Title

Commuters' Normal And Shift Decisions In Unexpected Congestion: Pre-trip Response To Advanced Traveler Information Systems

Authors

Khattak, Asad
Polydoropoulou, Amalia
Ben-akiva, Moshe

Publication Date
1996

CkLIFORNIA PATH PROGRAM
INSTITUTE OF TRANSPORTATION STUDIES
UNIVERSITY OF CALIFORNIA, BERKELEY

Commuters' Normal and Shift Decisions in Unexpected Congestion: Pre-trip Response to Advanced Traveler Information Systems

Asad Khattak
Amalia Polydoropoulou
Moshe Ben-Akiva

California PATH Research Report
UCB-ITS-PRR-96-7

This work was performed as part of the California PATH Program of the University of California, in cooperation with the State of California Business, Transportation, and Housing Agency, Department of Transportation; and the United States Department of Transportation, Federal Highway Administration.

March 1996

ISSN 1055-1425

COMMUTERS'NORMALANDSHIFI'DECISIONSIN UNEXPECTEDCONGESTION: PRE-TRIPRESPONSETO ADVANCEDTRAVELERINFORMATIONSYSTEMS

Volume 1

Asad Khattak

PATH Program, Institute of Transportation Studies
University of California at Berkeley
&
Department of City and Regional Planning
University of North Carolina at Chapel Hill

Amalia Polydoropoulou

Center for Transportation Studies
Massachusetts Institute of Technology

Moshe Ben-Akiva

Center for Transportation Studies
Massachusetts Institute of Technology

Submitted to:

California Department of Transportation

(MOU 68 & MOU 8604)

March 18,1996

ACKNOWLEDGEMENT

Mr. Mark Skandera was crucial to the development of the survey. He helped in the design, refinement, distribution and analysis of the survey. Professor Khattak has received valuable input from Professor Adib Kanafani and Professor Randolph Hall and useful comments from Professors David Gillen, Haitham Al-Deek, and Dr. Steven Shladover. Mr. Robert Warren of the Golden Gate Bridge, Highway, and Transportation District and Ms. Joy Dahlgren were instrumental in distributing the survey forms. Finally, Mr. Robert Ratcliff and Ms. Shara Lynn Kelsey of the Office of New Technology at the California Department of Transportation were instrumental in the success of this study.

ABSTRACT

Advanced Traveler Information Systems (ATlS) offer benefits to travelers and may improve transportation system performance in congested areas. An understanding of how information impacts travelers' decisions can help in evaluating benefits and designing demand management strategies. The objective of this study is to explore how people deal with unexpected congestion during the pre-trip stage and how might they respond to ATIS. Travelers' route, departure time and mode selection decisions were investigated through a survey of Bay Area automobile commuters. The effects of various factors are examined, such as sources of congestion information (radio traffic reports versus observation), trip characteristics, and route attributes on traveler response to unexpected congestion. The pre-trip response to future ATIS technologies is explored through stated preferences (hypothetical scenarios).

We develop a combined reported and stated preference model of traveler response using the multinomial logit formulation. The estimations show that travel time and information are important determinants of changes in travel decisions in response to unexpected delays. The model indicates a strong relationship between reported and stated preferences. The results show that ATIS overcomes behavioral inertia and that individuals are more likely to change their travel patterns in response to prescriptive information. The paper also discusses more specific findings and their implications for ATIS design.

EXECUTIVE SUMMARY

New technologies present opportunities to address transportation problems. Advanced Traveler Information Systems (ATIS) offer benefits to travelers and may improve transportation system performance in congested areas. An understanding of how information impacts travelers' decisions can help in evaluating benefits and designing demand management strategies. The objective of this study is to understand how people deal with unexpected congestion during the pre-trip stage and how might they respond to ATIS. Travelers' route, departure time and mode selection decisions were investigated through a survey of Bay Area automobile commuters. We investigate the effects of various factors, such as sources of congestion information (radio traffic reports versus observation), traveler and trip characteristics, route attributes and environmental conditions on traveler response to unexpected congestion through survey research. By using stated preferences (hypothetical scenarios), we explore the response to future ATIS technologies. A feature of the survey is that it intertwines stated and reported preferences and by doing so, it enables us to judge the validity of the stated preference responses.

We found that of those who at least once had become aware of unexpected congestion before getting into their vehicles, slightly more became aware at work than at home. Travelers learned of congestion by observing it directly before entering their vehicles, or by radio and television reports. These travelers initially expected congestion to add about a half hour to their trips, and later found their expectations to be somewhat shorter. In spite of having advance information, 45% of the travelers did not change their travel plans. Those who did change their plans generally departed either earlier or later than usual (37%) and/or took an alternate route (21%); only 2% used public transportation and 2% canceled their trip altogether. About 5% added or canceled intermediate stops. When faced with the hypothetical situation of having an ATIS device give them information, respondents were somewhat willing to use this information. Across various ATIS messages, IO-25% would leave earlier than usual, IO-20% would leave later, and 10% would take an alternate route (25% if the ATIS device specifically suggested to do so). Almost none (2%) were willing to take public transportation (18% if the device specifically suggested to do so). The responses are further analyzed using multivariate models.

