone's share of the market would decline from 0.56 to 0.46, whereas the other modes would gain in proportion to their base mode share. If the total number of person trips to work each day in the base case were 100,000, then rationing and an increase of ten minutes in the wait time to buy gas would cause the demand for drive alone to decline from 56,000 person trips per day (0.56 x 100,000) to 46,000 person trips per day (0.46 x 100,000).

If an analyst desires to determine a range describing how a change in a variable affects mode split, it is suggested that two values be used for the coefficient, corresponding to its upper and lower 95% confidence limits. The approximate upper and lower 95% confidence limits for a coefficient b are b $\pm$ two standard errors of the coefficient. Thus, to obtain a range one would first perform the pivot point analysis using b + two standard errors and then using b - two standard errors. These bounds are generally quite wide. (The standard errors of the coefficients are found from the logit or regression results, or are computed as the coefficient times its t-statistic.)

9.4 Chained Pivot-Point Analysis

Many policies intended to change travel behavior will affect not only mode shares, but also the total number of trips. Models such as the intercity models shown in Chapter 8 can be used to analyze these changes by considering both mode choice and frequency (generation). Because frequency and mode choice decisions are interrelated, a special technique called chained pivot-point analysis is used to estimate the effects of changes on both types or choices together.

The pivot-point equation used previously was:

$$P'_i = \frac{P_i e^{\Delta U_i}}{\sum_{\substack{\text{all} \\ i}} P_i e^{\Delta U_i}}$$

where i is the travel mode. This equation is still appropriate for analyzing mode split changes, but the change in trip generation depends on the change in utility across all modes.

The Wisconsin DOT intercity model estimates two levels of demand -- mode choice and frequency (see Chapter 8). The mode split model is in the standard logit form. The trip frequency model is dependent on the utilities of all the modes (total travel is a function of overall accessiblity over all modes) and is written as:

$$P_1 = \frac{e^{\Theta_1 \ln \sum_i e^{U_i}}}{e^{U_0} + e^{\Theta_1 \ln \sum_i e^{U_i}}}$$

$$P_0 + P_1 = 1$$

where P_0 = probability of not making an intercity trip

P_1 = probability of making an intercity trip

Θ_1 = "logsum" coefficient

ln = natural logarithm

i = all modes i

U_0 = utility of making no trip (= constant)

Thus, the utility of making a trip is the logsum coefficient Θ_1 times the logarithm of the sum of the exponentiated utilities of the available modes.

Using the logsum coefficient, the chained pivot-point logit equation is analagous to the simple pivot-point equation:

$$P_j' = \frac{P_j e^{\Theta_j (\sum_i P_i' \Delta U_i)}}{\sum_{\text{all } j} P_j e^{\Theta_j (\sum_i P_i' \Delta U_i)}} \quad \text{OR} \quad P_1' = \frac{P_1 e^{\Theta_1 (\sum_i P_i' \Delta U_i)}}{P_0 + P_1 e^{\Theta_1 (\sum_i P_i' \Delta U_i)}}$$

where j is a second level decision (e.g., frequency) and i is the initial decision (e.g., mode choice). Θ_j is the logsum coefficient for choice j.

Suppose that a Wisconsin study has shown that for recreational trips, 90 percent of all travelers use auto, five percent go by air, and 2.5 percent each go by bus and rail.

Suppose that a gas shortage causes a two-cent per mile rise in gas price and forces gas stations to close on weekends. What will be the effect on trip frequency and mode choice? The revised mode shares can be estimated using the simple pivot-point logit procedure. The revised mode shares with these policy changes turn out to be 80% auto, 10% air, and 5% each for bus and rail, based on the model in Table 8.4.

In such a fuel shortage, one would not expect that each person who declines to use an auto would switch to an alternative mode. Many would probably decline to make the trip at all. Assume that, from previous survey results, it appears that 23 percent of the population makes a trip in a given time period. Thus, P_1 = probability of making a trip = 0.23, and P_0 = frequency of not making a potential trip = 0.77.

From Table 8.5, the recreation trip logsum coefficient, Θ_1, is 0.717. Since the utility of not making a trip remains constant, $\Delta U_0 = 0$. The only modal utility that changes is that for auto, $\Delta U_h = -.792$. This is found from Table 8.4:

$$
\begin{aligned}
\Delta U_h &= -.71\Delta CW - .041\Delta g \\
&= -.71 \cdot 1 - .041 \cdot 2 \\
&= -.792
\end{aligned}
$$

The revised probability of making a trip is now:

$$
\begin{aligned}
P_1' &= \frac{0.23 \cdot e^{0.717 \cdot 0.80 \cdot (-0.792)}}{0.77 + 0.23 \cdot e^{0.717 \cdot 0.80 \cdot (-0.792)}} \\
&= \frac{0.146}{0.77 + 0.146} = .159
\end{aligned}
$$

Thus, the fuel shortage and price increase cuts the total number of trips by almost one-third. If 1000 households were the group of interest, their recreation tripmaking would fall from 230 trips (P_1=.23) to 159 trips (P_1' = .159). The mode shares for these 159 trips are given by the standard pivot point model.

In many cases, trip generation, destination and mode choice DUA model systems will be estimated without the use of "logsum" variables. In these cases, each model is written as a standard logit model; for example, trip frequency is given by:

$$P_1 = \frac{e^{U_1}}{e^{U_0} + e^{U_1}}$$

and

$$P_1' = \frac{P_1 e^{\Delta U_1}}{P_0 e^{\Delta U_0} + P_1 e^{\Delta U_1}}$$

No explicit relationship to the mode choice model is used. This approach is simpler than the chained approach, but it lacks the consistency conditions of the logsum variables. When forecasting with unlinked models, therefore, the analyst must check for consistency constantly. For example, take a base case where 20 transit trips and 80 auto trips are made. Assume that the mode choice model predicts a 10% increase in transit market share (from .20 to .30) and a 20% increase in total travel due to an improvement in transit service. This implies there are 36 transit trips and 84 auto trips after the change. This is impossible, however, because an improvement in transit cannot increase auto trips (from 80 to 84). Logsum variables inherently prevent this situation from occurring, but care is required in non-logsum models to avoid illogical results. In this case, auto trips should be reduced to their "before" value of 80.

9.5 Elasticities

This chapter has focused on pivot point techniques, which are used in the same way that elasticities have been with other demand models. Pivot-point estimates are more accurate than elasticity-based estimates in logit models, and so they are generally preferred. Nonetheless, one may wish to compute elasticities as a comparative check on model coefficients.

The elasticity of demand is defined as the percent change in demand resulting from a one percent change in the value of one of the explanatory variables. For logit models it is computed on the probabilities of the choices and is given by:

$$e_{x_i,\ i} = \Theta_i \bar{x}_i\ (1-p_i)$$

where $e_{x_i,\ i}$ = elasticity of choice probability i with respect to variable x_i

Θ_i = coefficient of variable x_i

$\bar{x}_i$ = average value of variable x_i

p_i = probability of choosing alternative i

This elasticity is not constant, but varies as p_i varies.

A related measure is the cross-elasticity; for logit models, it is given by:

$$e_{x_j,\ i} = -\Theta_j \bar{x}_j p_j$$

where $e_{x_j,\ i}$ = elasticity of choice probability i with respect to variable x_j of choice j, $j \neq i$

Logit models have uniform cross-elasticities. See Spear (1977) for a more general discussion and WisDOT (1980) for an example of deriving elasticities from DUA models.

A brief example is given here, using the Madison drive-alone gas price coefficient, -.234, from Table 9.3. If the average gas price ($\bar{x}_i$) is \$1.20 and the auto mode share (p_i) is 0.56 then the elasticity of auto trips with respect to gas price is:

$$e_{GP,\ auto} = -.234 \cdot 1.20 \cdot (1-.56) = -.12$$

Thus, a 1% increase in gas price would result in a .12% decrease in auto use, or a 10% increase in price would create a 1.2% decrease.

The cross-elasticity of transit use to gas price is:

$$e_{GP,\ transit} = -(-.234 \cdot 1.20 \cdot .56) = .16$$

Every 1% increase in gas price produces a .16% increase in transit ridership over its base level. Note that the cross elasticity depends only on auto variables, so that the cross-elasticity of all other modes to gas price is equal.

9.6 Summary

Direct utility assessment models can be effective in assessing tradeoffs involved in various policies, or in selecting certain policies for more detailed analysis. Surveys can be designed, administered, analyzed in a short time to provide accurate information on policy issues. Pretested survey designs are now available for use in many transportation applications. Complete DUA model systems are also available, although these should be validated on local data before use in policy analysis.

Three features make DUA models especially appropriate for policy analysis. First, no past observations are required. Thus, innovative and unprecedented policies can often be considered. Second, the models can be developed quickly. Third, the models may be used in a quick-response pivot-point and chained pivot-point analysis mode. The sensitivity of estimates to various policy inputs can be readily determined.

In this chapter, we have included examples of policy analysis for both new services and service level changes. We have also illustrated forecasts of exogenous (fuel shortage) impacts on travel demand.

CHAPTER 10

FURTHER WORK

This report has summarized several modeling efforts using, validating and applying DUA models in transportation planning studies. However, several outstanding issues remain in using such techniques for forecasting and policy analysis.

These issues are summarized here for the benefit of planners who may wish to develop innovative approaches to solve these potential problems, and also a set of cautions in some cases where problems may occur.

1. Our survey response scale ranges from 1 to 5. Options for future model development include expanding the scale so it provides more resolution (a response scale from 1 to 11, for example) or letting the response scale consist of probabilities so there is a one-to-one correspondence to the logistic function. Also, one might try letting the dependent variable be a 0-1 dummy, where 1 is drive alone, and 0 refers to the other choice on the experiment. One could then directly estimate a logit model from the experimental data instead of first estimating a utility function using linear regression. Many goodness-of-fit and other statistical issues are involved.
2. More attention needs to be given to screening out correlated variables in the experiment. The orthogonal design ensures the factors in an experiment are completely uncorrelated. This amounts to an assumption that those

variables are also uncorrelated in the real world. However, a respondent may correlate the variables in his or her mind, and thus violate the underlying assumptions in the experiment. In one study, we assumed that a respondent could treat different types of travel time (wait, walk and in-vehicle) independently of one another. The regressions on the experiments indicated the respondents reacted primarily to total travel time. Therefore, future studies based on DUA analysis should pretest instruments containing several types of travel time very carefully, and explore innovative ways to make them clear to respondents.

3. A major methodological issue is how to optimally combine revealed preference models with models based upon conjoint or direct utility analysis. This study used a somewhat ad hoc procedure. In the future, we could develop some decision criteria -- minimize risk, for example -- to combine information concerning stated behavioral intentions and actual behavior.
4. Further work is needed in building validation data sets for DUA. More refined disaggregate behavioral data would be useful in some studies.
5. The results of the mode split model are sensitive to what mode is selected for the base. In future studies it would be interesting to avoid using a base mode in some cases and compare the results obtained using driving alone as the base mode.

6. Most of our models have only a single income variable which captures the propensity of people to drive alone or use a competing mode as a function of income. Future work should consider including much richer socio-economic variable sets.
7. More attention must be paid to establishing the levels of variables in the experiments. Optimal spacings may possibly be derived; only an ad-hoc procedure is used in this report.
8. The issue of interactions needs to be explored further.
9. The issues of interval versus rank-order data must be researched further; Green and Srinavasan (1978) provide a good summary of the issues and the current state of knowledge.

REFERENCES

Atherton, Terry J. and M. Ben-Akiva (1975), "Transferability and Updating of Disaggregate Travel Demand Models," Transportation Research Record 610.

Blalock, Herbert (1979), Social Statistics, Revised Second Edition, New York, McGraw-Hill.

Cambridge Systematics, Inc. (1976), Guidelines for Travel Demand Analyses of Program Measures to Promote Carpools, Vanpools and Public Transportation, prepared for Federal Energy Administration.

Cochran, William G. and G. Cox (1957), Experimental Designs, Second Edition, New York, Wiley.

Dixon, William J. (1977), BMD - Biomed Statistical Package, Computing Center, University of California at Los Angeles.

Green, Paul E., J. Carroll, F. Carmone (1978), "Some New Types of Fractional Factorial Designs for Marketing Experiments," Research in Marketing, Vol. I, ed. J. N. Sheth, Greenwich, CT, JAI Press.

Green, Paul E. and V. Srinavasan (1978), "Conjoint Analysis in Consumer Research: Issues and Outlook," Journal of Consumer Research, Vol. 5, September 1978.

Hahn, G. J. (1980), "Planning Experiments: An Annotated Bibliography," Chemtech, January, 1980, pp. 36-39.

Hahn, G. J. and S. Shapiro (1966), "A Catalog and Computer Program for the Design and Analysis of Orthogonal Symmetric and Asymmetric Fractional Factorial Experiments," Technical Information Series, Schenectady, NY, General Electric.

Hensher, D. A., and L. W. Johnson (1981), Applied Discrete Choice Modeling, Croom Helm: London, Chapter 4.

Kocur, George (1981), "An Intercity Travel Demand Model System Estimated from Data on Behavioral Intentions," Proceedings of Seminar on New, Practical Transportation Analysis Methods, University of Iowa.

Kocur, G., W. Hyman and B. Aunet (1982), "Wisconsin Urban Work Trip Mode Choice Models Based on Functional Measurement and Disaggregate Behavioral Data," presented at 1982 Meeting of Transportation Research Board, Washington, D.C.

Krantz, D. H., and A. Tversky (1971), "Conjoint Measurement Analysis of Composition Rules in Psychology," Psychological Review, 78.

Kruskal, Joseph B. (1965), "Analysis of Factorial Experiments by Estimating Monotone Transformations of the Data," Journal of the Royal Statistical Society, Series B, 27.

Lerman, Steve and Charles Manski (1979), "Sample Design for Discrete Choice: State of the Art," Transportation Research, 13A(1).

Louviere, Jordan, and nine others (1981), "The Development and Test of Mathematical Models of Traveler Perceptions and Decisions," Institute of Urban and Regional Research, Final Report 27, University of Iowa.

Meyer, Robert J., I. Levin, and J. Louviere (1978), "Functional Analysis of Mode Choice," Transportation Research Record 673.

Montgomery , D. C. (1976), Design and Analysis of Experiments, New York, Wiley.

National Analysts (1980), An Analysis of the U.S. Market for Automated Guideway Transit; Volume 3: A Case Study of Consumer Attitudes, Report UMTA-IT-06-0165-79-4, prepared under subcontract to Cambridge Systematics, Inc.

Spear, Bruce D. (1977), "Applications of New Travel Demand Forecasting Techniques to Transportation Planning," Federal Highway Administration, U.S. Department of Transportation.

Statistical Package for the Social Sciences (SPSS, 1970), New York, McGraw-Hill.

Urban Transportation Planning System (UTPS), Office of Planning Methods and Support, Urban Mass Transportation Administration, U.S. Department of Transportation.

Wisconsin Department of Transportation (1980), State Highway Plan Special Report: Passenger Travel Demand Model and Analysis, Division of Planning and Budget.

Wisconsin Department of Transportation (1981), "Development of Wisconsin Work Trip Models for Forecasting Modal Choice," Division of Planning and Budget.

Wonnacott, Ronald J. and T. Wonnacott (1970), Econometrics, New York, Wiley.

APPENDIX A: SAMPLE EXPERIMENTAL DESIGNS

A.1 Introduction

The material in this appendix is condensed from "A Catalog and Computer Program for the Design and Analysis of Orthogonal Symmetric and Asymmetric Fractional Factorial Experiments," by G.J. Hahn and S.S. Shapiro, Report 66-C-165, May 1966, General Electric Research and Development Center, Schenectady, New York. An extended set of experimental plans and further analysis techniques are available in the original document.

The appendix includes the following types of experimental plans:

a. Full factorial plans.

b. Fractional factorial plans to estimate main effects and all two-factor interactions, assuming higher order interactions negligible (known as Resolution V plans).

c. Fractional factorial plans to estimate main effects and all two-factor interactions involving k of the r variables with all others, where $k < r$, assuming all other interactions to be negligible.

d. Fractional factorial plans to estimate main effects and all combinations of two-factor interactions involving m of the r variables, where $m < r$, assuming all other interactions to be negligible.

e. Fractional factorial plans to estimate main effects independently of two-factor interactions, assuming all higher order interactions to be negligible (known as Resolution

IV plans).

f. Fractional factorial plans to estimate main effects only assuming all interactions to be negligible (known as Resolution III or main effect plans).