The results show that the currently available real-time traffic information broadcast through the electronic media provides a basis for making travel decisions. Further, individuals expressed a certain willingness to use ATIS. However, a majority of the respondents would not necessarily follow ATIS advice, possibly due to behavioral inertia. More specific findings and their implications for ATIS design are discussed in the paper.

KEYWORDS: traveler behavior, traffic congestion, ATIS, Bay Area

TABLE OF CONTENTS

1. Introduction

Traffic congestion is a major problem in most metropolitan areas. On a national level, United States residents spend two billion hours in over 18 1 million cars delayed in traffic jams each year. One way of alleviating congestion is by providing real-time, location specific, traffic and transit information to travelers. Alternate types of Advanced Traveler Information Systems (ATIS), such as route guidance systems, telephone information services, Variable Message Signs, beepers, etc., are under development and/or in their initial stages of implementation/operation in the USA, Europe and Japan. However, the user acceptance and potential effects of such systems on transportation system performance are currently unknown.

The focus of this research is to assess the effects of ATIS by developing and estimating behavioral models of travelers' response to ATIS. The developed models could then be directly implemented in traffic simulations, enabling the assessment of alternate types of ATIS on transportation system performance.

This study refines and validates the frameworks for assessing the impacts of ATIS technologies on travelers' behavior in unexpected delay situations developed earlier by Khattak (1991) and Ben-Akiva et al. (1994). This evaluation focuses on the pre-trip decisions (as opposed to en-route choices), where individuals have a larger set of options--such as cancel trip, and trip mode, departure time, and route choice. We use a detailed survey of San Francisco Bay Area commuters in the Golden Gate Bridge corridor for model estimation (Khattak 1993).

To know what aspects of travel information are important to travelers, we develop behavioral hypotheses and empirically test them in a real-life context with currently available travel information and hypothetical ATIS scenarios. Key research issues are: does providing qualitative, quantitative or predictive delay information support traveler decisions? Will commuters follow ATIS suggestions on taking alternate modes and routes in unexpected delay situations? What role do knowledge, experience and behavioral inertia play in commuters' response to ATIS?

Section 2 of this paper presents a short literature review of research conducted on users' response to ATIS. Section 3 describes the travel behavior framework. Section 4 presents the structure and survey design, and summarizes the sample used for modeling. Section 5 presents the modeling framework and section 6 provides the estimation results. Section 7 presents the application of the model. Finally section 8 concludes the paper.

2. Literature Review

Current research efforts on ATIS fall into two main categories: traveler behavior modeling and traffic simulation. An extensive literature review on traveler behavior modeling is presented in Ben-Akiva et al. (1993). According to this review, most research has focused on modeling ATIS usage and travel response decisions based on data from travel simulators and travel surveys (see for example Wachs 1967; Daniels et al. 1976; McFadden et al. 1977; Dudek et al. 1978; Abkowitz 1981; Hendrickson and Plank 1984; Abu-Eisheh and Mannering 1987; Shirazi et al. 1988; Haselkom et al. 1989; Mannering 1989; Kbattak 1991; Polak and Jones 1991; Abdel-Aty et al. 1993; Polydoropoulou et al. 1994; Jou and Mahmassani 1994; Khattak and de Palma 1995). Most of the above research concentrates on travelers' mode, departure time and route choice behavior, with the bulk of the research focusing on route switching decisions due to information provided by conventional information sources, such as radio.

The behavioral models used mostly travelers' socioeconomic characteristics and attributes of usual travel patterns as explanatory variables. However, thus far none of the models developed with real data contain the complete set of travelers choices, including the cancel trip, change mode, departure time, route choice alternatives (with the exception of the Polak and Jones (199 1) study which investigates the mode choice decisions--largely in a hypothetical context). Furthermore, travelers' response to ATIS has only been investigated in travel simulator studies (see Koutsopoulos et al. 1995 for a comprehensive literature review). Although these studies provide useful insights on how people would behave in hypothetical situations when ATIS is available to them, their validity regarding actual decision making needs to be demonstrated.

Another research stream focuses on the development of simulation tools to evaluate the effect of ATIS on transportation system performance. In most simulation models, different behavioral response to ATIS recommendations is assumed (guided versus unguided vehicles), but no behavioral models are currently incorporated, nor are origin-destination flows generated by ATIS explicitly introduced. Clearly, such simulation models cannot accurately assess the impacts of ATIS in a transportation network. A behavioral model that includes actual attributes of the alternative choices, such as travel times, delays, and congestion levels, together with specific ATIS manifestations directly implemented in traffic simulation models will give more meaningful results.

The "Congestion in the Bay Area" behavioral survey (Khattak 1993) provides us the data needed to develop behavioral models. It allows us to investigate the influence of (a) unexpected and expected congestion, (b) various types and quality of information received about congestion, and (c) travelers' experience with congestion and related information, on the whole spectrum of pre-trip decisions. Importantly, the relationship between traveler response to qualitative, quantitative, predictive delay information, and prescriptive information in a hypothetical ATIS context is modeled in combination with actual behavior.

3. Travel Behavior Framework

The ultimate objective of this research is to assess the benefits of ATIS implementation in a transportation network. The modeling framework that supports our objective includes a combination of revealed and stated preference data.