The catalog includes designs involving up to four levels per variable and designs with variables at differing numbers of levels. No design involving more than 32 tests has been included.

All the designs in this appendix are orthogonal. This means that those effects and interactions which are estimable in a given design can be estimated without correlation with other main effects or with those interactions which are not assumed negligible. There are other types of fractional factorial designs which permit "near orthogonal" estimation. Such plans might on occasion have advantages in terms of sample size, but they are more difficult to analyze and interpret.

A.2 Considerations in Practical Application of Plans

A.2.1 General

Appendix A provides a detailed listing of the experimental points for a number of plans. However, there are many other aspects to planning a survey in addition to determining the design.

A.2.2 Considerations in Collapsing Variables

In the catalog of experimental plans, some of the variables appear at more levels than are required for that particular plan (in particular, variables in the designs indicated by an asterisk in Column 9 of the Design Index). For example, one plan involves a design with two variables at two levels each and three variables at three levels each, requiring a total of 27 tests. The actual experiment is constructed using Columns 1, 2, 5, 10, and 13 of Master Plan 8 in the manner described below.

However, Plan 8 lists five variables each at three levels, with each level represented a total of nine times. For two of the three variables, the number of levels must be changed from three to two to meet the requirements of the specified design.

Thus, it is necessary to re-assign all nine tests at one of the three levels to one of the two remaining levels. In the final plan, nine tests will then be conducted at one of the remaining levels and 18 tests will be run at the second level. This is referred to as "collapsing the variable." Collapsing also arises in plans involving more than three levels.

Since the validity of the analysis is unaffected by which levels are chosen to be run a greater number of times the levels selected in the collapsing procedure could be picked randomly. However, the results at the condition with the heavier concentration of tests can be estimated with higher precision. Thus, it is desirable to arrange the collapsing so that those levels which are of greatest interest are tested most frequently.

A.2.3 Considerations in Assuming Certain Interactions Negligible

An economy in the number of experimental trials is achieved by the plans in the catalog by assuming certain interactions to be non-existent or negligible. The analyses will be affected in several ways if this assumption is incorrect.

Interactions which are assumed insignificant may be classified into two groups for most plans. First, interactions are frequently "lumped together" to make up the residual terms in the analysis. The word "residual" derives from the fact that these terms measure the fluctuation in the experimental results after the effects which are not assumed negligible have been considered. If the assumptions of the experimental model are correct, the residual variation is a measure of experimental error.

The second group of interactions assumed negligible are directly "confounded" with those main effects or interactions which one desires to estimate. This means that their contribution is inseparable from that of some main effects or two-factor interaction of direct interest. If the corresponding value in the analysis is found significant, the logical conclusion is that this is due to terms initially assumed to be of interest (rather than those initially assumed negligible).

The consequences of <u>incorrectly</u> assuming interactions negligible may therefore be:

a. Such interactions remain undetected.

b. The experimental error is inflated by the inclusion of significant terms (and thus the power of the experiment to detect the significance of the effects is decreased).

c. Incorrect conclusions are drawn about the significance of the main effects and interactions of prime interest.

The first consequence is obvious. The property which allows one to reduce the required experimentation by assuming certain interactions insignificant, leads to the inability to estimate the effect of such interactions.

Whether a particular interaction which has incorrectly been assumed insignificant results in consequence b or consequence c depends upon whether that interaction was included as part of the experimental error or whether it was confounded completely with a main effect or interaction of prime interest and is therefore inseparable from it. This can be determined from a detailed study of the properties of the experimental plan. Some of the plans have the property that no main effect is confounded with any two-factor interaction, irrespective of what two-factor interactions have been assumed insignificant and these plans are identified in Column 5 of the design index. Thus, if the confounding of main effects with two-factor interactions is a matter of concern, a plan designated "yes" in Column 5 of the design index should be employed.

The question of choosing which interactions to assume negligible must be based upon an understanding of the underlying physical situation and what variables one reasonably might expect to interact. In practice, it is frequently found that those main effects which are themselves most likely to be significant are also the ones which are most likely to lead to interactions, especially amongst themselves. Sometimes, it must be recognized that assuming some interactions to be negligible represents only a first order approximation which must be verified by further experimentation. Such an assumption is often necessary to get some initial information about main effects and those lower order interactions which cannot be ignored.

A.3 Description of Index and Plans

A.3.1 Introduction

The catalog of fractional factorial designs has been prepared to facilitate the construction of experimental plans. All designs in the catalog allow for the orthogonal estimation of the main effects and denoted interactions; i.e., all estimates of effects obtained from the design are uncorrelated. The catalog has been constructed so that the user can easily select a plan to fit a given set of requirements (within the size limitations stated below). However, in so doing, one should be aware of the limitations and assumptions necessary for use of each plan.

The catalog consists of two parts -- an index and a set of master plans. The index is a listing and description of the experimental plans contained in the catalog. The master plan gives the specific combinations of variables for each experimental trial for the plans listed in the index. Thus, one locates the desired plan from the description in the index and refers to the master plan to determine the specific design.

To facilitate the subsequent discussion, the following notation will be used. Let n represent the total number of variables or factors in an experiment. Let $A^{n1} \times B^{n2} \times C^{n3}$ represent n_1 variables with A levels, n_2 variables with B levels and n_3 variables at C levels, where $n = n_1 + n_2 + n_3$. For example, the plan $2^3 \times 3 \times 4^2$ represents an experiment with three variables at two levels each, one variable at three levels, and two variables at four levels each.

A.3.2 Description of the Index

The Design Index contains a listing of experimental plans requiring at the most 32 trials. The Index contains the following information for each plan:

i) Column 1 Experimental Plan Code Number.
This column identifies a specific plan.

ii) Column 2 Total Number of Variables.
This column indicates the total number of variables for which the plan is applicable; in our notation, it is equal to n. Thus, a plan with five variables has a 5 in Column 2.

iii) Column 3 Number of Variables at 2, 3, 4 and 5 levels (Columns 3a, 3b, 3c, and 3d).
This column indicates the number of variables at two levels (Column 3a), three levels (Column 3b), four levels (Column 3c) and five levels (Column 3d). Thus, for example, the plan $2^2 \times 3 \times 4^3$ would have a 2 in Column 3a, a 1 in Column 3b, a 3 in Column 3c and a 0 in Column 3d. This column replaces the notation $2^{n1} \times 3^{n2} \times 4^{n3} \times 5^{n4}$ and identifies specifically the experimental conditions for which it can be used. Note that $n_1 + n_2 + n_3 + n_4 = n$.

iv) Column 4 Number of Tests Required.
This column gives the total number of experimental trials needed to run one replicate of the experiment. The designs within a family requiring the fewest number of trials are

listed first.

v) Column 5 Are all the main effects independent of two-factor interactions?

This column, which contains either a "yes" or "no" entry, indicates whether or not the main effects can be estimated free of two-factor interactions, i.e., whether or not the main effects are unconfounded with two-factor interactions. If a "no" appears in the column, in order to use the plan, certain two-factor interactions (not indicated in the index) must be presumed non-existent in the analysis of certain main effects.

vi) Column 6 Number of Independent Two-Factor Interactions under Assumed Model.

This column indicates the number of two-factor interactions which can be estimated independent of main effects and other estimable two-factor interactions. The number indicated gives the total number of such interactions. The specific interactions are given in Column 10. The notation "All" is used to denote plans for which all two-factor interactions can be estimated.

vii) Column 7 (Not Used).

viii) Column 8 Master Plan Number.

This column indicates the plan in the master list from which to select the exact treatment combinations. The exact columns to choose from this master plan are indicated in Column 9. Several of the full factorial designs have the entry FF in this column. These designs, which are not included in the plan, can be constructed by taking all possible combinations of levels for each of the variables.

ix) Column 9 Using Columns Number.

This column specifies the exact columns to choose from the master plan indicated in Column 8. The columns in the plan give the combination of experimental variables to use for each trial. Each variable will be associated with a column in the chosen plan. The two-level factors are associated with the columns containing only 0's and 1's. The three-level factors are assigned to the columns containing 0's, 1's and 2's, the four-level factors are assigned to the columns containing 0's and 3's, and the five-level factors are assigned to the columns containing 0's and 4's. In the case of plans for which there are no interactions estimable, the variables are assigned at random to the specific columns subject to the number of levels of the variable coinciding with the number of levels in the column.

For the plans which contain estimable interactions, the variables whose interactions are desired must be assigned to the column numbers indicated in Column 10. All other assignments should be made randomly.

For the plans denoted by an asterisk in Column 9, the number of levels in some of the columns in the plan will be greater than the number of levels of the assigned variable. In these cases, a collapsing of levels is necessary after the assignment has been made. In particular, if a three-level variable is matched with a four-level column (contains 0, 1, 2, 3) then all number 3's in the column are changed to 0. If a two-level variable is assigned to a four-level column, then the numbers 2 and 3 are changed to 1 and 0, respectively. If a two-level variable is assigned to a three-level column, then all number 2's are changed to 0's.

x) Column 10 Columns from which Two-Factor Interactions can be Estimated.

This column states for which variables the two-factor interactions can be estimated from the design. It indicates to which columns in the plan the variables whose two-factor interactions are desired should be assigned.

The code AC in this column denotes that the interaction of all combinations of the variables associated with the columns indicated, can be estimated free of main effects and each other. Thus, for example, the entry AC: 1, 2, 3 indicates that the interactions of the variables assigned to Columns 1 and 2, 1 and 3, and 2 and 3 can be estimated free of main effects and each other. All other two-factor interactions are assumed to be negligible. The WAO notation in Column 10 indicates that the interactions of the variables assigned in the columns shown with all other variables in the design can be estimated free of main effects and each other. Thus, in a six variable experiment, using Columns 1, 2, 3, 4, 5, and 6 of the plan, the notation WAO: 1, 2, 3 indicates that the interactions of the variables assigned to Columns 1 and 2, 1 and 3, 1 and 4, 1 and 5, 1 and 6, 2 and 3, 2 and 4, 2 and 5, 2 and 6, 3 and 4, 3 and 5, and 3 and 6 can be estimated free of main effects and each other. All other interactions, such as between the variables assigned to Columns 4 and 6, are assumed negligible.

A.3.3 Description of the Master Plan.

The plan contains tables of experimental treatment combinations for sample sizes, ranging from 4 to 32. The plans are listed in sequence according to the number of trials required.

The heading of each plan gives the master plan number, which is referenced in Column 8 of the index, and the number of trials, referenced in Column 4 of the index. Below the heading are the column numbers referenced in Columns 9 and 10 of the index. The numbers in the body of the plan indicate the levels of the variable for a given experimental trial. Thus, for two-level factors, the numbers 0 and 1 indicate the low and high levels of the factor, for three-level factors, 0, 1 and 2 represent the low, middle and high levels of the factor, etc. (the terms low, middle and high have meaning for quantitative variables. They are assigned arbitrarily for qualitative variables).

A.3.4 Example of Selection of an Experimental Design

There are many ways in which the catalog can be used. Two such ways are indicated below.

Situation 1. The exact number of variables in the experiment, the levels of each and the non-zero interactions are fixed, and one desires to locate a plan from which the above effects can be estimated with a minimum number of trials. In this case, one locates the appropriate family and chooses that design with the smallest sample size which meets the desired requirements.

Assume, for example, that an experiment has five variables -- A, B, C, D, and E -- and variables C and D have two levels each and variables A, B and E have three levels each ($2^2 \times 3^3$ situation). We wish to estimate the interactions between AB, AC and BC, but can assume that all other interactions are negligible. Scanning Columns 2 and 3 in the index to find a five variable design with a 2 in Column 3a, 3 in Column 3b and a 0 in Columns 3c and 3d, we locate Family 45 as the desired design family. Plan 45a, requiring only 16 trials, is clearly not appropriate since the entry "none" in Column 6 indicates that no interactions can be estimated. Both Plans 45b and 45c allow the estimation of some interactions. If we assign variables A, B, C, D, and E to Plan Columns 1, 2, 5, 10 and 13, respectively (see Column 9), Plan 45b allows estimation of interactions AB, AC and BC (from Column 10 - AC: 1, 2, 5), while Plan 45c (using Plan Columns 1, 2, 5, 8 and 9) allows the estimation of AB, AC, AD and AE (from Column 10 - WAO: 1). Thus, Plan 45b with 27 trials is the desired design.

Situation 2. The number of experimental situations is fixed (due to respondent or budget limitations). The number of variables and interactions is fixed, but the number of levels of some of the variables can be adjusted to keep the experiment within the desired maximum number of trials. A variation of this situation is where it is desirable to add one or more variables to the experiment if a design can be found which meets the sample size limitations. In this case, one would locate the family of plans which allowed the estimation of the minimum configuration and then investigate whether it is possible to increase either the number of variables or levels without increasing the sample size, decreasing the number of estimable interactions below the number desired, or decreasing the residual degrees of freedom below a minimum level.

This situation is illustrated by the following problem. We can afford at most a total of 16 experimental trials. There are eight variables, A, B, C, D, E, F, G and H, which we definitely wish to investigate and a ninth variable, which we would like to add to the experiment, if possible.

All variables except A and B are at two levels. If necessary, the latter could also be run at two levels, but it would be preferable to have them at three levels. The only interactions of relevance are AB, AC, AD, AE and AF; all others can be assumed to be negligible. From the index, we see that Plan 7b can be used if we limit the experiment to eight variables at two levels.

If we assign Variable A to Master Plan 5, Column 15, the interaction of A with all other variables can be estimated.

Nine variables each at two levels can be run using Plan 8b. We cannot, however, add the ninth variable without giving up estimation of the interactions AE and AF. Plan 8b allows estimation of nine variables at two levels with six interactions. For example, if we assign variables A, B, C, and D to Plan Columns 11, 12, 14 and 15, we can estimate interactions AB, AC, AD, BC, BD and CD, but not AE and AF.

Finally, if we want to run variables A and B at three levels, we are forced to give up all interactions for both eight and nine variables; see Plan 70a and Plan 74a.

A.4 Index and Master Plans

The following figures present the Index and Master Plans.

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
Experimental Plan Code No.	Total No. of Variables	Number of Variables at 2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Are All Main Effects Independent of 2-Factor Interactions?	Number of Independent Two-Factor Interactions Under Assumed Model	Master Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
2a	3	3	0	0	0	4	No	0	1	1,2,3	None
2b	3	3	0	0	0	8	Yes	3(All)	2(FF)	3,4,6	All
3a	4	4	0	0	0	8	Yes	3	2	3,4,6,9	AC: 3,4,6 or WAO:3
3b	4	4	0	0	0	16	Yes	6(All)	5(FF)	12,13,14,15	All
4a	5	5	0	0	0	8	No	1	2	3,4,5,6,9	AC: 4,6
4b	5	5	0	0	0	16	Yes	10(All)	5	11,12,14,15,19	All
4c	5	5	0	0	0	32	Yes	10(All)	9(FF)	19,20,22,23,46	All
5a	6	6	0	0	0	8	No	1	2	3,4,5,6,7,9	AC: 4,6
5b	6	6	0	0	0	16	Yes	6	5	11,12,14,15,20,24	AC:11,12,14,15 or WAO:11
5c	6	6	0	0	0	32	Yes	15(All)	9	19,20,22,23,27,46	All
6a	7	7	0	0	0	8	No	0	2	3,4,5,6,7,8,9	None
6b	7	7	0	0	0	16	Yes	6	5	11,12,14,15,20,24,25	AC:11,12,14,15 or WAO:11
6c	7	7	0	0	0	32	Yes	15	9	19,20,22,23,27,36,46	AC:19,20,22,23,27,46
6d	7	7	0	0	0	32	No	18	9	19,20,22,23,27,45,46	WAO:19,20,22,23
7a	8	8	0	0	0	12	No	0	4	Any 8 Columns	None
7b	8	8	0	0	0	16	Yes	6	5	11,12,14,15,20,22,24,25	AC:11,12,14,15 or WAO:11
7c	8	8	0	0	0	32	Yes	15	9	19,20,22,23,27,28,36,46	AC:19,20,22,23,27,46
7d	8	8	0	0	0	32	No	18	9	19,20,22,23,27,45,46,47	WAO: 20,22,23
8a	9	9	0	0	0	12	No	0	4	Any 9 Columns	None
8b	9	9	0	0	0	16	No	6	5	11,12,14,15,19,20,22, 24,25	AC: 11,12,14,15
8c	9	9	0	0	0	32	Yes	15	9	19,20,22,23,27,28,35, 36,46	AC: 19,20,22,23,27,46
8d	9	9	0	0	0	32	No	21	9	19,20,22,23,27,32,45, 46,47	WAO: 20,22,23

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
		Number of Variables at					Are All Main Effects Independent of 2-Factor Interactions?	Number of Independent Two-Factor Interactions Under Assumed Model			Columns From Which 2-Factor Interactions Can Be Estimated
Experimental Plan Code No.	Total No. of Variables	2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required			Master Plan No.	Using Columns Number	
9a	10	10	0	0	0	12	No	0	4	Any 10 Columns	None
9b	10	10	0	0	0	16	No	3	5	11,12,13,14,15,17,19, 20,22,24	AC:12,14,15
9c	10	10	0	0	0	32	Yes	15	9	19,20,22,23,27,28,33, 35,36,46	AC:19,20,22,23,27,46
9d	10	10	0	0	0	32	No	9	9	19,20,21,22,23,33,46, 47,48,49	WAO:23
10a	11	11	0	0	0	12	No	0	4	All Columns	None
10b	11	11	0	0	0	16	No	3	5	11,12,13,14,15,17,19, 20,22,23,24	AC:12,14,15
10c	11	11	0	0	0	32	Yes	15	9	19,20,22,23,27,28,33, 35,36,41,46	AC:19,20,22,23,27,46
10d	11	11	0	0	0	32	No	10	9	19,20,21,22,23,29,33, 46,47,48,49	WAO:23
11a	12	12	0	0	0	16	No	3	5	11,12,13,14,15,17,19, 20,22,23,24,25	AC:12,14,15
11b	12	12	0	0	0	32	Yes	15	9	19,20,22,23,27,28,29, 33,35,36,41,46	AC:19,20,22,23,27,46
11c	12	12	0	0	0	32	No	11	9	19,20,21,22,23,25,29, 33,46,47,48,49	WAO:23
12a	13	13	0	0	0	16	No	1	5	11,12,13,14,15,17,18, 19,20,21,22,23,24	AC:14,15
12b	13	13	0	0	0	32	Yes	15	9	19,20,22,23,25,27,28, 29,33,35,36,41,46	AC:19,20,22,23,27,46
12c	13	13	0	0	0	32	No	12	9	19,20,21,22,23,25,29, 33,37,46,47,48,49	WAO:23

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
		Number of Variables at					Are All	Number of Independent			
Experimental Plan Code No.	Total No. of Variables	2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Main Effects Independent of 2-Factor Interactions?	Two-Factor Interactions Under Assumed Model	Master Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
13a	14	14	0	0	0	16	No	1	5	11,12,13,14,15,17,18, 19,20,21,22,23,24,25	AC:14,15
13b	14	14	0	0	0	32	Yes	15	9	19,20,22,23,25,27,28, 29,33,35,36,41,46,49	AC:19,20,22,23,27,46
13c	14	14	0	0	0	32	No	13	9	19,20,21,22,23,25,29, 33,37,40,46,47,48,49	WAO:23
14a	15	15	0	0	0	16	No	0	5	All Columns	None
14b	15	15	0	0	0	32	Yes	15	9	19,20,22,23,25,27,28, 29,33,35,36,41,42,46, 49	AC:19,20,22,23,27,46
14c	15	15	0	0	0	32	No	14	9	19,20,21,22,23,25,29, 33,34,37,40,46,47,48, 49	WAO:23
15	2	0	2	0	0	9	Yes	1(All)	3(FF)	1,2	All
16a	3	0	3	0	0	9	Yes	0	3	1,2,4	None
16b	3	0	3	0	0	27	Yes	3(All)	8(FF)	1,2,5	All
17a	4	0	4	0	0	9	No	0	3	1,2,3,4	None
17b	4	0	4	0	0	27	Yes	3	8	1,2,5,13	AC:1,2,5, or WAO:1
17c	4	0	4	0	0	27	No	3	8	1,2,5,8	WAO:1
18a	5	0	5	0	0	16	No	0	5	6,7,8,9,10	None
18b	5	0	5	0	0	27	No	3	8	1,2,5,10,13	AC:1,2,5
18c	5	0	5	0	0	27	No	4	8	1,2,5,8,9	WAO:1
19a	6	0	6	0	0	18	No	0	6	1,2,3,4,5,6	None
19b	6	0	6	0	0	27	No	3	8	1,2,5,10,11,13	AC:1,2,5

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
		Number of Variables at									
Experimental Plan Code No.	Total No. of Variables	2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Are All Main Effects Independent of 2-Factor Interactions?	Number of Independent Two-Factor Interactions Under Assumed Model	Master Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
20a	7	0	7	0	0	18	No	0	6	1,2,3,4,5,6,7	None
20b	7	0	7	0	0	27	No	3	8	1,2,5,10,11,12,13	AC:1,2,5
21	8	0	8	0	0	27	No	1	8	1,2,5,6,10,11,12,13	AC:1,2
22	9	0	9	0	0	27	No	1	8	1,2,5,6,7,10,11,12,13	AC:1,2
23	10	0	10	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12, 13	AC:1,2
24	2	0	0	2	0	16	Yes	1(All)	5(FF)	1,2	All
25	3	0	0	3	0	16	No	0	5	1,2,3	None
26	4	0	0	4	0	16	No	0	5	1,2,3,4	None
27	5	0	0	5	0	16	No	0	5	1,2,3,4,5	None
28	6	0	0	6	0	25	No	0	7	7,8,9,10,11,12	None
29	2	0	0	0	2	25	Yes	1	7	1,2	All
30	3	0	0	0	3	25	No	0	7	1,2,4	None
31	4	0	0	0	4	25	No	0	7	1,2,4,6	None
32	5	0	0	0	5	25	No	0	7	1,2,3,4,6	None
33	6	0	0	0	6	25	No	0	7	1,2,3,4,5,6	None
34	2	1	1	0	0	6	Yes	1(All)	FF	-	All

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
Experimental Plan Code No.	Total No. of Variables	Number of Variables at 2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Are All Main Effects Independent of 2-Factor Interactions?	Number of Independent Two-Factor Interactions Under Assumed Model	**Master** Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
35a	3	1	2	0	0	9	No	0	3	1,2,8	None
35b	3	1	2	0	0	18	Yes	3(All)	6(FF)	1,2,14	All
36a	4	1	3	0	0	9	No	0	3	1,2,3,8	None
36b	4	1	3	0	0	27	Yes	3	8	1,2,5,13*	AC:1,2,5 or WAO:1
36c	4	1	3	0	0	27	No	3	8	1,2,5,8*	WAO:1
37a	5	1	4	0	0	16	No	0	5	6,7,8,9,25	None
37b	5	1	4	0	0	27	No	3	8	1,2,5,10,13*	AC:1,2,5
37c	5	1	4	0	0	27	No	4	8	1,2,5,8,9*	WAO:1
38a	6	1	5	0	0	18	No	0	6	1,2,3,4,5,14	None
38b	6	1	5	0	0	27	No	3	8	1,2,5,10,11,13*	AC:1,2,5
39a	7	1	6	0	0	18	No	0	6	1,2,3,4,5,6,14	None
39b	7	1	6	0	0	27	No	3	8	1,2,5,10,11,12,13*	AC:1,2,5
40	8	1	7	0	0	27	No	1	8	1,2,5,6,10,11,12,13*	AC:1,2
41	9	1	8	0	0	27	No	1	8	1,2,5,6,7,10,11,12,13*	AC:1,2
42	10	1	9	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12,13*	AC:1,2
43a	3	2	1	0	0	8	No	0	2	2,6,7	None
43b	3	2	1	0	0	12	Yes	3(All)	4	-	All
44a	4	2	2	0	0	9	No	0	3	1,2,7,8	None
44b	4	2	2	0	0	27	Yes	3	8	1,2,5,13*	AC:1,2,5, or WAO:1
44c	4	2	2	0	0	27	No	3	8	1,2,5,8*	WAO:1

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
		Number of Variables at						Number of			
Experimental Plan Code No.	Total No. of Variables	2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Are All Main Effects Independent of 2-Factor Interactions?	Independent Two-Factor Interactions Under Assumed Model	Master Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
45a	5	2	3	0	0	16	No	0	5	6,7,8,24,25	None
45b	5	2	3	0	0	27	No	3	8	1,2,5,10,13*	AC:1,2,5
45c	5	2	3	0	0	27	No	4	8	1,2,5,8,9*	WAO:1
46a	6	2	4	0	0	16	No	0	5	6,7,8,9,24,25	None
46b	6	2	4	0	0	27	No	3	8	1,2,5,10,11,13*	AC:1,2,5
47a	7	2	5	0	0	18	No	0	6	1,2,3,4,5,13,14	None
47b	7	2	5	0	0	27	No	3	8	1,2,5,10,11,12,13*	AC:1,2,5
48	8	2	6	0	0	27	No	1	8	1,2,5,6,10,11,12,13*	AC:1,2
49	9	2	7	0	0	27	No	1	8	1,2,5,6,7,10,11,12,13*	AC:1,2
50	10	2	8	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12, 13*	AC:1,2
51a	4	3	1	0	0	8	No	0	2	2,6,7,8	None
51b	4	3	1	0	0	24	Yes	6(All)	FF	-	All
52a	5	3	2	0	0	16	No	0	5	6,7,23,24,25	None
52b	5	3	2	0	0	27	No	3	8	1,2,5,10,13*	AC:1,2,5
52c	5	3	2	0	0	27	No	4	8	1,2,5,8,9*	WAO:1
53a	6	3	3	0	0	16	No	0	5	6,7,8,23,24,25	None
53b	6	3	3	0	0	27	No	3	8	1,2,5,10,11,13*	AC:1,2,5
54a	7	3	4	0	0	16	No	0	5	6,7,8,9,23,24,25	None
54b	7	3	4	0	0	27	No	3	8	1,2,5,10,11,12,13*	AC:1,2,5
55	8	3	5	0	0	27	No	1	8	1,2,5,6,10,11,12,13*	AC:1,2

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
		Number of Variables at						Number of			
Experimental Plan Code No.	Total No. of Variables	2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Are All Main Effects Independent of 2-Factor Interactions?	Independent Two-Factor Interactions Under Assumed Model	**Master** Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
56	9	3	6	0	0	27	No	1	8	1,2,5,6,7,10,11,12,13*	AC:1,2
57	10	3	7	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12, 13*	AC:1,2
58a	5	4	1	0	0	8	No	0	2	2,6,7,8,9	None
58b	5	4	1	0	0	27	No	3	8	1,2,5,10,12*	AC:1,2,3
58c	5	4	1	0	0	27	No	4	8	1,2,5,8,9*	WAO:1
59a	6	4	2	0	0	16	No	0	5	6,7,12,13,14,15	None
59b	6	4	2	0	0	27	No	3	8	1,2,5,10,11,13*	AC:1,2,5
60a	7	4	3	0	0	16	No	0	5	6,7,8,12,13,14,15	None
60b	7	4	3	0	0	27	No	3	8	1,2,5,10,11,12,13*	AC:1,2,5
61	8	4	4	0	0	27	No	1	8	1,2,5,6,10,11,12,13*	AC:1,2
62	9	4	5	0	0	27	No	1	8	1,2,5,6,7,10,11,12,13*	AC:1,2
63	10	4	6	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12, 13*	AC:1,2
64a	6	5	1	0	0	16	No	0	5	6,21,22,23,24,25	None
64b	6	5	1	0	0	27	No	3	8	1,2,5,10,11,13*	AC:1,2,5
65a	7	5	2	0	0	16	No	0	5	6,7,21,22,23,24,25	None
65b	7	5	2	0	0	27	No	3	8	1,2,5,10,11,12,13*	AC:1,2,5
66a	8	5	3	0	0	16	No	0	5	6,7,8,21,22,23,24,25	None
66b	8	5	3	0	0	27	No	1	8	1,2,5,6,10,11,12,13*	AC:1,2

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
Experimental Plan Code No.	Total No. of Variables	Number of Variables at 2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Are All Main Effects Independent of 2-Factor Interactions?	Number of Independent Two-Factor Interactions Under Assumed Model	Master Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
67	9	5	4	0	0	27	No	1	8	1,2,5,6,7,10,11,12,13*	AC:1,2
68	10	5	5	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12, 13*	AC:1,2
69a	7	6	1	0	0	16	No	0	5	6,20,21,22,23,24,25	None
69b	7	6	1	0	0	27	No	3	8	1,2,5,10,11,12,13*	AC:1,2,5
70a	8	6	2	0	0	16	No	0	5	6,7,20,21,22,23,24,25	None
70b	8	6	2	0	0	27	No	1	8	1,2,5,6,10,11,12,13*	AC:1,2
71a	9	6	3	0	0	16	No	0	5	6,7,8,20,21,22,23,24, 25	None
71b	9	6	3	0	0	27	No	1	8	1,2,5,6,7,10,11,12,13*	AC:1,2
72	10	6	4	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12, 13*	AC:1,2
73a	8	7	1	0	0	16	No	0	5	6,19,20,21,22,23,24,25	None
73b	8	7	1	0	0	27	No	1	8	1,2,5,6,10,11,12,13*	AC:1,2
74a	9	7	2	0	0	16	No	0	5	6,7,19,20,21,22,23,24, 25	None
74b	9	7	2	0	0	27	No	1	8	1,2,5,6,7,10,11,12,13*	AC:1,2
75	10	7	3	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12, 13*	AC:1,2
76a	9	8	1	0	0	16	No	0	5	6,18,19,20,21,22,23, 24,25	None
76b	9	8	1	0	0	27	No	1	8	1,2,5,6,7,10,11,12,13*	AC:1,2

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
Experimental Plan Code No.	Total No. of Variables	Number of Variables at 2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Are All Main Effects Independent of 2-Factor Interactions?	Number of Independent Two-Factor Interactions Under Assumed Model	Master Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
77a	10	8	2	0	0	16	No	0	5	6,7,18,19,20,21,22,23, 24,25	None
77b	10	8	2	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12, 13*	AC:1,2
78a	10	9	1	0	0	16	No	0	5	6,17,18,19,20,21,22, 23,24,25	None
78b	10	9	1	0	0	27	No	1	8	1,2,5,6,7,8,10,11,12, 13*	AC:1,2
79	2	1	0	1	0	8	Yes	1(All)	2(FF)	1,9	All
80a	3	1	0	2	0	16	No	0	5	1,2,25	None
80b	3	1	0	2	0	32	Yes	3(All)	9(FF)	1,2,46	All
81	4	1	0	3	0	16	No	0	5	1,2,3,25	None
82	5	1	0	4	0	16	No	0	5	1,2,3,4,25	None
83	6	1	0	5	0	25	No	0	7	7,8,9,10,11,24	None
84a	3	2	0	1	0	8	No	0	2	1,8,9	None
84b	3	2	0	1	0	16	Yes	3(All)	5(FF)	1,24,25*	All
85	4	2	0	2	0	16	No	0	5	1,2,24,25	None
86	5	2	0	3	0	16	No	0	5	1,2,3,24,25	None
87	6	2	0	4	0	16	No	0	5	1,2,3,4,24,25	None
88a	4	3	0	1	0	8	No	0	2	1,7,8,9	None
88b	4	3	0	1	0	32	Yes	6(All)	9(FF)	1,22,23,46	All

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
		Number of Variables at									
Experimental Plan Code No.	Total No. of Variables	2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Are All Main Effects Independent of 2-Factor Interactions?	Number of Independent Two-Factor Interactions Under Assumed Model	Master Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
89	5	3	0	2	0	16	No	0	5	1,2,24,25	None
90	6	3	0	3	0	16	No	0	5	1,2,3,23,24,25	None
91	5	4	0	1	0	8	No	0	2	1,6,7,8,9	None
92	6	4	0	2	0	16	No	0	5	1,2,22,23,24,25	None
93	6	5	0	1	0	16	No	0	5	1,21,22,23,24,25	None
94	2	0	1	1	0	12	Yes	1(All)	FF	-	All
95	3	0	1	2	0	16	No	0	5	1,2,10	None
96	4	0	1	3	0	16	No	0	5	1,2,3,10	None
97	5	0	1	4	0	16	No	0	5	1,2,3,4,10	None
98	6	0	1	5	0	25	No	0	7	7,8,9,10,11,18	None
99	3	0	2	1	0	16	No	0	5	1,9,10	None
100	4	0	2	2	0	16	No	0	5	1,2,9,10	None
101	5	0	2	3	0	16	No	0	5	1,2,3,9,10	None
102	6	0	2	4	0	25	No	0	7	7,8,9,10,17,18	None
103	4	0	3	1	0	16	No	0	5	1,8,9,10	None
104	5	0	3	2	0	16	No	0	5	1,2,8,9,10	None