The behavioral responses of ATIS users could vary across travelers. Various choice dimensions such as telecommuting decisions, travel mode, departure time, route and parking choices are available to individuals. Commuters often have a pre-planned travel pattern that might change when new travel information is acquired. If a traveler does not acquire traffic/transit information she or he will continue to use her/his habitual travel pattern.

A behavioral model based on our earlier work (Ben-Akiva et al. 1991 and 1993; Khattak et al. 1993; Schafer et al. 1993; Khattak et al. 1994; Ben-Akiva et al. 1994) is summarized as follows. Incident bottlenecks are prevalent in urban transportation systems. Travelers receive information about their performance through self-observation and the electronic media. They interpret the information in light of their current knowledge. The interpretation translates into perceptions of travel time and delay. Perceptions, restrictions and individual's characteristics form preferences for certain alternatives (modes, routes and departure times). The preferences also depend on previously acquired knowledge, stored in the memory, and on thresholds. For example, if the perceived delays before taking the trip to work exceed a threshold, then preferences may change, e.g., travelers may prefer to depart earlier or later than normal. Preferences result in observable choices that have outcomes. An outcome could be the arrival time at work. If the outcome is satisfactory, then the same choice is likely to be repeated on the next trip, forming a commute pattern. The repetition of a choice in the commute context also depends on future or anticipated outcomes. Outcomes also provide feedback to the memory in the form of knowledge updates. In unexpected delay situations, the anticipated outcomes are often unsatisfactory and have high uncertainty, triggering a review of preferences and changes in normal travel patterns. The important aspects of this behavioral model are elaborated on below.

Incident congestion, to the extent that it adds more time to a trip than the normal travel time variability, is less likely to be accepted by travelers when compared with recurring congestion. That is, people may be more likely to change their normal commute patterns in response to unexpected delays. Moreover, the likelihood to change their normal commute patterns will increase with longer delays. However, the issue of delay perception is complicated because self-observation of congestion may result in incremental perception of delay. That is, due to their inability to see the beginning of queued traffic and the cognitive difficulty in translating queue !ength into delays, people may only approximate the delay. On the other hand, the traffic information provider may not give accurate delay information due to errors in measurement and the time needed to process and disseminate information. Thus commuters rely on uncertain estimates of delay, whether the delay information is obtained directly through observation or indirectly through electronic media. Even if the traffic information provider wants to give accurate travel information, all relevant details about an incident cannot be known immediately for dissemination, thus limiting the provider’s ability to forecast incident duration and delays. Consequently, travelers will always try to piece together partial information about incidents to estimate delays.

Various aspects of travel information influence traveler decisions. The processing of information depends on its content or meaning, format or presentation style, nature (whether it is static, dynamic or predictive) and type (whether it is quantitative or qualitative) (also see Schafer et al. 1993). In addition, travelers are more likely to rely on relevant and accurate information (Abdel-Aty et al. 1994, Polydoropoulou et al. 1994, Khattak et al. 1994). Under incident congestion, the perception of delay and the quality of real-time (delay) information are critically important in changing traveler behavior. Also, various aspects of event-related information influence traveler response. People may be more likely to respond to quantitative information or estimates of delay (especially when the estimates are high) compared with qualitative delay information (Bonsall 1995). Alternatively, people may be more likely to change their travel patterns with qualitative information due to its ambiguity. Their response would depend on how individuals transform qualitative delay information into quantitative measures. Furthermore, predictive information, i.e., giving future estimates of unexpected congestion, may have a more pronounced influence on behavioral changes.

The effect of incident congestion may be compounded when it occurs with recurrent congestion. Commuters who regularly experience bottleneck delays are more likely to divert in response to incident congestion compared with those who do not have a recurrent bottleneck.

Review of travel decisions occurs when thresholds of expectations are approached or reached (Mahmassani et al. 1993). Travelers have a set of restrictions that partly determine their commute pattern. A restriction could be the need to arrive at work before the start time. Even for a worker who is on “flex time” there may exist a preferred arrival time, which is somewhat similar to the required arrival times of fixed schedule workers. Any diversion from the preferred arrival time is likely to be onerous (see also Noland et al. 1995).

4. Data Collection

This section describes the survey design, the data collection methodology, and the sample.

4.1 Survey Distribution

The “congestion in the Bay Area” survey was an instrument designed to examine traveler behavior. The criteria for identifying the corridor and target population are as follows:

- Presence of traffic congestion.
- Real-time travel information availability.
- Automobile availability to all respondents.
- Transit accessibility.
- Alternate route availability.

The Golden Gate Bridge was selected for survey distribution because it adequately satisfies the above criteria. For a complete analysis of sample representatives and the survey instruments used, see Khattak (1993).

The mail-back questionnaires were distributed to peak period automobile commuters crossing the Golden Gate Bridge, during both the morning and the afternoon rush hours (6:00 A.M. to 10:00 A.M. and 4 P.M. to 6 P.M.) in February of 1993. People were asked to respond only if they used a vehicle regularly (at least once a week) for their work trips in the Bay Area. Money incentives (a drawing of 25 Golden Gate Bridge toll ticket books, each good for twenty toll crossings and valued at $60.00), conditional on completion of the survey, were successful in achieving a good response rate: more than a third of the 9000 copies distributed were returned. A total of 3238 surveys were coded and error checked.