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
		Number of Variables at									
Experimental Plan Code No.	Total No. of Variables	2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required	Are All Main Effects Independent of 2-Factor Interactions?	Number of Independent Two-Factor Interactions Under Assumed Model	Master Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
105	6	0	3	3	0	25	No	0	7	7,8,9,16,17,18	None
106	5	0	4	1	0	16	No	0	5	1,7,8,9,10	None
107	6	0	4	2	0	25	No	0	7	7,8,15,16,17,18	None
108	6	0	5	1	0	25	No	0	7	7,14,15,16,17,18	None
109a	3	1	1	1	0	16	No	0	5	1,7,25	None
109b	3	1	1	1	0	24	Yes	3(All)	FF	-	All
110	4	1	1	2	0	16	No	0	5	1,2,8,25	None
111	5	1	1	3	0	16	No	0	5	1,2,3,9,25	None
112	6	1	1	4	0	25	No	0	7	7,8,9,10,17,24	None
113	4	1	2	1	0	16	No	0	5	1,8,9,25	None
114	5	1	2	2	0	16	No	0	5	1,2,8,9,25	None
115	6	1	2	3	0	25	No	0	7	7,8,9,16,17,24	None
116	5	1	3	1	0	16	No	0	5	1,7,8,9,25	None
117	6	1	3	2	0	25	No	0	7	7,8,15,16,17,24	None
118	6	1	4	1	0	25	No	0	7	7,14,15,16,17,24	None
119	4	2	1	1	0	16	No	0	5	1,7,24,25	None

INDEX OF EXPERIMENTAL PLANS

1	2	3a	3b	3c	3d	4	5	6	8	9	10
		Number of Variables at					Are All Main Effects Independent of 2-Factor Interactions?	Number of Independent Two-Factor Interactions Under Assumed Model			
Experimental Plan Code No.	Total No. of Variables	2 Levels	3 Levels	4 Levels	5 Levels	Number of Tests Required			Master Plan No.	Using Columns Number	Columns From Which 2-Factor Interactions Can Be Estimated
120	5	2	1	2	0	16	No	0	5	1,2,8,24,25	None
121	6	2	1	3	0	16	No	0	5	1,2,3,9,24,25	None
122	5	2	2	1	0	16	No	0	5	1,7,8,24,25	None
123	6	2	2	2	0	16	No	0	5	1,2,8,9,24,25	None
124	6	2	3	1	0	16	No	0	5	1,7,8,9,24,25	None
125	5	3	1	1	0	16	No	0	5	1,7,23,24,25	None
126	6	3	1	2	0	16	No	0	5	1,2,8,23,24,25	None
127	6	3	2	1	0	16	No	0	5	1,7,8,23,24,25	None
128	6	4	1	1	0	16	No	0	5	1,7,22,23,24,25	None

B Detailed Master Plans

MASTER
PLAN 1: 4 trials

123
000
011
101
110

MASTER
PLAN 2: 8 trials

1	2	3456789
0	0	0000000
0	0	0001111
1	1	0110011
1	1	0111100
2	2	1010101
2	2	1011010
3	1	1100110
3	1	1101001

MASTER
PLAN 3: 9 trials

1234	5678
0000	0000
0112	0110
0221	0001
1011	1011
1120	1110
1202	1000
2022	0000
2101	0101
2210	0010

MASTER
PLAN 4: 12 trials

12345	11 678901
00000	000000
11011	100010
01101	110001
10110	111000
01011	011100
00101	101110
00010	110111
10001	011011
11000	101101
11100	010110
01110	001011
10111	000101

MASTER
PLAN 5: 16 trials

12345	678910	11111 12345	11112 67890	22222 12345
00000	00000	00000	00000	00000
01123	01121	00001	10111	01110
02231	02211	00010	11011	10011
03312	01112	00011	01100	11101
10111	10111	01100	00110	11011
11032	11012	01101	10001	10101
12320	12120	01110	11101	01000
13203	11201	01111	01010	00110
20222	20222	10100	01011	01101
21301	21101	10101	11100	00011
22013	22011	10110	10000	11110
23130	21110	10111	00111	10000
30333	10111	11000	01101	10110
31210	11210	11001	11010	11000
32102	12102	11010	10110	00101
33021	11021	11011	00001	01011

MASTER
PLAN 6: 18 trials

	11111
1234567	8901234
0000000	0000000
0112111	0110111
0221222	0001000
1011120	1011100
1120201	1100001
1202012	1000010
2022102	0000100
2101210	0101010
2210021	0010001
0021011	0001011
0100122	0100100
0212200	0010000
1002221	1000001
1111002	1111000
1220110	1000110
2010212	0010010
2122020	0100000
2201101	0001101

MASTER
PLAN 7: 25 trials

123456	111 789012	111111 345678	122222 901234
000000	000000	000000	000000
011234	011230	011220	011110
022413	022013	022012	011011
033142	033102	022102	011101
044321	000321	000221	000111
101111	101111	101111	101111
112340	112300	112200	111100
123024	123020	122020	111010
134203	130203	120202	110101
140432	100032	100022	100011
202222	202222	202222	101111
213401	213001	212001	111001
224130	220130	220120	110110
230314	230310	220210	110110
241043	201003	201002	101001
303333	303333	202222	101111
314012	310012	210012	110011
320241	320201	220201	110101
331420	331020	221020	111010
342104	302100	202100	101100
404444	000000	000000	000000
410123	010123	010122	010111
421302	021302	021202	011101
432031	032031	022021	011011
443210	003210	002210	001110

MASTER
PLAN 8: 27 trials

00000	00001	111	11111	12222	222
12345	67890	123	45678	90123	456
00000	00000	000	00000	00000	000
00001	12121	212	00001	10101	010
00002	21212	121	00000	01010	101
01120	00111	122	01100	00111	100
01121	12202	001	01101	10000	001
01122	21020	210	01100	01000	010
02210	00222	211	00010	00000	011
02211	12010	120	00011	10010	100
02212	21101	002	00010	01101	000
10110	11001	111	10110	11001	111
10111	20122	020	10111	00100	000
10112	02210	202	10110	00010	000
11200	11112	200	11000	11110	000
11201	20200	112	11001	00000	110
11202	02021	021	11000	00001	001
12020	11220	022	10000	11000	000
12021	20011	201	10001	00011	001
12022	02102	110	10000	00100	110
20220	22002	222	00000	00000	000
20221	01120	101	00001	01100	101
20222	10211	010	00000	10011	010
21010	22110	011	01010	00110	011
21011	01201	220	01011	01001	000
21012	10022	102	01010	10000	100
22100	22221	100	00100	00001	100
22101	01012	012	00101	01010	010
22102	10100	221	00100	10100	001

MASTER
PLAN 9: 32 trials

123456789	111111111 012345678	12222 90123	22222 45678	23333 90123	33333 45678	34444 90123	44 45	4444 6789
000000000	000000000	00000	00000	00000	00000	00000	00	0000
011231111	011211111	00001	10111	01110	01101	10110	11	0000
022312222	022112222	00010	11011	10011	10110	11011	01	0000
033123333	011121111	00011	01100	11101	11011	01101	10	0000
101111032	101111012	01100	00110	11011	01100	01101	01	0011
110320123	110120121	01101	10001	10101	00001	11011	10	0011
123203210	121201210	01110	11101	01000	11010	10110	00	0011
132032301	112012101	01111	01010	00110	10111	00000	11	0011
202223102	202221102	10100	01011	01101	11001	10001	01	0101
213012013	211012011	10101	11100	00011	10100	00111	10	0101
220131320	220111120	10110	10000	11110	01111	01010	00	0101
231300231	211100211	10111	00111	10000	00010	11100	11	0101
303332130	101112110	11000	01101	10110	10101	11100	00	0110
312103021	112101021	11001	11010	11000	11000	01010	11	0110
321020312	121020112	11010	10110	00101	00011	00111	01	0110
330211203	110211201	11011	00001	01011	01110	10001	10	0110
002130213	002110211	00000	01010	11110	00010	10111	10	1111
013301302	011101102	00001	11101	10000	01111	00001	01	1111
020222031	020222011	00010	10001	01101	10100	01100	11	1111
031013120	011011120	00011	00110	00011	11001	11010	00	1111
103021221	101021221	01100	01100	00101	01110	11010	11	1101
112210330	112210110	01101	11011	01011	00011	01100	00	1100
121333003	121111001	01110	10111	10110	11000	00001	10	1100
130102112	110102112	01111	00000	11000	10101	10111	01	1100
200313311	200111111	10100	00001	10011	11011	00110	11	1010
211122200	211122200	10101	10110	11101	10110	10000	00	1010
222001133	222001111	10110	11010	00000	01101	11101	10	1010
233230022	211210022	10111	01101	01110	00000	01011	01	1010
301202323	101202121	11000	00111	01000	10111	01011	10	1001
310033232	110011212	11001	10000	00110	11010	11101	01	1001
323110101	121110101	11010	11100	11011	00001	10000	11	1001
332321010	112121010	11011	01011	10101	01100	00110	00	1001

APPENDIX B: PRETESTED INSTRUMENTS

This appendix contains a series of survey forms which have been successfully administered in different settings: mailout, central group interview, and home interview.

B.1 Mailout Surveys

The following surveys from a Wisconsin urban mode choice modeling project are included:

B.1 Shared Ride and Auto ($2^4 \cdot 4$)

B.2 Walk and Auto (2^6)

B.3 Bicycle and Auto (2^6)

B.4 Commuter Train and Auto (2^7)

B.5 Express Bus and Auto (2^7)

B.6 Local Bus and Auto (2^7)

All of these surveys have introductory pages identical to Figure B.7 and background questions similar to Figure B.8. All were used in a large study which obtained 9,000 responses to about 16,000 questionnaires sent out. These designs are generally simple and allow no interactions to be estimated; the type of design is indicated above.

Figures B.9 and B.10 show mailout designs used in an earlier study of inter-city travel in Wisconsin. These surveys received only a 15% response rate, but are shown as examples of the variables and levels used. By eliminating the page of explanation and by improving the layout of the experiment, the response rate could be substantially improved. Figure B.9 is a rail/bus/auto survey for business trips, which uses a $4^3 \cdot 2^4$ design. Similar versions were used for recreational and personal travel. Figure B.10 contains a pair of surveys for air/auto and auto alone, which use $2^4 \cdot 4$ and $2^3 \cdot 4$ designs, respectively. These also were created for personal, recreational and business trip purposes. Figures B.9 and B.10 illustrate surveys that address trip generation and destination issues in addition to mode choice. The experiments in Figures B.6, B.9 and B.10 appear to validate without adjustment, and thus can possibly be used without validation. The others should be validated in all cases, if possible.

B.2 Central Group Interview Materials

The following pages show materials used in a mode choice survey in Atlanta. The first three pages are a screening form used to recruit respondents to fill specific quotas of travel and socioeconomic characteristics. After recruitment, respondents completed the remaining portion of the survey in groups of ten at a central location, under the direction of an interviewer. A 5-minute slide presentation was used to introduce the material. Each situation was printed on a card (example shown), which was then placed on a board with the numbers "1" through "5". Respondents then recorded their responses on the survey form and continued with background questions.

Such surveys typically obtain 85% response rates from recruited individuals, but two or three times the desired number may have to be called on the telephone if specific demographic characteristics are desired. The survey has 32 situations; it is a $4^5 \cdot 2^4$ design, larger than is possible with mailout surveys.

Such materials can also be used in home interview surveys. However, home interviews are generally not necessary in DUA studies. In fact, much of the time is absorbed by the DUA experiment, during which the interviewer has little to do. The models derived from this survey appeared to require no validation adjustments.

FIGURE B.1.

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR SHARE A RIDE (CAR POOL/VAN POOL) TO WORK?

Consider that you are going to work and that driving alone or sharing a ride in a car pool or van pool are your only choices.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or share a ride to work.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or share a ride to work.

	AUTO FACTORS			CAR POOL/VAN POOL FACTORS		PLEASE– ANSWER IN THIS COLUMN HOW LIKELY ARE YOU TO DRIVE ALONE OR SHARE A RIDE? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Parking Cost to Drive Alone	People You Share A Ride With	Employee Work Schedule	Always Drive Alone	Probably Drive Alone	In-different	Probably Share A Ride	Always Share A Ride
SITUATION 1	Ample Supply	$1.30/gallon	Free	Co-Worker/ Neighbor	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	Free	General Public (Carpool Matching)	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 3	Ration of 10 gallons/week*	$2.00/gallon	$30/month	Co-Worker/ Neighbor	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 4	Ample Supply	$2.60/gallon	$30/month	Co-Worker/ Neighbor	Fixed 8 hour day	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$1.70/gallon	Free	Co-Worker/ Neighbor	Fixed 8 hour day	1	2	3	4	5
SITUATION 6	Ample Supply	$2.00/gallon	Free	General Public (Carpool Matching)	Fixed 8 hour day	1	2	3	4	5
SITUATION 7	Ample Supply	$1.70/gallon	$30/month	General Public (Carpool Matching)	Flexi-time (hours can vary daily)	1	2	3	4	5
SITUATION 8	Ration of 10 gallons/week*	$1.30/gallon	$30/month	General Public (Carpool Matching)	Fixed 8 hour day	1	2	3	4	5

***If your car gets 15 miles per gallon, you can travel 150 miles per week.**

OVER →

T-277D-80

FIGURE B.2.

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR WALK?

Consider a trip short enough so that driving alone in an automobile or walking are realistic choices.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or walk to make a one half or one mile trip.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or walk.

	AUTO FACTORS			WALK FACTORS			PLEASE– ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE ALONE IN AN AUTO OR WALK? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Average Wait Time at Station to Buy Gas	Length of Trip	Amount of Sidewalk on the Way	Season	Always Auto	Probably Auto	In-different	Probably Walk	Always Walk
SITUATION 1	Ample Supply	$1.30/gallon	5 minutes	½ mile	All the way	Winter	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	5 minutes	½ mile	Part way	Summer	1	2	3	4	5
SITUATION 3	Ration of 10 gallons/week*	$1.30/gallon	20 minutes	½ mile	Part way	Winter	1	2	3	4	5
SITUATION 4	Ample Supply	$2.60/gallon	20 minutes	1 mile	Part way	Winter	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$1.30/gallon	20 minutes	1 mile	All the way	Summer	1	2	3	4	5
SITUATION 6	Ample Supply	$1.30/gallon	5 minutes	1 mile	Part way	Summer	1	2	3	4	5
SITUATION 7	Ample Supply	$2.60/gallon	20 minutes	½ mile	All the way	Summer	1	2	3	4	5
SITUATION 8	Ration of 10 gallons/week*	$2.60/gallon	5 minutes	1 mile	All the way	Winter	1	2	3	4	5

*If your car gets 15 miles per gallon, you can travel 150 miles per week.

OVER →

T-277E-80

FIGURE B.3.

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR RIDE YOUR BIKE?

Consider a trip short enough so that driving alone in an automobile or riding a bicycle are realistic choices. Assume the weather is nice.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or ride a bike to make a one or three mile trip.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or ride a bike.

	AUTO FACTORS		BIKE FACTORS				PLEASE– ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE ALONE IN YOUR AUTO OR RIDE YOUR BIKE? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Length of Trip	Whether There is a Bike Lane	Street Surface	Level of Auto and Truck Traffic Along Route	Always Auto	Probably Auto	In-different	Probably Bike	Always Bike
SITUATION 1	Ample Supply	$2.60/gallon	3 miles	Marked bike lane in street	Smooth	Quiet	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	1 mile	Marked bike lane in street	Smooth	Busy	1	2	3	4	5
SITUATION 3	Ration of 10 gallons/week*	$1.30/gallon	3 miles	None	Smooth	Busy	1	2	3	4	5
SITUATION 4	Ample Supply	$2.60/gallon	1 mile	None	Rough	Busy	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$1.30/gallon	1 mile	Marked bike lane in street	Rough	Quiet	1	2	3	4	5
SITUATION 6	Ample Supply	$1.30/gallon	1 mile	None	Smooth	Quiet	1	2	3	4	5
SITUATION 7	Ample Supply	$1.30/gallon	3 miles	Marked bike lane in street	Rough	Busy	1	2	3	4	5
SITUATION 8	Ration of 10 gallons/week*	$2.60/gallon	3 miles	None	Rough	Quiet	1	2	3	4	5

*If your car gets 15 miles per gallon, you can travel 150 miles per week.

T-277A-80

OVER →

FIGURE B.4.

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR RIDE A TRAIN TO WORK?

Consider that you are going to work in Milwaukee and that driving alone or taking a new commuter train service to work are your only choices. If you take the train, assume you drive to the train station and park your car there free.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or ride a new commuter train to work.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or take a new commuter train to work.

	AUTO FACTORS			TRAIN FACTORS					PLEASE– ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE AN AUTOMOBILE OR TAKE THE TRAIN? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Cost to Park Auto at Work	Train Fare —One Way—	Morning Train Arrival Times (AM)	Evening Train Departure Times (PM)	How You Get To Work from Downtown Train Station	Total Train Travel Time (Home to Work)	Always Auto	Probably Auto	In-different	Probably Train	Always Train
SITUATION 1	Ample Supply	$1.30/gallon	Free	$1.50	7:30 only	5:00 only	5 minute walk	Same as auto	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	Free	$2.50	7:30 only	5:00 only	10 minute bus ride	Same as auto	1	2	3	4	5
SITUATION 3	Ample Supply	$2.60/gallon	$30/month	$2.50	7:30 & 8:30	4:45 & 5:30	5 minute walk	Same as auto	1	2	3	4	5
SITUATION 4	Ample Supply	$2.60/gallon	$30/month	$1.50	7:30 only	5:00 only	10 minute bus ride	15 minutes slower than auto	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$1.30/gallon	$30/month	$1.50	7:30 & 8:30	4:45 & 5:30	10 minute bus ride	Same as auto	1	2	3	4	5
SITUATION 6	Ration of 10 gallons/week*	$2.60/gallon	Free	$1.50	7:30 & 8:30	4:45 & 5:30	5 minute walk	15 minutes slower than auto	1	2	3	4	5
SITUATION 7	Ration of 10 gallons/week*	$1.30/gallon	$30/month	$2.50	7:30 only	5:00 only	5 minute walk	15 minutes slower than auto	1	2	3	4	5
SITUATION 8	Ample Supply	$1.30/gallon	Free	$2.50	7:30 & 8:30	4:45 & 5:30	10 minute bus ride	15 minutes slower than auto	1	2	3	4	5

*If your car gets 15 miles per gallon, you can travel 150 miles per week.

OVER →

T-277-80

FIGURE B.5.

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR TAKE AN EXPRESS BUS TO WORK?

Consider that you are going to work in Madison and that driving alone or taking an express or commuter bus to work are your only choices. Assume you drive to where you pick up the express bus and can park there free.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or ride an express or commuter bus to work.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or take an express or commuter bus to work.

	AUTO FACTORS			BUS FACTORS				PLEASE– ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE AN AUTOMOBILE OR TAKE THE BUS? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Cost to Park Auto at Work	Bus Fare —One Way—	When Bus Arrives During Rush Hours and Leaves Down town	How You Get to Work from Downtown Express Bus Stop	Total Bus Travel Time (Home to Work)	Always Auto	Probably Auto	In-different	Probably Bus	Always Bus
SITUATION 1	Ample Supply	$1.30/gallon	Free	$1.00	Arrives 7:30 am Leaves 5:00 pm	5 minute walk	5 min. slower than auto	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	$30/month	$1.00	Arrives 7:30 am Leaves 5:00 pm	5 minute walk	15 min. slower than auto	1	2	3	4	5
SITUATION 3	Ample Supply	$2.60/gallon	$30/month	$2.00	Arrives 7:30 am Leaves 5:00 pm	10 minute bus ride	5 min. slower than auto	1	2	3	4	5
SITUATION 4	Ample Supply	$2.60/gallon	Free	$1.00	Every Hour on the hour	10 minute bus ride	15 min. slower than auto	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$1.30/gallon	Free	$2.00	Arrives 7:30 am Leaves 5:00 pm	10 minute bus ride	15 min. slower than auto	1	2	3	4	5
SITUATION 6	Ration of 10 gallons/week*	$2.60/gallon	Free	$2.00	Every hour on the hour	5 minute walk	5 min. slower than auto	1	2	3	4	5
SITUATION 7	Ration of 10 gallons/week*	$1.30/gallon	$30/month	$1.00	Every hour on the hour	10 minute bus ride	5 min. slower than auto	1	2	3	4	5
SITUATION 8	Ample Supply	$1.30/gallon	$30/month	$2.00	Every hour on the hour	5 minute walk	15 min. slower than auto	1	2	3	4	5

***If your car gets 15 miles per gallon, you can travel 150 miles per week.**

OVER →

T-277B-80

FIGURE B.6.

UNDER WHAT SITUATIONS WOULD YOU DRIVE ALONE OR TAKE THE BUS TO WORK?

Consider that you are going to work and that driving alone or taking the bus are your only choices. Assume there is a bus stop within three blocks of both your home and place of work.

Below are a number of factors describing eight different situations where you are faced with choosing whether to drive alone or ride the bus to work.

Look at each situation across the entire line and please answer in the last column to the right how likely you are to drive alone or take the bus to work.

	AUTO FACTORS			BUS FACTORS				PLEASE– ANSWER IN THIS COLUMN: HOW LIKELY ARE YOU TO DRIVE AN AUTOMOBILE OR TAKE THE BUS? (CIRCLE A NUMBER)				
	Gas Availability	Gas Price	Auto Parking Cost	Transfer	Bus Fare —One Way—	How Often Bus Comes During Rush Hours (runs on schedule)	Total Time Spent on Bus	Always Auto	Probably Auto	In-different	Probably Bus	Always Bus
SITUATION 1	Ample Supply	$1.30/gallon	Free	5 min. transfer	$ .40	Every 10 minutes	20 minutes more than auto	1	2	3	4	5
SITUATION 2	Ration of 10 gallons/week*	$2.60/gallon	Free	5 min. transfer	$ .80	Every 20 minutes	20 minutes more than auto	1	2	3	4	5
SITUATION 3	Ration of 10 gallons/week*	$1.30/gallon	$30/month	5 min. transfer	$ .80	Every 10 minutes	10 minutes more than auto	1	2	3	4	5
SITUATION 4	Ample Supply	$1.30/gallon	Free	No transfer	$ .80	Every 20 minutes	10 minutes more than auto	1	2	3	4	5
SITUATION 5	Ration of 10 gallons/week*	$2.60/gallon	Free	No transfer	$ .40	Every 10 minutes	10 minutes more than auto	1	2	3	4	5
SITUATION 6	Ample Supply	$2.60/gallon	$30/month	5 min. transfer	$ .40	Every 20 minutes	10 minutes more than auto	1	2	3	4	5
SITUATION 7	Ration of 10 gallons/week*	$1.30/gallon	$30/month	No transfer	$ .40	Every 20 minutes	20 minutes more than auto	1	2	3	4	5
SITUATION 8	Ample Supply	$2.60/gallon	$30/month	No transfer	$ .80	Every 10 minutes	20 minutes more than auto	1	2	3	4	5

***If your car gets 15 miles per gallon, you can travel 150 miles per week.**

OVER →

T-277C-80

FIGURE B.7.

State of Wisconsin \ DEPARTMENT OF TRANSPORTATION

OFFICE OF THE SECRETARY

ADDRESS INQUIRIES TO:

William Hyman
Division of Planning & Budget
P. O. Box 7913
Madison, WI 53707
(608) 266-9657

Dear Wisconsin Motorist:

Because of inflation and a tight budget, we are faced with difficult decisions on how to best meet Wisconsin's transportation needs.

Please take a few minutes and say how you would respond to the situations presented on the next page. Also, please answer the questions on the back and return the completed questionnaire with your driver's license renewal. Your views are important and we will take them directly into account as we plan and budget for the future.

BE ASSURED THAT YOUR RESPONSES WILL BE KEPT COMPLETELY CONFIDENTIAL. Thank you for your time and cooperation.

Sincerely,

Lowell B. Jackson

Lowell B. Jackson, P.E.
Secretary

P.S. If you do not need a vision test, please mail the completed questionnaire back with your license renewal. If you require a vision test, bring the completed questionnaire to the license examiner's office near you. Thank you.

FIGURE B.8.

PLEASE ALSO ANSWER THE FOLLOWING QUESTIONS:

1. How do you usually get to work? *(check one)*:

☐ 1. Drive alone
☐ 2. Bus
☐ 3. Carpool (with ____ people).
☐ 4. Vanpool (with ____ people)
☐ 5. Share a ride with family member.
☐ 6. Bicycle
☐ 7. Motorcycle
☐ 8. Walk
☐ 9. Taxi
☐ 10. Do not work outside home
☐ 11. Other *(please specify)*: ____________

2. Where do you live? City ____________ Zip code ________

3. Where do you work? City ____________ Zip code ________ ☐ Not applicable

4. About how far is it from your home to work in miles? ______ miles ☐ Not applicable

5. How many miles per gallon does the motor vehicle you drive most often get?

______ miles per gallon *(city driving)* ☐ Not applicable

6. How old are you ? ________ years

7. What is your sex? ☐ Male ☐ Female

8. Do you have any disabilities that prevent you from taking the bus? ☐ Yes ☐ No

9. How many people are in your household? ______ adults *(16 and over)* ______ children *(under 16)*

10. How many motor vehicles does your household own? ______ vehicles

11. How much must you pay to park at work? $ ________ /month ☐ Do not work

12. About how far from your home is the nearest bus route or park and ride stop where you can pick up a bus to work? ______ Blocks ☐ Not applicable

What is the name of the bus route? ____________________

13. About how far from your work place is the nearest bus stop? ______ Blocks ☐ Not applicable

14. Must you transfer buses between home and work? ☐ Yes ☐ No ☐ Not applicable

15. How often does the nearest bus come during rush hour? Every ________ minutes ☐ Not applicable

16. How long does the nearest bus take to go to work compared to driving alone?

______ minutes slower
______ minutes faster
☐ the same amount of time
☐ Not applicable

17. What is your total household income before taxes? *(optional)*

☐ Under $5,000
☐ $5,000-$9,999
☐ $10,000-$14,999
☐ $15,000-$19,999
☐ $20,000 - $24,999
☐ $25,000-$29,999
☐ $30,000-$39,999
☐ $40,000- and over

COMMENTS: *(optional)*:

THANK YOU FOR COMPLETING THE QUESTIONNAIRE

FIGURE B.9.

BUSINESS TRAVEL SURVEY

The Wisconsin Department of Transportation is developing plans to meet Wisconsin's transportation needs in the face of potential energy problems. We would appreciate your help. Please answer this questionnaire and return it to us with your driver's license renewal. Thank you for your time and cooperation. If you have any questions about completing this survey, please call Jim Etmanczyk at (608)-266-1167.

Roger D Schrantz
R. L. Schrantz, Administrator
Division of Planning and Budget

The purpose of this survey is to obtain your reaction to using bus or train services for business travel, given various levels of gasoline prices and availability.

We want you to think about what you would do if you were making a business trip which is 100 miles one-way. A business trip is travel for your business or employer. We will describe various situations and ask you how likely you are to make the trip by auto or by train or bus, and how likely you are to make the trip at all.

The train and bus services that we are describing are not necessarily those that currently exist, but which could exist to meet Wisconsin's travel needs. For this survey, consider that a train would be available from your city or town to many locations. You would drive to the train station near your home to begin your trip; inexpensive parking would be available. No reservations are necessary; baggage may be checked. At the end of your trip, a bus, local taxi, or rental car is available to take you to your final location.

Bus service would also be available to many locations. You would drive to the bus station; you may check baggage and no reservations are necessary. Buses, local taxis, or rental cars are available at the end of your trip.

Seven factors make up the situations we are presenting to you. The first two factors define the situation for driving your car, and the next five factors describe the bus or train service available. The factors are:

1. Gas Availability - Gas is either available:

   a. Every Day, without restrictions, as it has been in the past.

   b. Alternate Days, using an odd/even license plate rule.

   c. Rationing, in which your household received 12 gallons of gas per car per week, this is the plan proposed in Congress.

   d. Rationing, in which your household received 20 gallons of gas per car per week.

2. Gas Price - Gas costs either:

   a. $1.30/gallon or $20 for the total trip.

   b. $2.60/gallon or $40 for the total trip.

The next factors describe the bus or train:

3. Form of Travel

   Either train or bus.

4. Total Cost

   The bus or train fare is either $10, $15, $20, $25. This price is the round trip fare for one adult. In those situations in which rental car is the only way to get around during the day, its extra cost had been added in the total cost.

5. Time Spent in the Bus or Train

   The bus or train either takes the same time, one half, or one and one half hours longer than driving your car from your home to your destination.

6. Bus or Train Schedule Convenience

   The bus or train either operates exactly when you want to travel, or two hours later than you would prefer to leave.

7. Transportation at the End of Your Trip

   This is how you get around at your destination. With local taxi you might share the ride with other people. Its cost is included in the total cost of the trip by bus or train.

   A rental car might be the only available option in some cases. Its cost is included in the total cost.

FIGURE B.9 (cont.)

Below are the seven factors describing different situations with various bus and train services available. We would like you to consider yourself in each situation. Once again, you are taking a business trip which is 100 miles one-way and assume the bus and train will be available for your trip. Look at each situation across the entire line, and then answer a) how likely are you to drive your auto or use the bus or train, and b) how likely are you to make the trip at all. Please answer both questions for all sixteen situations and the questions on the following pages.

AUTO FACTORS		BUS OR TRAIN FACTORS					YOUR CHOICES		
Gas Availability	Gas Price	Form of Travel	Total Cost (Including Taxi or Rental Car)	Time Spent In The Bus or Train	Bus or Train Schedule Convenience	Transportation At End Of Trip	How Likely Are You To Use Your Auto or Bus/Train? (Circle One) Probably Auto … Probably Bus/Train	How Likely Are You To Make the Trip At All? (Circle One) Probably Wouldn't Go … Probably Would Go	For Office Use
Every Day	$40	Train	$20	1/2 Hour More	2 Hours Later	Taxi	1 2 3 4 5	1 2 3 4 5	
Alternate Days	$40	Bus	$25	1 1/2 Hours More	When You Want	Taxi	1 2 3 4 5	1 2 3 4 5	
Alternate Days	$20	Train	$15	1 Hour More	2 Hours Later	Taxi	1 2 3 4 5	1 2 3 4 5	
20 Gals.Per Week	$40	Train	$30	1 1/2 Hours More	2 Hours Later	Rental Car	1 2 3 4 5	1 2 3 4 5	
12 Gals.Per Week	$20	Train	$45	Same as Auto	2 Hours Later	Rental Car	1 2 3 4 5	1 2 3 4 5	
20 Gals.Per Week	$20	Train	$25	1/2 Hour More	When You Want	Taxi	1 2 3 4 5	1 2 3 4 5	
Alternate Days	$40	Train	$40	Same as Auto	When You Want	Rental Car	1 2 3 4 5	1 2 3 4 5	
Every Day	$20	Bus	$10	Same as Auto	When You Want	Taxi	1 2 3 4 5	1 2 3 4 5	
12 Gals.Per Week	$40	Bus	$35	1/2 Hour More	When You Want	Rental Car	1 2 3 4 5	1 2 3 4 5	
20 Gals.Per Week	$40	Bus	$15	Same as Auto	2 Hours Later	Taxi	1 2 3 4 5	1 2 3 4 5	
12 Gals.Per Week	$20	Bus	$20	1 1/2 Hours More	2 Hours Later	Taxi	1 2 3 4 5	1 2 3 4 5	
Every Day	$20	Train	$35	1 1/2 Hours More	When You Want	Rental Car	1 2 3 4 5	1 2 3 4 5	
Alternate Days	$20	Bus	$30	1/2 Hour More	2 Hours Later	Rental Car	1 2 3 4 5	1 2 3 4 5	
12 Gals.Per Week	$40	Train	$10	1 Hour More	When You Want	Taxi	1 2 3 4 5	1 2 3 4 5	
Every Day	$40	Bus	$45	1 Hour More	2 Hours Later	Rental Car	1 2 3 4 5	1 2 3 4 5	
20 Gals.Per Week	$20	Bus	$40	1 Hour More	When You Want	Rental Car	1 2 3 4 5	1 2 3 4 5	

FIGURE B.9 (cont.)