The survey contained sixty-two questions that fall into five categories:

1. Normal travel patterns. Normal patterns include day-to-day behaviors such as work schedule, route choice, and response to recurring congestion.
2. Pre-trip response to unexpected congestion information. When trave!ers know before entering their vehicle that road conditions are abnormal, they may choose to change certain decisions such as departure time and route choice.
3. En-route response to unexpected congestion information. When travelers learn of abnormal road conditions while driving, they may change certain decisions to a limited extent.
4. Willingness to change driving patterns. Given some incentive, travelers are sometimes willing to leave early, take an alternate route, or participate in an experiment.
5. Personal information. Travelers age, occupation and gender may influence certain behaviors.

In the interest of keeping the questionnaire short, not all questionnaires contained every question. We created two questionnaire forms: **Form One** includes all questions from categories 1, 2, 4, and 5, while **Form Two** includes all questions from categories 1, 3 4, and 5. Approximately 4500 copies of each form were distributed. In the following section, categories 1, 4, and 5 are discussed jointly, and category 2 separately. The pre-trip model presented in this paper used the **Form One** data set. The en-route model presented in Polydoropoulou et al. (1996) used the **Form Two data** set.

4.2 Surve y Design

The relevant portions of the survey are designed as follows.

Reported Situation: Revealed Preference

The situation explored was the "Reported Unexpected Delay Response" in a real-life context. Respondents were asked to recall a time when they were made aware, at home or at office, of unexpected congestion by conventional media (radio, television, etc.) and observation or word-of-mouth along their usual route and report whether they modified their travel plans. Detailed data about the context (weather, trip direction, expected and experienced delay duration etc.) when the most recent unexpected delay occurred were obtained. In this paper we will use data on travelers that became aware of unexpected congestion on their home-to-work trips.

Stated Preference Scenario: Qualitative Information

The hypothetical situation was tied with the reported situation and was used to explore changes in travel behavior in the presence of ATIS that provided qualitative information. Respondents were asked to report whether they would change travel decisions to earlier or later if they were alerted of a similar delay situation by a "special device" which gives "accurate" information on delays. The specific message 'displayed by the device (represented to the respondent as a picture of a television screen with text) was "unexpected congestion on your usual route." This situation is equivalent to the currently available information in the Bay Area, i.e., ATIS presents qualitative delay information. The thrust is toward understanding how people want to respond to qualitative delay information presented to them through new technologies.

Stated Preference Scenario: Quantitative Information

The hypothetical situation provided numerical information and explored the response to quantitative information. This situation is similar to the previous scenario, except the device displayed the "the expected length of delay on your usual route (your expected delay [in the reported preference situation]) at the present time." Note that by this stage the respondent had reported the expected length of time added by the delay in the reported situation and this was used to anchor the hypothetical question.

Stated Preference Scenario: Predictive Information

The hypothetical situation explored the effects of predictive information. Respondents were asked what they would do in terms of changing travel choices if "the device tells you the length of delay at the present time, and accurately predicts the length of delay it will cause 15 and 30 minut& into the future."

Stated Preference Scenarios: Prescriptive Information

Two hypothetical situations explored the response to recommendations to switch to public transit or to take the best alternate route. The specific messages were “The device gives you the message of unexpected delay on your usual route” and suggests that you “use public transportation instead of your car”; and “The device gives you the message unexpected delay on your usual route and suggests that you take your best alternate route.”

4.3 Sample Description: pre-trip response to unexpected traffic congestion

A total of 586 home to work trips during which pre-trip information was acquired were reported. Table 1 summarizes the travelers’ reported behavior under unexpected traffic congestion. Travelers learned of congestion by observing it directly before entering their vehicles, or by radio and television reports. These travelers initially expected congestion to add about a half hour to their trips, and later found that the actual delay was somewhat shorter than they had expected. In spite of having advance information, 37% of the travelers did not change their travel plans, probably due to transaction costs associated with changes. Those who did change their plans generally departed either earlier or later than usual (37%) and/or took an alternate route (20%); only 2% used public transportation. In response to congestion, some commuters canceled their work trips. Table 2 summarizes the travelers’ responses to the stated preference experiment. When faced with the hypothetical situation of having an ATIS device give them accurate delay information on the same trip, the majority of respondents were willing to use this information. Across various ATIS messages, 10-25% would leave earlier than usual, 10-20% would leave later, and 10% would take an alternate route (25% if the ATIS device specifically suggested to do so). Almost none (2%) were willing to take public transportation (18% if the device specifically suggested to do so).

5. Modeling Framework

A unique aspect of this research is the estimation of ATIS user response model with multiple data sources: 1) revealed preference (RP data), where the actual behavioral response to unexpected delay is reported and 2) stated preference data (SP data), where traveler behavior in hypothetical ATIS scenarios is reported.

Stated preferences are subject to concerns such as (a) was the hypothetical context realistic, (b) were the situational factors often present at the time of the decision adequately described to the respondent, (c) was the respondent overstating his or her response to please the researcher, (d) do the responses reflect cognitive dissonance? The design of the SP experiments is aimed at minimizing such biases. Furthermore, by combining stated preference data with revealed preference data we can overcome a

Table 1: Reported Behavior: Response to Unexpected Traffic Congestion (Percentages may not add up to 100)

Survey Question	Frequency %
Information Source	
Radio	72
Television	30
Telephone	4
Own Observation	22
Word of Mouth	3
Other	3
Reason of Congestion	
Disabled vehicle	5
Accident	34
Bad weather	58
Construction/road work	3
Don't know the reason	4
Due to some other reason	25
Expected Length of Delay	
O-IO min	13
1 l-20 min	37
21-30 min	31
3 l-40 min	3
41-50 mm	6
>51 min	9
Actual Length of Delay	
O-10 min	22
1 l-20 mm	32
21-30 min	24
3 l-40 min	4
41-50 min	7
>51 min	9
Reported Response	
Not change	37
Leave earlier	21
Leave later	10
Change route	15
Leave earlier and change route	5
Take public transportation	2
Cancel trip	2

Table 2: Stated Behavior - Response to Unexpected Traffic Congestion

ATIS Scenarios	Frequency %
Oualitative Information	
Leave early	44
Leave later	14
Take alternate route	14
Use public transportation	6
Cancel trip	0
Can't say	22
Quantitative Information	
Leave early	44
Leave later	22
Take alternate route	12
Use public transportation	6
Cancel trip	1
Can't say	13
Predictive Real-Time Information	
Leave early	46
Leave later	22
Take alternate route	13
Use public transportation	6
Cancel trip	0
Can't sav	14
Prescriptive Information: Switch to an alternate route	
Leave early	24
Leave later	7
Take alternate route	43
Use public transportation	6
Cancel trip	1
Can't say	19
Prescriptive Information: Use public transportation	
Leave early	24
Leave later	9
Take alternate route	18
Use public transportation	22
Cancel trip	6
Can't say	21

variety of potential biases and obtain more accurate and credible models (Morikawa 1991).

To be more specific, ATIS is a new information medium that will provide more accurate quantitative information, hence traveler response would be similar to the reported preference situation in most respects. However, response could be more pronounced in terms of switching. As structured in this survey, the five ATIS scenarios examine aspects of information that can shape trip change decisions. Also, because the device is said to provide "accurate" information, if the respondent considers the information, he or she should not have to grapple with issues concerning its accuracy, but rather its content and type. The respondents were asked to state their preference to change in response to unexpected delay encountered in the reported preference situation, if fifteen minutes before their departure they were provided with delay information by ATIS. Since the responses to the hypothetical situations were tied to reported preferences, they provided a realistic context. However, the "anchoring" of the respondents to the RP situation might reduce the effect of the information sources, and lead to the same choices as the actual behavior. Such preference inertia or justification biases will be captured in the model estimations.

The utility maximized by each traveler in the RP context is given by:

$$U_{RP} = V_{RP} + \varepsilon$$

where V_{RP} is the systematic utility function influencing the RP decisions; and
ε represents the random utility components influencing the RP decisions.

The utility maximized by each traveler in the SP context is given by:

$$U_{SP} = V_{SP} + \text{v}$$

where V_{SP} is the systematic utility function influencing the SP decisions; and
ν represents the random utility components influencing the SP decisions.

We assume that the non-measured components of the RP utility (E) and the SP utilities (ν) are independently and identically Gumbell distributed, and the level of noise in the data sources is represented by the variance of ε and ν. We define θ^2 to be the ratio of the variances:

$$\theta^2 = \text{var}(\varepsilon) / \text{var}(\text{ v})$$

and therefore the SP utilities can be scaled by θ :

$$\theta U_{SP} = \theta V_{SP} + \theta\nu$$

so that the random variable (ev) has a variance equal to that in the RP utility (ε). It is possible to use both RP and SP observations in a logit estimation procedure that requires equal variance across observations. Note, however, that the SP utilities are scaled by an unknown constant θ which needs to be estimated. In the following sections we will discuss the specification of the systematic utilities in the RP, the SP, and the combined model.

We define our systematic utilities as follows:

$V_{RP} = a'w + \beta'x + \delta'c$

$\theta_i V_{SP_i} = (a_i'w + \beta'x + \gamma'z)\theta_i$ where i denotes the specific ATIS scenario.

Vectors **w** represent the dummy variables for the alternative specific constants of each model. All relative coeffkients (a , a_i) are unconstrained. The SP constants capture the influence of each ATIS scenario on travelers' decisions. Therefore the comparison of the RP and the SP constants will give us the pre-trip switching propensity due to information provided by ATIS.

Sharing β in both RP and SP models implies that trade-offs among attributes included in x are the same in both actual travel behavior and the SP behavior. In our model the x vectors represent all travel related coefficients, such as travel time, expected delay, congestion level on alternate route, and schedule delay variables. These variables are not affected by the information provision, but are actual characteristics of the alternatives.

Vectors c are specific to the RP model and include the information source variables used in the RP context.

Factors inherent in Stated Preferences are represented by z with the corresponding coefficients γ . In our case, a variable representing the actual choice, included in z may capture the effect of justification bias. In the combined model we restrict the coefftcients γ to be the same among the 5 SP models, assuming the same marginal contribution of z to the SP utilities.