NOW WE WOULD LIKE TO ASK YOU A FEW MORE QUESTIONS ABOUT YOUR BUSINESS TRAVEL PATTERNS AND ABOUT YOUR HOUSEHOLD

1. What is your family size?

   ___________ Adults ___________ Children (under 16)

2. How many business trips over 50 miles do you take per year? Count a round trip as one trip. ___________ trips

3. What is the average one-way length of these trips?

   ___________ Miles ___________ Hours/Minutes

4. In all the trips you have taken in the past year, have you ridden in: (Circle "Yes" or "No")

a.	A City Bus	Yes	No	d.	An Airplane	Yes	No
b.	An Intercity Bus (i.e. Greyhound)	Yes	No	e.	A Taxi	Yes	No
c.	A Train	Yes	No	f.	A Rental Car	Yes	No

5. In what city, village or township and county do you reside?

   City ___________________________ County ___________________________

6. How many autos does your family own? __________

7. What is the occupation of the major wage earner of the household?

Farmer	1	Service Worker	6
Professional or Technical	2	Operator or Laborer	7
Manager, Officer, or Proprietor	3	Homemaker, Student Military or Retired	8
Clerical or Sales	4	Other (specify__________)	9

8. What is your total family income before taxes:

☐ Under $5,000	☐ $5,000-$9,999	☐ $10,000-$14,999	☐ $15,000 $19,999
☐ $20,000-$24,999	☐ $25,000-$29,999	☐ $30,000-$49,999	☐ $50,000 and over

FIGURE B.9 (cont.)

9. If you were to make fewer long business trips due to energy problems, would you be more likely to:

- [ ] Use the telephone instead of making the trip
- [ ] Combine trips
- [ ] Use company representatives in the area.
- [ ] Other ______________________________

10. Do you favor a 50 mph speed limit in Wisconsin? (Circle One) Yes No

Why or why not? ______________________________

____

____

In your selection of any travel mode for a business trip which is 100 miles one-way, circle whether the factors listed below are not important at all, or "1", up to very important, or "5".

	Not at All Important				Very Important
Bus or Train Schedule Convenience	1	2	3	4	5
Gas Price	1	2	3	4	5
Cost of the Bus or Train	1	2	3	4	5
Free Parking at the Bus or Train Station	1	2	3	4	5
Bus of Train Station Cleanliness	1	2	3	4	5
Bus or Train Travel Time	1	2	3	4	5
Arriving and Leaving on Time	1	2	3	4	5
Baggage Space	1	2	3	4	5
Gas Availability	1	2	3	4	5
Comfort of the Bus or Train	1	2	3	4	5
Ease of Baggage Handling	1	2	3	4	5
Bus or Train Station Near Your Home	1	2	3	4	5
Having a Mode of Travel Available at Your Destination	1	2	3	4	5
Highway Congestion	1	2	3	4	5

FIGURE B.10.

RECREATION TRAVEL SURVEY

The Wisconsin Department of Transportation is developing plans to meet Wisconsin's transportation needs in the face of potential energy problems. We would appreciate your help. Please answer this questionnaire and return it to us with your driver's license renewal. Thank you for your time and cooperation. If you have any questions about completing this survey, please call Jim Etmanczyk at 608-266-1167.

R. L. Schrantz, Administrator
Division of Planning and Budget

The purpose of this survey is to obtain your reactions to using auto and airplane service for recreational travel, given various levels of gasoline prices and availability.

We want you to think about what you would do if you were making a weekend recreation trip from your city which is 200 miles one-way. We will describe various situations and ask you how likely you are to make the trip by auto or by airplane, and how likely you are to make the trip at all.

The airplane service that we are describing is not necessarily what currently exists, but is an alternative service which could exist to meet Wisconsin's travel needs. For this survey, consider the following:

> Airplane service is readily accessible from and to your locations. Reservations are suggested, but not required. You may check up to three pieces of baggage not to exceed 70 pounds each; recreational equipment, such as skis or camping gear, may also be checked. Bicycles may be checked for an additional fee, but the owner must assume responsibility. You may carry one small piece of baggage on board with you.

Various factors make up the situations we are presenting for you to rate your preferences of travel choices. Some describe the situation for driving your car, and some describe the air services available. The factors are explained here:

Auto Factors

1. Gas Availability - Gas is either available:
   a. Every day, without restrictions, as it has been in the past.
   b. Alternate days, assume gas stations are closed Friday and Sunday for your license plate number.
   c. Closed weekends, when all stations would be closed all day Saturday and Sunday.
   d. Rationing, in which your household received 12 gallons of gas per car per week; this is the plan proposed in Congress.
2. Gas Price - Gas costs either:
   a. \$1.30/gallon or \$40 for a 400 mile round trip.
   b. \$2.60/gallon or \$80 for a 400 mile round trip.
3. Wait Time to Obtain Gas

   You can either obtain gas when you want it, or you must wait in line for 30 minutes.
4. Highway Congestion

   There is either no significant highway congestion, or highway congestion is such that your trip takes one hour longer to complete.

Air Service Factors

1. Air Fare

   Air fare is either \$60 or \$120.
   This price includes round trip fare for two adults and two children.
2. Schedule Convenience

   The airplane departs either when you want to travel or two hours later than you would prefer to leave.
3. Time Spent in the Airplane

   The airplane either takes one or three hours less than driving your car from your home to your recreation area.

For Office Use

The following eight situations describe various alternatives of gas price and availability, and air service. We would like you to consider yourself in each situation taking a weekend recreation trip which is 200 miles in length one-way. Look at each situation across the entire line, and then answer a) how likely you are to drive your auto, or travel by airplane; and b) how likely you are to make the trip at all. Please answer both questions for all eight situations.

AUTO FACTORS		AIRPLANE FACTORS			YOUR CHOICES									
Gas Availability	Gas Cost	Air Fare	Airplane Schedule Convenience	Time Spent in the Airplane versus Auto	How Likely Are You to use Your Auto or Airplane (Circle One) Probably Auto				Probably Airplane	How Likely Are You To Make the Trip At All? (Circle One) Probably Wouldn't Go				Probably Would Go
Every Day	$80	$120	2 hours later	3 hours less	1	2	3	4	5	1	2	3	4	5
Closed Wkends	$40	$ 60	2 hours later	3 hours less	1	2	3	4	5	1	2	3	4	5
Closed Fri & Sun	$80	$ 60	2 hours later	1 hour less	1	2	3	4	5	1	2	3	4	5
Closed Fri & Sun	$40	$120	when you want	3 hours less	1	2	3	4	5	1	2	3	4	5
12 gals per wk	$40	$120	2 hours later	1 hour less	1	2	3	4	5	1	2	3	4	5
12 gals per wk	$80	$ 60	when you want	3 hours less	1	2	3	4	5	1	2	3	4	5
Every Day	$40	$ 60	when you want	1 hour less	1	2	3	4	5	1	2	3	4	5
Closed Wkends	$80	$120	when you want	1 hour less	1	2	3	4	5	1	2	3	4	5

The eight situations describe only auto alternatives. Again, considering yourself to be taking the same trip, read each situation but this time answer a) how likely you are to still make a long trip versus a shorter trip; and b) how likely you are to still make a trip at all. Note that this set of factors is concerned with auto travel <u>only</u>. Please answer both questions for all eight situations.

AUTO FACTORS				YOUR CHOICES									
Gas Availability	Gas Cost	Wait Time to Obtain Gas	Highway Congestion	How Likely Are You To Still Make a Long Trip Versus a Shorter Trip? (Circle One) Probably Long Trip				Probably Short Trip	How Likely Are You To Still Make a Trip At All? (Circle One) Probably Wouldn't Go				Probably Would Go
Every Day	$80	30 min.	Extra Hour	1	2	3	4	5	1	2	3	4	5
Closed Wkends	$40	0	Extra Hour	1	2	3	4	5	1	2	3	4	5
Closed Fri & Sun	$80	0	Extra Hour	1	2	3	4	5	1	2	3	4	5
Closed Fri & Sun	$40	30 min.	None	1	2	3	4	5	1	2	3	4	5
12 gals per wk	$40	30 min.	Extra Hour	1	2	3	4	5	1	2	3	4	5
12 gals per wk	$80	0	None	1	2	3	4	5	1	2	3	4	5
Every Day	$40	0	None	1	2	3	4	5	1	2	3	4	5
Closed Wkends	$80	30 min.	None	1	2	3	4	5	1	2	3	4	5

FIGURE B.10 (cont.)

NOW WE WOULD LIKE TO ASK YOU A FEW MORE QUESTIONS ABOUT

YOUR RECREATIONAL TRAVEL PATTERNS AND ABOUT YOUR HOUSEHOLD

1. If airplane service oriented to weekend recreation travel were provided, what would be the most convenient departure time for you on Fridays? __________ What would be the most convenient departure time for your return trip on Sundays? __________

2. What is the usual size of your traveling group on weekend recreational trips?

   __________ Adults __________ Children (under 16)

3. How many recreation trips over 50 miles do you take per year? Count a round trip as one trip; include vacation travel. __________ trips

4. What is the average one-way length of these trips?

   __________ Miles __________ Hours/Minutes

5. In all the trips you have taken in the past year, have you ridden in: (Circle "Yes" or "No")

a. A City Bus	Yes	No		d. An Airplane	Yes	No
b. An Intercity Bus (i.e. Greyhound)	Yes	No		e. A Taxi	Yes	No
				f. A Rental Car	Yes	No
c. A Train	Yes	No				

6. In what city, village or township and county do you reside?

   City ______________________ County ______________________

7. How many autos does your family own? __________

8. Does your family own a motor home or travel trailer? (Circle One)

   Yes No

9. Does your family own a second or vacation home? (Circle One)

   Yes No

10. What is the occupation of the major wage earner of the household?

Farmer	1	Service Worker	6
Professional or Technical	2	Operator or Laborer	7
Manager, Officer, or Proprietor	3	Homemaker, Student, Military or Retired	8
Clerical or Sales	4	Other (specify_________)	9
Craftsman or Foreman	5		

11. What is your total family income before taxes?

☐ Under $5,000	☐ $5,000-$9,999	☐ $10,000-$14,999	☐ $15,000-$19,999
☐ $20,000-$24,000	☐ $25,000-$29,999	☐ $30,000-$49,999	☐ $50,000 and over

12. If you were to make fewer long recreation trips due to energy problems, would you be more likely to: (Circle the one that applies)

Just stay home on those weekends or Take a shorter trip (How many miles ____________)

13. Do you favor a 50 mph speed limit in Wisconsin? (Circle One) Yes No

Why or why not? ____

____

____

In your selection of any travel mode for a recreation trip which is 200 miles one-way, circle whether the factors listed below are not important at all, or "1", up to very important, or "5".

	Not at All Important				Very Important
Airplane Schedule Convenience	1	2	3	4	5
Gas Price	1	2	3	4	5
Cost of the Airplane	1	2	3	4	5
Free Parking at the Airport	1	2	3	4	5
Airport Cleanliness	1	2	3	4	5
Airplane Travel Time	1	2	3	4	5
Arriving and Leaving on Time	1	2	3	4	5
Baggage Space for Your Recreation Equipment	1	2	3	4	5
Gas Availability	1	2	3	4	5
Comfort of the Airplane	1	2	3	4	5
Ease of Baggage Handling	1	2	3	4	5
Airport Near Your Home	1	2	3	4	5
Having a Mode of Travel Available at Your Destination	1	2	3	4	5
Highway Congestion	1	2	3	4	5

Card 01

NATIONAL ANALYSTS
A Division of Booz·Allen &
Hamilton Inc.

Study #: 1-016
OMB #: 004-S79001
Expires: Sept.,1979

Transit Study

- Screening Form -

INTRODUCTION: Hello, I'm ____________, representing National Analysts, a survey research firm located in Philadelphia, PA. We are conducting a survey in the Atlanta area for the U.S. Department of Transportation under the Urban Mass Transportation Act. The purpose of the survey is to gather information on people's attitudes toward public transit, which will be used to evaluate several forms of public transportation. This information will be used for statistical purposes only. Your participation in this important study is entirely voluntary, and, should you choose not to participate, there is no penalty to you. Your answers will remain strictly confidential.

1. Do you have an automobile available for your use? This includes owning a car, leasing a car, or having a business or government car available to you.

11

CONTINUE	Yes	1
TERMINATE SCREENING	No	2

2. Do you work in the downtown area of the city, that is, where there is a concentration of business establishments, shops, hotels and the like, or do you work in the outskirts of the city or in a suburb around the city?

12

	Work downtown	1
	Work outskirts of city	2
	Work in suburbs	3
SKIP TO Q.4	Do not work	4

3. What mode of transportation do you use most often to get to work?

13

CIRCLE ONLY ONE CODE

Bus	1
Auto	2
Other: SPECIFY ______ ______	0

4. How often to you go to the downtown area of the city for shopping, leisure or recreational events? Would you say:

14

Once a week or more,	1
Not once a week, but at least once a month, or	2
Less than once a month?	3

5. What mode of transportation do you use most often to go to the downtown area of the city for shopping, leisure or recreational events?

CIRCLE ONLY ONE CODE

15

Bus	1
Auto	2
Other: SPECIFY ______________	0

6. How often do you go to a major shopping center or recreational facility in the outskirts or suburbs around the city for shopping, leisure or recreational events? Would you say:

16

Once a week or more,	1
Not once a week, but at least once a month, or	2
Less than once a month?	3

7. What mode of transportation do you use most often to go to a major shopping center or recreational facility in the outskirts or suburbs around the city for shopping, leisure or recreational events?

CIRCLE ONLY ONE CODE

17

Bus	1
Auto	2
Other: SPECIFY ______________	0

8. What is your age?

ENTER # OF YEARS: ______________
18,19

9. What is your sex?

20

Male	1
Female	2

0. What is your race?

21

White	1
Black	2
Other: SPECIFY ______________	0

(11.) What was your total household income before taxes and other deductions last year, that is in 1978? Was it:

22

Under $5,000,	1
$5,000 - $9,999,	2
$10,000 - $14,999,	3
$15,000 - $19,999,	4
$20,000 - $24,999,	5
$25,000 - $29,999,	6
$30,000 - $49,999,or	7
$50,000 and over	8

RECRUIT ELIGIBLE PERSONS FOR FULL INTERVIEW ACCORDING TO THESE GROUPS:

A.	PERSONS WHO WORK IN DOWNTOWN AND USE BUSES TO GET THERE	→ Q.2 - CODE 1 AND Q.3 - CODE 1	USE VERSION 1
B.	PERSONS WHO WORK IN DOWNTOWN AND USE AUTO TO GET THERE	→ Q.2 - CODE 1 AND Q.3 - CODE 2	
C.	PERSONS WHO WORK IN OUTSKIRTS OR SUBURBS AROUND CITY	→ Q.2 - CODES 2 OR 3	USE VERSION 2
D.	PERSONS WHO SHOP/LEISURE IN DOWNTOWN AT LEAST ONCE A MONTH OR MORE OFTEN	→ Q.4 - CODES 1 OR 2	USE VERSION 3
E.	PERSONS WHO SHOP/LEISURE IN OUTSKIRTS OR SUBURBS AT LEAST ONCE A MONTH OR MORE OFTEN	→ Q.6 - CODES 1 OR 2	USE VERSION 4

RECORD GROUP LETTER HERE: ____________ 23

INTERVIEW DATE/TIME: ____________

Respondent's Name: ____________

Street Address: ____________

City: ____________ State: ____________ Zip Code: ____________

Telephone #: ____________

24

DATE OF SCREENING: ____________ INTERVIEWER'S NAME: ____________

End Card 01

Card 02

NATIONAL ANALYSTS
A Division of Booz.Allen &
Hamilton Inc.

Study #: 1-016
OMB#: 004-S79001
Expires: Sept., 1979

TRANSIT STUDY

This survey is being conducted by National Analysts, a survey research firm located in Philadelphia, PA. The survey is being conducted in the Atlanta area for the U.S. Department of Transportation, under the Urban Mass Transportation Act. The purpose of the survey is to gather data about people's attitudes toward public transit, which will be used to evaluate several forms of public transportation. This information will be used for statistical purposes only. Your participation in this important survey is entirely voluntary, and, should you choose not to participate, there is no penalty to you. Your answers will remain strictly confidential.

12-15 Time Began: _______	16 A.M.	1
	P.M.	2
17-20 Time Ended: _______	21 A.M.	1
	P.M.	2

Name: ______________________________

Street Address: ______________________________

Date: _______ / _______ / _______
MONTH DAY YEAR
22-23 24-25

PLEASE TURN THE PAGE
AND BEGIN READING

11

WORK/DOWNTOWN | 1

(1.) The purpose of this research study is to get your reactions to different types or modes of public transit. We will give you a set of cards which describe particular transit types or modes and ask you to rate each one. After you rate the cards, a few more questions will be asked.

Each transit mode we want you to rate has a variety of different features. When it comes to the specific features of transit modes, different people have different needs. We want you to think about what you would do if you were making a trip to the downtown area of the city, that is, where there is a concentration of business establishments, shops, hotels, etc., for the purpose of getting to work. Imagine you are making this trip by automobile and it takes 30 minutes. We will ask you to decide how likely it is that you would use the transit mode described to you for this purpose.

IN FRONT OF YOU ARE TWO SETS OF CARDS AND A SORT BOARD. PICK UP ONE SET OF CARDS AND WAIT FOR FURTHER EXPLANATION.

ONCE THE FEATURES HAVE BEEN EXPLAINED TO YOU, TURN THE PAGE AND CONTINUE READING.

CARD 1

TRANSIT MODE

Rail

FREQUENCY OF SERVICE

On demand - every 5 minutes

VEHICLE SIZE

4-6 passengers

TRAVEL TIME-DIFFERENCE FROM AUTO

15 minutes less

PRICE-DIFFERENCE FROM AUTO

$1.00 less

SEAT GUARANTEE

100% guaranteed

DISTANCE TO STATION/BUS STOP FROM HOME

One block

DISTANCE TO DESTINATION FROM STATION/BUS STOP OF ARRIVAL

One block

CARD 2

TRANSIT MODE

Rail

FREQUENCY OF SERVICE

Every 15 minutes

VEHICLE SIZE

10 passengers

TRAVEL TIME-DIFFERENCE FROM AUTO

15 minutes more

PRICE-DIFFERENCE FROM AUTO

$.50 more

SEAT GUARANTEE

100% guaranteed

DISTANCE TO STATION/BUS STOP FROM HOME

One block

DISTANCE TO DESTINATION FROM STATION/BUS STOP OF ARRIVAL

One block

The Sort Board

Look at the Sort Board in front of you. It is a piece of cardboard with five squares drawn on it. The squares are numbered from "1" to "5" to represent the five possible ratings you can give to a transit mode. Square number "5" is where you place the cards describing the transit modes which you would be "most likely to use". Square number "1" is where you place the cards describing the transit mode you would be "least likely to use". The squares marked "2", "3", and "4" are where you place the cards that you wish to rate somewhere between "1" and "5".

How to Place the Cards on the Sort Board

First, look at the cards briefly. You can see that some of the cards describe similar transit modes, but that no two cards are exactly alike. Imagine that you are making a trip to the downtown area of the city for the purpose of getting to work. Imagine you are making this trip by automobile and it takes 30 minutes. How likely is it that you would take each of the transit modes? As you decide on the ratings for each card, place that card on the appropriate square on the Sort Board.

Keep in mind these rules when placing the cards on the Sort Board:

1. All 16 cards must be placed on the Sort Board.
2. You may place as many or as few cards as you wish on any of the five squares.
3. Rate the transit mode <u>only</u> according to the features described on the cards. Assume that all features that are not listed on the cards are <u>identical for all transit modes</u>.

NOW RATE ALL 16 DESCRIPTIONS BY PLACING EACH ON ONE OF THE FIVE SQUARES. WHEN YOU FINISH PLACING ALL 16, TURN TO THE NEXT PAGE AND RECORD YOUR RATINGS BY LISTING THE CARD NUMBERS IN THE APPROPRIATE COLUMNS.

CARD 03

RATING SHEET (O.1)

1 Least Likely to Use	2	3	4	5 Most Likely to Use	1 Of- fic Use Onl
					13
					15
					17
					19
					21
					23
					25
					27
					29
					31
					33
					35
					37
					39
					41
					43

REMOVE ALL 16 CARDS FROM SORT BOARD AND PLACE RUBBER BAND AROUND THEM. TURN THE PAGE AND CONTINUE.

END CARD 0

(2.) How many persons are there in your household, including yourself?

NUMBER IN HOUSEHOLD: ____________
26-27

(3.) What was the last grade in school you completed?

28

8th grade or less	1
Some high school (9-11)	2
Completed high school (12)	3
Some college	4
Graduated college or beyond	5

(4.) Which one of these best describes your current occupation? (CIRCLE ONE AND ONLY ONE CODE)

29

Professional and Technical: (Examples: Accountants; computer programmers; civil, chemical, electrical engineers; lawyers; doctors; registered nurses; scientists; teachers; artists; clergy; religious education workers; etc.)	1
Managers, Officers and Proprietors: (Examples: Department heads; sales managers; administrators; executive buyers; company officers; etc.)	2
Farmers (owners and managers)	3
Clerical or Sales Workers: (Examples: Bank tellers; mail carriers; office machine operators; clerical workers; secretaries; sales persons; insurance and real estate agents; etc.)	4
Craftsmen and Foremen: (Examples: Carpenters; electricians; road equipment operators; mechanics and repairmen; painters; plumbers; telephone installers; tool and die makers; etc.)	5
Operatives: (Examples: Gas station attendants; bus, taxi, and truck drivers; food graders and packers; meat cutters; laundry operatives; etc.)	6
Service Workers and Other Similar Jobs: (Examples; Restaurant workers; janitors; car washers; groundskeepers; farm workers; laborers, etc.)	7
Homemakers; student; military service; retired	8
Some other occupation: Specify ____________	0

PLEASE TURN PAGE AND CONTINUE READING

PICK UP THE SECOND SET OF CARDS
AND READ THE INSTRUCTIONS BELOW

5. The next step is for you to rate the second set of descriptions in the same way you rated the first set. As you decide on a rating for each card, place that card on the appropriate square on the Sort Board.

Keep in mind the same rules you used before:

1. All 16 cards must be placed on the Sort Board.
2. You may place as many or as few as you wish on any of the five squares.
3. Rate the transit modes only according to the features described on the cards. Assume that all features that are not listed on the cards are identical for all transit modes.

NOW RATE ALL 16 DESCRIPTIONS BY PLACING EACH ON ONE OF THE FIVE SQUARES. WHEN YOU FINISH PLACING ALL 16, TURN TO THE NEXT PAGE AND RECORD YOUR RATINGS BY LISTING THE CARD NUMBERS IN THE APPROPRIATE COLUMNS.

Card 04

RATING SHEET (Q.5)

1 Least Likely to Use	2	3	4	5 Most Likely to Use	Of-fice Use Only 12
					13,14
					15,16
					17,18
					19,20
					21,22
					23,24
					25,26
					27,28
					29,30
					31,32
					33,34
					35,36
					37,38
					39,40
					41,42
					43,44

REMOVE ALL 16 CARDS FROM SORT BOARD AND PLACE RUBBER BAND AROUND THEM. TURN THE PAGE AND CONTINUE.

End Card 04

6. What mode or modes of transportation do you use to get to work? CIRCLE AS MANY AS APPLY.

	30
Bus	1
Auto	2
Other: SPECIFY ____________ ____________	0

IF MORE THAN ONE MODE OF TRANSPORTATION CIRCLED IN Q.6 ANSWER Q.7, OTHERWISE SKIP TO Q.8

7. What mode of transportation do you use <u>most often</u> to get to work? CIRCLE ONLY ONE.

	31
Bus	1
Auto	2
Other: SPECIFY ____________ ____________	0

8. Thinking now of the mode of transportation you use most often to get to work, approximately how many minutes does it usually take you?

NUMBER OF MINUTES: ______ 32-34

IF AUTO IS ONE OF THE MODES OF TRANSPORTATION USED, BUT NOT THE MOST OFTEN MODE USED, ANSWER Q.9, OTHERWISE SKIP TO Q.10.

9. Approximately how many minutes would it usually take for you to get to work using an automobile?

NUMBER OF MINUTES: ______ 35-37

10. How many times per week do you travel to and from work? Count each round trip, that is, to and from work on one day, as one time.

NUMBER TIMES PER WEEK: ______ 38,39

(11) If you were making a 30-minute trip to the downtown area of the city for the purpose of getting to work, would you be willing to pay $.35 for a one-way trip on AGT?

	40	
SKIP TO Q.13	Yes	1
CONTINUE	No	2

12. Would you be willing to pay $.15 for this trip on AGT?

41	
Yes	1
No	2

(13) People often consider different factors in their selection of public transportation. Some of these may be more important than others. For each of the factors listed below, circle one number on the scale which represents how important that factor is to you in your selection of public transportation. If you circle a "1" it means that factor is not at all important to you. If you circle a "5" it means that factor is very important to you. A "2", "3" or "4" means you are somewhere in between.

		Not at All Important				Very Important
Guarantee of a seat	42	1	2	3	4	5
A comfortable seat	43	1	2	3	4	5
Size of vehicle	44	1	2	3	4	5
Frequency of service	45	1	2	3	4	5
Attendants or drivers on vehicle	46	1	2	3	4	5
Price	47	1	2	3	4	5
Transit mode	48	1	2	3	4	5
Covered or enclosed bus stops/ station entrances and exits	49	1	2	3	4	5
Travel time	50	1	2	3	4	5
Distance of bus stop/station from your home	51	1	2	3	4	5
Attendants inside stations	52	1	2	3	4	5
Distance of bus stop/station from your destination	53	1	2	3	4	5
Quality of ride, that is, noise level, smoothness and the like	54	1	2	3	4	5
Well lit bus stops/station entrances, platforms, and exits	55	1	2	3	4	5

(14) Think now of the reliability of the four types of public transportation, that is, their potential for meeting time schedules, possible breakdowns and the like. For each type of transportation, circle one number on the scale from "1" to "5", with "1" being very unreliable and "5" being very reliable, that comes closest to your view of that type of public transportation's reliability.

	Very Unreliable				Very Reliable
Rail 56	1	2	3	4	5
Local Bus 57	1	2	3	4	5
Express Bus 58	1	2	3	4	5
AGT 59	1	2	3	4	5

(15) If you had to make a choice, would you prefer a rail or automated guideway transit (AGT) system that was:

	60
Above ground,	1
Below ground, or	2
On ground level?	3

(16.) Why do you feel this way? What factors contribute to your preference?

61
62

63
64

(17) If you had to make a choice on the size of vehicle in which to ride public transit, would you prefer one that holds:

	65
4 to 6 passengers,	1
10 passengers,	2
30 passengers, or	3
50 or more passengers?	4

18. Why do you feel this way? Why is this size vehicle better than other sizes?

66
67

68
69

19. Aside from driving the vehicle, what other functions do you feel drivers or other attendants provide on public transit?

70
71

72
73

20. Thinking now of all the times you have taken public transportation, have you ever ridden on a:

CIRCLE EITHER A YES OR NO CODE FOR EACH

	Yes	No
Rail System? 74	1	2
Local Bus System? 75	1	2
Express Bus System? 76	1	2
AGT System? 77	1	2

21. Thinking of the four ~~types~~ of public transportation we have been talking about, which mode do you prefer most? 78

CIRCLE ONLY ONE

Rail	1
Local Bus	2
Express Bus	3
AGT	4

End Card 02

APPENDIX C: ANALYSIS PROGRAMS

C.1 Introduction

This Appendix reviews: a) the data processing step to transform raw survey responses to a form on which multiple linear regression can be performed, b) use of standard multiple linear regression programs, c) the data processing step to prepare the validation data set, based on the regression model, current values of all variables, and current actual behavior, and d) the control cards for a multinomial logit program which performs the validation.

C.2 Data Processing for Regression

The responses to each survey are usually coded on a single record per respondent. Each record has three sections: identification of respondent and survey type, responses to the experiment, and responses to background questions. The experiment itself is not coded or keypunched, since it is the same in all cases. Instead, it is added to the data set using a short computer program.

Figure C.1 shows the program, called DP1, in outline. The bicycle example shown in Figure 5.3 and Figure 5.4 is used. The experiment file simply contains the pattern of variables in the design; in this case, there are only eight lines (or records) in the file. The survey response records have the three sections mentioned above; there are as many records as individuals. Only the first two records are shown in the example.

FIGURE C.1.
Data Processing for Regression

Experiment File

0	2.60	3	1	1	1
1	2.60	1	1	1	0
1	1.30	3	0	1	0
0	2.60	1	0	0	0
1	1.30	1	1	0	1
0	1.30	1	0	1	1
0	1.30	3	1	0	0
1	2.60	3	0	0	1

Survey Response File

ID	Experimental Responses	Background Responses
001	45535444	1 402...
002	13111111	6 407...
.	.	.
.	.	.
.	.	.

Program DP1

Regression Data Set

ID	Experiment						Experimental Responses	Background Responses
001	0	2.60	3	1	1	1	4	1 402 ...
001	1	2.60	1	1	1	0	5	1 402 ...
001	1	1.30	3	0	1	0	5	1 402 ...
001	0	2.60	1	0	0	0	3	1 402 ...
001	1	1.30	1	1	0	1	5	1 402 ...
001	0	1.30	1	0	1	1	4	1 402 ...
001	0	1.30	3	1	0	0	4	1 402 ...
001	1	2.60	3	0	0	1	4	1 402 ...
002	0	2.60	3	1	1	1	1	6 407 ...
002	1	2.60	1	1	1	0	3	6 407 ...
.			.				.	. .
.			.				.	. .
.			.				.	. .

The program takes every survey response record and turns it into eight records, one for each situation in the survey. Each experimental response is matched with the corresponding line of the experiment, and forms a separate record in the regression data set. Identification and background responses are appended for convenience. Figure C.2 includes the program listing and Figure C.3 example output.

On IBM systems, data sets 3, 4 and 5 are defined through JCL.

This program is written for the binary case only; extensions are required to treat multiple-alternative cases. Data checking and other extensions may be added as desired.

C.3 Standard Packages Available for Regression

Once the data set 'REGDATA' is created, any standard regression package can be used to analyze the experimental data. One common package is SPSS, the Statistical Package for the Social Sciences (Nie, Best and Hull, 1970). Chapter 15 describes the subprogram REGRESSION in the package, including many examples.

Another common package is the BMD (Biomedical Package, see UCLA (1979)). Its regression routine is titled BMD1R, and it is again described in detail.

The UTPS program UREGRE is also available (UMTA, 1979).

Users should access whatever regression package is readily available at their installation. Most packages can treat weighted observations (see Section 4.4) and piecewise linear and dummy variables, although exact procedures may vary.

FIGURE C.2.
Program Listing -- DP1

```
* PROGRAM DP1
* THIS PROGRAM PREPARES A REGRESSION DATA SET ('REGDATA') FROM A
* SURVEY DATA SET ('SURVEY') AND A DATA SET CONTAINING THE EXPERIMENT
* AND DIMENSIONS OF THE PROBLEM ('CONTROL').
* 'CONTROL' CONTAINS, IN THE FIRST RECORD:
*   NSIT - NUMBER OF SITUATIONS IN EXPERIMENT
*   NVAR - NUMBER OF VARIABLES IN EXPERIMENT
*   NBACK - NUMBER OF BACKGROUND QUESTIONS ON SURVEY
*   NOBS - NUMBER OF RESPONDENTS
*IF ANY OF THESE EXCEED THE FOLLOWING MAXIMUMS, DIMENSIONS MUST BE
* CHANGED INTHE PROGRAM: NVAR:8, NSIT,NBACK:16, NOBS:NO LIMIT.
* 'CONTROL' THEN CONTAINS THE EXPERIMENT, ONE SITUATION PER RECORD.
* 'SURVEY' CONTAINS THE RAW SURVEY RESPONSES.
* 'REGDATA' IS THE OUTPUT OF THIS PROGRAM.
* FORMAT STATEMENTS MUST BE MODIFIED TO FIT EACH INDIVIDUAL STUDY
*
 REAL EXPER(16,8)/128*0./,ID,EXPRESP(16)/16*0./,BACKRESP(16)/16*0./
 OPEN(5,'CONTROL')
 READ (5,10) NSIT,NVAR,NBACK,NOBS
10 FORMAT(4I3)
 READ (5,40) ((EXPER(I,J),J=1,NVAR),I=1,NSIT)
40 FORMAT (6F4.0)
 CLOSE(5)
*
OPEN(3,'REGDATA')
OPEN(4,'SURVEY')
 DO 25 K=1,NOBS
 READ (4,15) ID,(EXPRESP(I),I=1,NSIT),(BACKRESP(I),I=1,NBACK)
15 FORMAT (15F4.0)
 DO 30 L=1,NSIT
 WRITE (3,35) ID,(EXPER(L,J),J=1,NVAR),EXPRESP(L),(BACKRESP(M),M=1,NBACK)
35 FORMAT (14F7.2)
30 CONTINUE
25 CONTINUE
 CLOSE(4)
 CLOSE(3)
 END
```

Note that '*' denotes a comment, usually denoted by 'C'.