The joint estimation of revealed and stated preferences data is conducted by using the "tree logit methodology. The construction of the artificial tree and the required steps for the model estimation are described by Bradley and Daiy (199 1).

6. Model Specification and Estimation Results

This section first presents the specifications for the RP and SP portions of the combined model, and then discusses the model estimation results.

6.7 Reported Situation

The RP portion of the model describes travelers' decisions when they become aware of unexpected congestion on their usual route. The following alternatives were used in estimation:

- did not change normal travel pattern,
- changed route,
- left earlier,
- left later,
- used public transportation,
- left earlier and changed route, and
- canceled trip.

Table 3 presents the specification of the RP portion of the model. The following section describes the specification of the variables. Six major categories of variables were included in the model: 1) Travel time, 2) Expected delay, 3) Schedule delay, 4) Usual bottleneck delay, 5) Congestion on alternate route, 6) Knowledge of travel times, and 7) Information sources.

1) Travel time

Travel time is included as a generic variable. Travel time in each alternative was defined as follows:
1. *Do not change alternative.* The reported usual travel time was used for estimation;
2. *Change to alternate route alternative.* The reported travel time on alternate route was used and 0 if not known;
3. *Leave earlier alternative.* The reported travel time was used if the person left for work 30 minutes earlier and 0 if travel time was not reported;
4. *Leave Zater alternative. The* minimum of the usual travel time and the "leave earlier" time was used. We made this assumption based on the following reasoning.
(a) Peak hour travelers. The reported travel time for the "leave earlier" alternative can be considered as the non-peak hour travel time. This travel time should be close to the travel time that the traveler will experience if he/she leaves later than usual, and therefore travels under non congestion.
(b) Non-peak hour travelers. If the traveler usually travels during off-peak hours and if he or she leaves later, then the travel time experienced would be the same as the usual travel time. Note that when the travel time of "leave earlier" is not reported, we assume the travel time in the "leave later" alternative as the usual travel time.
5. *Public transportation alternative.* The transit travel time was used if reported, and 0 otherwise.
6. *Leave earlier and change to alternate route alternative. The* minimum of travel time between the "leave earlier" option and the "change to alternate route" option, if those are

reported was used and 0 otherwise. It is assumed that this joint decision is the outcome of a trade-off between the two options under consideration. A person will change both decisions if and only if this choice results in a better outcome than changing only one decision.

7. Cancel trip alternative. For the cancel trip alternative the travel time is zero.

2) Expected delay

The expected delay on the usual route is included as an alternative specific variable on the "do not change" alternative. More specifically the natural logarithm of the expected delay minus 2 minutes is used in the estimations. By using the logarithm we assume that travelers' have a reduced sensitivity to increasing delays. Since the minimum reported expected delay was 3 minutes, we assumed that a delay under 2 minutes will not cause any traveler to change his/her travel pattern (see also Section 7.0). By using the difference (delay - 2 minutes) we assure that the probability of diversion becomes zero when delay approaches zero.

3) Schedule delay

Early and late schedule delay were calculated.
Define:

t_d = departure time
I, = arrival time
I' = desired arrival time
A = flexibility in arrival time

Then

- Late schedule delay $t_a > t^{*}$

$$LSD=\max\ [\ 0,\ t_a - t^{*} - \Delta\ ]$$

- Early schedule delay $t_a < t^{*}$

$$ESD=\max[O,\ t^{*} - t_a]$$

This variable was calculated only for the people with a required work start time. Note that A was reported by the respondents.

Table 4: Pre-Trip Model - SP Behavior

Alternat ivts	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1) Do not change	0	0	0	0	TT on Usual Route (UR)	In (exp. delay - 2min)	Late sch delay I	Early sch Delay I	0	0	0	0	0	0	0	0	0	I if Do Not change in RP/ 0 o/w	0	0	0	0	0	0
2) Change Route	1	0	0	0	TT on Alt. Route (AR) if known 0 o/w	0	Late sch delay 2	Early sch. Delay 2	I if Usual Bot., 0 o/w	0	0	0	cong. level	1 If TT on AR =0, 0 o/w	0	I if act - exp del.> 0 0 o/w	0	0	1 if CR in RP/ 0 o/w	1 if CR & LE in RP/ 0 o/w	0	0	0	0
3) Leave Early	0	I	0	0	TT if leave earlier (LE) 0 o/w	0	Late sch. delay 3	Early sch Delay 3	0	I if Usual Bot.. 0 o/w	0	0	0	0	I if TT =0, 0 o/w	0	1 if act-exp del.> 0 0 o/w	0	0	0	I if LE in RP/ 0 o/w	I if LE& CR in RP/ 0 o/w	0	0
4) Leave Later	0	0	I	0	minim mum TT of UR,LE	0	Late sch. delay 4	Early sch delay 4	0	0	1 if Usual Bot . 0 o/w	0	0	0	0	0	0	0	0	0	0	0	1 if LL in RP/ 0 ow	0
5) Change to Public Transp	0	0	0	I	TT on PBL if known 0 o/w	0	Late sch. delay 5	Early sch Delay 5	0	0	0	I if Usual Bot ,0 o/w	0	0	0	0	0	0	0	0	0	0	0	1 if CM in RP/ 0 ow

4) Usual Bottleneck Delay

The usual bottleneck delay is a dummy variable that takes the value of 1 if travelers have a usual bottleneck and 0 otherwise. This delay is most likely to occur on the Golden Gate Bridge toll plaza.

5) Congestion on alternate route

The congestion level of the alternate route is a dummy variable that takes the value of 0 if not congested, and 1 if usually congested or heavily congested. The alternative route congestion level was included in the "change route" and the "change departure time and change route" alternative.

6) Knowledge of Travel Times

To capture the effect of knowledge and of experience on choice behavior, five alternative specific dummy variables were created for the alternatives that had observations with non-reported travel time. The dummy variable is equal to 1 if travel time was unknown and 0 otherwise.

7) Information sources

Travelers were informed about the unexpected delay by the following information sources:

1. Electronic sources, such as radio, TV, telephone and computer;
2. Non-electronic sources, such as own observation and word-of-mouth; or
3. Both electronic and non-electronic sources.

We constructed dummy variables for the information acquisition from electronic sources, and both electronic and non-electronic sources, and we include them in the no change alternative, leaving the non-electronic sources as the base case.

6.2 Stated Preference

The SP portion of the model examines commuter response to ATIS. For each ATIS a multinomial logit model was developed with the alternatives being the following:

- can not say - we assume that these people would not change their travel pattern,
- change route,.
- leave earlier,
- leave later, and
- take public transportation.

Note that the "cancel trip" alternative was not included in the model specification due to few observations in this alternative. Table 4 presents the specification of the SP models. The main differences between these models and the RP model are the absence of other information sources (fixed as ATIS in this case) and the presence of experience/justification variables. These are alternative specific dummy variables, taking the value of 1 if the alternative was chosen under the RP situation and 0 otherwise. To capture potential biases introduced by the experienced delay, a dummy variable equal to 1 if actual delay experienced was higher than the initially expected delay reported in the RP. situation, was included in the departure time alternatives.

6.3 Es tima tion Results

Table 5 presents the results of a combined RP and SP model. All scale coefficients are significantly different than zero. We also estimated separate RP and SP models and found that the combined model has better fit than the separate RP and SP models, by utilizing the Akaike Information Criterion (see Ben-Akiva and Lerman, 1985).

RP constants (a)

The alternative specific constants reflect the average effects of omitted variables in the model. Compared to the base "do not change" alternative in the RP model, people are on average nor inclined to change their travel decisions (all else being equal). This reflects the presence of behavioral inertia despite the presence of unexpected delay. This result is consistent with Khattak (1991) who found that on average, downtown Chicago drivers were inclined to take the usual route rather than their best alternate route in unexpected delay situations. The relative magnitudes of the RP model parameters indicate that people are least likely to cancel their home-to-work trip; other relatively less likely alternatives are taking public transit and leaving earlier.

SP constants

The alternative specific constants in the SP models reflect the effects of omitted variables as well as the effect of information type presented by ATIS. Specifically, the differences between SP and RP constant terms reflect the effect of the relevant ATIS scenario. Table 6 presents the magnitude and direction of change in the SP constants compared to the RP model. Overall, the parameter estimates increase with the introduction of ATIS, meaning that on average, ATIS overcomes resistance to changing travel decisions in unexpected delay situations. This result coincides with that of Van der Mede and Van Berkum **(1991).**

Table 4: Pre-Trip Model - SP Behavior

Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
I) Do not change	0	0	0	0	TT on Usual Route (UR)	In (exp delay 2min)	Late sch delay I	Early sch. Delay I	0	0	0	0	0	0	0	0	0	I if Do Not change in RP/ 0 o/w	0	0	0	0	0	0
2) Change Route	1	0	0	0	TT on Alt. Route (AR) if known 0 o/w	0	Late sch. delay 2	Early sch. Delay 2	1 if Usual Bot., 0 o/w	0	0	0	cong. level	I if TT on AR =0, 0 o/w	0	I if act - exp del.> 0 0 o/w	0	0	1 if CR in RP/ 0 o/w	1 if CR & LE in RP/ 0 o/w	0	0	0	0
3) Leave Early	0	1	0	0	TT if leave earlier (LE) 0 o/w	0	Late sch. delay 3	Early sch. Delay 3	0	1 if Usual Bot., 0 o/w	0	0	0	0	I if TT =o, 0 o/w	0	1 if act-exp del.> 0 0 o/w	0	0	0	1 if LE in RP/ 0 o/w	1 if LE& CR in RP/ 0 o/w	0	0
4) Leave Later	0	0	1	0	minimum TT of UR,LE	0	Late sch. delay 4	Early sch. delay 4	0	0	1 if Usual Bot , 0 o/w	0	0	0	0	0	0	0	0	0	0	0	1 if LL in RP/ 0 ow	0
5) Change to Public Trrnsp	0	0	0	1	TT on PBL if known 0 o/w	0	Late sch. delay 5	Early sch. Delay 5	0	0	0	1 if Usual Bot ,0 o/w	0	0	0	0	0	0	0	0	0	0	0	1 if CM in RP/ 0 ow

First we discuss the impact of qualitative, quantitative and predictive ATIS delay information received prior to beginning the home-to-work trip, then we discuss the impacts of providing advice on changing mode (to public transit) and route (to the best alternate).