Input Data Sets:

CONTROL 23 Jul 81 12:01

8	6	6	2	
02.60	3	1	1	1
12.60	1	1	1	0
11.30	3	0	1	0
02.60	1	0	0	0
11.30	1	1	0	1
01.30	1	0	1	1
01.30	3	1	0	0
12.60	3	0	0	1

SURVEY 23 Jul 81 12:01

1	4	5	5	3	5	4	4	4	0	1	2	4	1	3
2	1	3	1	1	1	1	1	1	1	0	1	3	2	1

Output Data Set:

REODATA 23 Jul 81 12:05

1.00	0.00	2.60	3.00	1.00	1.00	1.00	4.00	0.00	1.00	2.00	4.00	1.00	3.00
1.00	1.00	2.60	1.00	1.00	1.00	0.00	5.00	0.00	1.00	2.00	4.00	1.00	3.00
1.00	1.00	1.30	3.00	0.00	1.00	0.00	5.00	0.00	1.00	2.00	4.00	1.00	3.00
1.00	0.00	2.60	1.00	0.00	0.00	0.00	3.00	0.00	1.00	2.00	4.00	1.00	3.00
1.00	1.00	1.30	1.00	1.00	0.00	1.00	5.00	0.00	1.00	2.00	4.00	1.00	3.00
1.00	0.00	1.30	1.00	0.00	1.00	1.00	4.00	0.00	1.00	2.00	4.00	1.00	3.00
1.00	0.00	1.30	3.00	1.00	0.00	0.00	4.00	0.00	1.00	2.00	4.00	1.00	3.00
1.00	1.00	2.60	3.00	0.00	0.00	1.00	4.00	0.00	1.00	2.00	4.00	1.00	3.00
2.00	0.00	2.60	3.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	3.00	2.00	1.00
2.00	1.00	2.60	1.00	1.00	1.00	0.00	3.00	1.00	0.00	1.00	3.00	2.00	1.00
2.00	1.00	1.30	3.00	0.00	1.00	0.00	1.00	1.00	0.00	1.00	3.00	2.00	1.00
2.00	0.00	2.60	1.00	0.00	0.00	0.00	1.00	1.00	0.00	1.00	3.00	2.00	1.00
2.00	1.00	1.30	1.00	1.00	0.00	1.00	1.00	1.00	0.00	1.00	3.00	2.00	1.00
2.00	0.00	1.30	1.00	0.00	1.00	1.00	1.00	1.00	0.00	1.00	3.00	2.00	1.00
2.00	0.00	1.30	3.00	1.00	0.00	0.00	1.00	1.00	0.00	1.00	3.00	2.00	1.00
2.00	1.00	2.60	3.00	0.00	0.00	1.00	1.00	1.00	0.00	1.00	3.00	2.00	1.00

FIGURE C.3. Example Data Sets -- DP1

C.4 Data Processing for Logit Validation

After the linear regressions are obtained from the experimental data, a second data processing step is required to prepare the data set for validation. Figure 6.6 shows the basic flow of the validation program. Figure C.4 gives a simple example program for this step.

The program initially reads level of service data in origin-destination matrices. It then reads each survey observation, looks up necessary level of service data, computes the utility value, and writes an output record for each survey observation. The subroutine COMPUTE is coded by the user, and contains the regression equation from the previous step.

Figure C.5 shows example input and output data sets.

C.5 Logit Validation

The last step is to estimate a logit equation relating the computed utility values to actual behavior in the status quo. The UTPS program ULOGIT may be used; see its documentation. An alternative program, based on card-image data, which may be easier to use in DUA applications, is called LOGIT (Ben-Akiva, 1973). It will be provided on request, with documentation, by:

Professor Thomas Adler
Resource Policy Center
Thayer School of Engineering
Hanover, NH 03755

The LOGIT program is in FORTRAN and is about 400 lines in length. It can handle multinomial logit models in many applications.

Note that "perfect" validation can occur with small samples,

FIGURE C.4.
Program Listing -- DP2

```
* PROGRAM DP2
* THIS PROGRAM PREPARES A VALIDATION DATA SET ('VALIDATA')
* FROM A SURVEY DATA SET ('SURVEY'), A LEVEL OF SERVICE DATA SET
* ('LEVELSER') AND A SET OF UTILITY EQUATIONS FROM THE EXPERIMENT,
* CONTAINED IN SUBROUTINE 'UTILITY'.
* THIS PROGRAM IS WRITTEN FOR BINARY VALIDATION, AND MUST BE EXTENDED
* TO HANDLE MULTINOMIAL VALIDATION.
* THE FIRST RECORD IN 'LEVELSER' CONTAINS THE SAME INFORMATION AS
* THE FIRST RECORD IN 'CONTROL' IN PROGRAM DP1: NSIT, NVAR, NBACK,
* NOBS.  ADDITIONALLY, IT READS:
*    NZON - NUMBER OF ZONES IN LEVEL OF SERVICE DATA
*    NLOS - NUMBER OF LEVEL OF SERVICE VARIABLES IN 'LEVELSER'
*
 REAL BACKRESP(16)/16*0./,LOS(6,20,20)/2400*0./
 OPEN(5,'LEVELSER')
 READ(5,10) NSIT, NVAR,NBACK, NOBS, NZON,NLOS
 READ(5,15) (((LOS(I,J,K),K=1,NZON),J=1,NZON),I=1,NLOS)
10 FORMAT(5I3)
15 FORMAT(3F2.0)
 CLOSE(5)
*
 OPEN(3,'VALIDATA')
 OPEN(4,'SURVEY')
 DO 25 K=1,NOBS
 READ(4,20) (BACKRESP(I),I=1,NBACK)
20 FORMAT(36X,6F4.0)
 CALL COMPUTE(LOS,BACKRESP,UTILITY)
*
* THIS EXAMPLE PROGRAM ASSUMES:
*    BACKRESP(1) IS THE ACTUAL MODE CHOICE (0=AUTO,1=BIKE)
*    BACKRESP(2) IS SEX (0=MALE,1=FEMALE)
*    BACKRESP(3) IS VEHICLES OWNED
*    BACKRESP(4) IS TRIP LENGTH
*    BACKRESP(5) IS ORIGIN ZONE
*    BACKRESP(6) IS DESTINATION ZONE
*    LOS(1) IS SIDEWALK VARIABLE (0=PART WAY, 1=ALL THE WAY)
 WRITE(3,30) (BACKRESP(I),I=1,NBACK),UTILITY
30 FORMAT(7F7.2)
25 CONTINUE
 CLOSE(4)
 CLOSE(3)
* EXTRA PROCESSING STEPS TO PUT THE FILE INTO THE REQUIRED INPUT
* FORMAT FOR THE LOGIT PROBRAM BEING USED MAY BE INCLUDED HERE
 END
*
 SUBROUTINE COMPUTE(LOS, BACKRESP,UTILITY)
 REAL BACKRESP(16),LOS(6,20,20),UTILITY
I1=BACKRESP(5)
I2=BACKRESP(6)
* THIS SUBROUTINE IS PREPARED BY THE USER BASED ON REGRESSION RESULTS
 UTILITY= 4.99-0.63*BACKRESP(2)-1.88*BACKRESP(3)+0.75*0.0+0.58*1.30
&+0.03*5.0-1.17*BACKRESP(4)+0.08*LOS(1,I1,I2)-0.75*0.0
 RETURN
 END
```

FIGURE C.5
Example Data Sets -- DP2

Input Data Sets:

```
LEVELSER  23 Jul 81  10:19

  8  6  6  2  3  1
 0 1 1
 1 0 0
 1 1 1
```

```
SURVEY     23 Jul 81  12:01

   1   4   5   5   3   5   4   4   4   0   1   2   4   1   3
   2   1   3   1   1   1   1   1   1   1   0   1   3   2   1
```

Output Data Set:

```
VALIDATA  23 Jul 81  10:20

  0.00   1.00   2.00   4.00   1.00   3.00  -3.18
  1.00   0.00   1.00   3.00   2.00   1.00   0.50
```

in which all users actually chose the alternative with the highest utility computed from the DUA experiment. In such cases the logit model will fail to converge because it has no error term; thus, the original DUA model is accepted. In all other cases, the logit validation should converge.

Statistical Issues and Simulation Results

This appendix discusses two important statistical issues that arise in the construction and interpretation of DUA datasets; the choice of response scale and the way in which invariant responses are treated. In order to understand the empirical effects of different choices in these areas, a data base was generated using Monte Carlo techniques and regression models were developed and compared for several different cases. The data base consisted of sets of six orthogonal attribute values for eight situations describing different auto/walk mode combinations, two socio-economic variables (sex and auto ownership) and a "choice".

The "choice" was generated using a fixed set of parameter values and adding a normally distributed disturbance. This "choice" variable was continuous over the range of 1 to 5; 1 representing certain choice of auto and 5 representing certain choice of walk. The "Base Model" constructed from this data set is shown in Table D.1.

The scale was then adjusted to take on only integer values between 1 and 5. The results, shown in Table D.2, are different from those obtained from the continuous response scale but numerical differences are small. However, when a binary (1,5) response scale was used (Table D.3), the change in values becomes somewhat more significant. In practical terms, the implication is that a five-point scale captures much of the information contained in a much more finely delineated scale, however, reduction to a binary scale appears to result in significant changes in coefficient values and increases in standard errors of the estimates.

Similar tests were made with the introduction of invariant responses (where a given individual gave the same 1 or 5 response to all situations) to the sample. The continuous choice variable was used for other (not invariant) responses. The results (Tables D.4 and D.5) show that introducing these invariant responses affects coefficient values and lowers both the t-statistics and multiple correlation coefficient (R^2). Thus, regressions using a sample that contains a large number of invariant responses can be expected to have somewhat lower statistical confidence.

Table D.1
Base Model (Linear)

EQUATION 1
****

DEPENDENT VARIABLE IS UTIL

INDEP VAR	ESTIMATED COEFFICIENT	STANDARD ERROR	T STATISTIC
CNST	4.835667	0.094570	51.13
SEX	-0.521775	0.035305	-14.78
VEH	-1.651541	0.026137	-63.19
SUPG	0.669127	0.034996	19.12
GASP	0.494011	0.026920	18.35
WAIT	0.025642	0.002333	10.99
WALK	-1.081708	0.069992	-15.45
SIDE	0.000672	0.034996	0.02
SEAS	-0.680620	0.034996	-19.45

0.8747 = R-SQUARED
0.1938E+03 = SUM OF SQUARED RESIDUALS
690.02 = F-TEST(8, 791)
2.0402 = D-W (ADJ FOR 0 GAPS)
0.4949E+00 = STANDARD ERROR OF REGRESSION
800 = NUMBER OF OBSERVATIONS

Table D.2
1-5 Integer Scale

EQUATION 1
****

DEPENDENT VARIABLE IS UTIL

INDEP VAR	ESTIMATED COEFFICIENT	STANDARD ERROR	T STATISTIC
CNST	4.846847	0.112135	43.22
SEX	-0.518726	0.041863	-12.39
VEH	-1.633953	0.030991	-52.72
SUPG	0.625000	0.041496	15.06
GASP	0.476923	0.031920	14.94
WAIT	0.023000	0.002766	8.31
WALK	-1.049999	0.082991	-12.65
SIDE	0.000000	0.041496	0.00
SEAS	-0.665000	0.041496	-16.03

0.8269 = R-SQUARED
0.2724E+03 = SUM OF SQUARED RESIDUALS
472.18 = F-TEST(8, 791)
2.0391 = D-W (ADJ FOR 0 GAPS)
0.5868E+00 = STANDARD ERROR OF REGRESSION
800 = NUMBER OF OBSERVATIONS

Table D.3
1,5 Binary Scale

EQUATION 1
****

DEPENDENT VARIABLE IS UTIL

INDEP VAR	ESTIMATED COEFFICIENT	STANDARD ERROR	T STATISTIC
CNST	5.382847	0.247076	21.79
SEX	-0.710421	0.092239	-7.70
VEH	-1.916524	0.068285	-28.07
SUPG	0.890000	0.091431	9.73
GASP	0.561539	0.070332	7.98
WAIT	0.022000	0.006095	3.61
WALK	-1.459999	0.182862	-7.98
SIDE	-0.030000	0.091431	-0.33
SEAS	-0.770000	0.091431	-8.42

0.5865 = R-SQUARED
0.1322E+04 = SUM OF SQUARED RESIDUALS
140.25 = F-TEST(8, 791)
2.0322 = D-W (ADJ FOR 0 GAPS)
0.1293E+01 = STANDARD ERROR OF REGRESSION
800 = NUMBER OF OBSERVATIONS

Table D.4
With 10% Fixed Response Added

EQUATION 1
****

DEPENDENT VARIABLE IS UTIL

INDEP VAR	ESTIMATED COEFFICIENT	STANDARD ERROR	T STATISTIC
CNST	4.476909	0.176202	25.41
SEX	-0.328482	0.067151	-4.89
VEH	-1.388668	0.050314	-27.60
SUPG	0.568182	0.066499	8.54
GASP	0.433567	0.051153	8.48
WAIT	0.020909	0.004433	4.72
WALK	-0.954545	0.132997	-7.18
SEAS	-0.604546	0.066499	-9.09

0.5519 = R-SQUARED
0.8483E+03 = SUM OF SQUARED RESIDUALS
153.45 = F-TEST(7, 872)
0.8234 = D-W (ADJ FOR 0 GAPS)
0.9863E+00 = STANDARD ERROR OF REGRESSION
880 = NUMBER OF OBSERVATIONS

Table D.5
With 20% Fixed Response Replacements

EQUATION 1
****

DEPENDENT VARIABLE IS UTIL

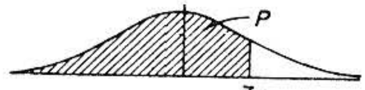
INDEP VAR	ESTIMATED COEFFICIENT	STANDARD ERROR	T STATISTIC
CNST	4.847013	0.196400	24.68
SEX	-0.584221	0.072794	-8.03
VEH	-1.557278	0.054311	-28.67
SUPG	0.520000	0.072644	7.16
GASP	0.365385	0.055880	6.54
WAIT	0.020333	0.004843	4.20
WALK	-0.839999	0.145289	-5.78
SIDE	-0.010000	0.072644	-0.14
SEAS	-0.525000	0.072644	-7.23

0.5759 = R-SQUARED
0.8349E+03 = SUM OF SQUARED RESIDUALS
134.25 = F-TEST(8, 791)
0.7644 = D-W (ADJ FOR 0 GAPS)
0.1027E+01 = STANDARD ERROR OF REGRESSION
800 = NUMBER OF OBSERVATIONS

APPENDIX E: NORMAL DISTRIBUTION

Table E.1 gives the normal distribution; it is taken from Natrella (1963).

TABLE E-1. CUMULATIVE NORMAL DISTRIBUTION — VALUES OF P



z_P

Values of P corresponding to z_P for the normal curve.

z is the standard normal variable. The value of P for $-z_P$ equals one minus the value of P for $+z_P$, e.g., the P for -1.62 equals $1 - .9474 = .0526$.

z_P	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998

APPENDIX F: PIVOT POINT ANALYSIS

The pivot point approach is based on the incremental form of the logit model. It predicts the revised mode shares of bicycle, walk, and other modes based only on knowledge of the existing mode shares and the changes in service levels brought about through the policy being analyzed. By employing this pivot point approach, data requirements are mininal: no knowledge of existing socio-economic or level of service data is required. The formula for the incremental logit model is:

$$P_i' = \frac{P_i e^{\Delta U_i}}{\sum_j P_j e^{\Delta U_j}}$$

where P_i' = new mode share, mode i

P_i = base or existing mode share, mode i

ΔU_i = change in utility of mode i

The derivation of this model is:

$$P_i' = \frac{e^{U_i + \Delta U_i}}{\sum_j e^{U_j + \Delta U_j}}$$

$$= \frac{e^{U_i} e^{\Delta U_i}}{\sum_j e^{U_j} e^{\Delta U_j}}$$

$$= \frac{e^{U_i} e^{\Delta U_i} / \sum_j e^{U_j}}{\sum_j e^{U_j} e^{\Delta U_j} / \sum_j e^{U_j}}$$

$$= \frac{(e^{U_i} / \sum_j e^{U_j}) \cdot e^{\Delta U_i}}{\sum_j (e^{U_j} / \sum_j e^{U_j}) \cdot e^{\Delta U_j}} \quad \text{(continued)}$$

$$= \frac{P_i e^{\Delta U_i}}{\Sigma P_j e^{\Delta U_j}}$$

This derivation is from Cambridge Systematics (1976).

☆U.S. GOVERNMENT PRINTING OFFICE: 1982-361-420/2224