Qualitative information constants (a,)

Qualitative delay information increases the chance of leaving earlier than normal and taking public transit. Such qualitative delay information was available in the Bay Area through electronic media at the time of the survey. This information then reflects the effect of increased accuracy of ATIS information (note that ATIS was described as giving "accurate" information).

Quantitative information constants (a,)

Quantitative information further increases peoples' propensity to change departure times, route and modes. Such information was not available at the time of the survey, indicating that with accurate quantitative information, **i.e.** firmer delay estimates, people are more willing to change their normal travel patterns. In particular they are willing to switch to public transit, despite the modest transit level of service in the Golden Gate Bridge corridor.

Predictive information constants (α_3)

The effect of predictive delay information differs little from the effect of quantitative information. Travelers may not perceive such information as valuable possibly due to their inability to clearly conceptualize the impacts of predictive delay information on their travel choice. Predictive information does increase the possibility of leaving earlier than normal, possibly because people expect that delays may worsen when predictions are made (and that they might "beat" such situations by leaving earlier).

Prescriptive information - take alternate route constants (a,)

ATIS' suggestion to take the best alternate route in an unexpected delay situation results in increased probability of route change, as expected. This means that a priori people have a propensity to comply with ATIS suggestions. In real life however, compliance will likely depend on the outcome of ATIS advice (e.g., whether their travel experiences are

Table 5: Combined RP and SP Model

Variables		Coefficients	t-statistics
Current Info -	**Constant 1 (CR)**	-1.47	-3.9
	Constant 2 (LE)	-1.82	-4.9
	Constant 3 (LL)	-2.51	-6.5
	Constant 4 (PBL)	-3.66	-7.7
	Constant 5 (LE & CR)	-2.54	-6.1
	Constant 6 (CANCEL)	-5.25	-9.2
Qualitative Info -	**Constant 1 (CR)**	-1.24	-3.2
	Constant 2 (LE)	-0.66	-2.2
	Constant 3 (LL)	-1.98	-4.1
	Constant 4 (PBL)	-1.74	-3.6
Quantitative -	**Constant 1 (CR)**	-0.63	-1.8
	Constant 2 (LE)	0.04	0.1
	Constant 3 (LL)	-0.71	-2.1
	Constant 4 (PBL)	-1.32	-3.0
Predictive -	**Constant 1 (CR)**	-0.49	-1.4
	Constant 2 (LE)	0.24	0.7
	Constant 3 (LL)	-0.69	-0.2
	Constant 4 (PBL)	-1.33	2.9
Prescr. Route -	**Constant 1 (CR)**	0.98	2.4
	Constant 2 (LE)	-0.88	-2.4
	Constant 3 (LL)	-2.75	-4.1
	Constant 4 (PBL)	-2.27	-3.6
Prescr. Mode -	**Constant 1 (CR)**	-0.56	-1.6
	Constant 2 (LE)	-0.86	-2.4
	Constant 3 (LL)	-2.36	-4.0
	Constant 4 (PBL)	-0.10	-0.3
Travel Time (x10hrs)		-6.47	-3.7
Log (Exp. Delay-2min) (Do not change)		-0.19	-2.4
Late Schedule Delay (x10hrs)		-4.35	-1.5
Early Schedule Delay (x10hrs)		-0.50	-1.9
Usual Bottleneck Dummy (CR)		0.28	1.1
Usual Bottleneck Dummy (LE)		-0.16	-0.7
Usual Bottleneck Dummy (LL)		-1.46	-2.8
Usual Bottleneck Dummy (PBL)		0.66	2.0
Usual Bottleneck Dummy (LE & CR)		1.05	2.1
Congestion Level (alt.route)		-0.23	-1.5
TT Dummy (CR)		-1.62	-4.7
TT Dummy (LE)		-0.39	-1.4
TT Dummy (PCL)		-2.84	-4.3
TT Dummy(LE & CR)		-2.10	-4.0

Table 5: Combined RP and SP Model (Cont.)

Info Both Dummy (Do not change)	**-3.76**	**-4.9**
Info electr. Dummy (Do not change)	-2.19	-4.1
Dummy Act.>Exp. Del. (LE)	**0.28**	**2.2**
Dummy Act.>Exp. Del. (LL)	**0.37**	**2.1**
Justification (Do not change)	-0.18	-1.2
Justification CR (CR)	1.62	**4.4**
Justification CR and LE (CR)	1.38	3.1
Justification LE (LE)	**1.33**	**4.4**
Justification CR and LE (LE)	1.01	**2.8**
Justification LL (LL)	**2.38**	**4.5**
Justification PBL (PBL)	**3.92**	**4.4**
Theta 1 (SP1 - Qualitative Info)	1.10	**4.6**
Theta 2 (SP2 - Quantitative Info)	1.05	**4.6**
Theta 3 (SP3 - Predictive Info)	**0.87**	**4.6**
Theta 4 (SP4 - Prescr. Route)	**0.68**	**4.5**
Theta 5 (SP5 - Prescr. Mode)	**0.74**	**4.5**
Log likelihood (initial)	**-4498.89**	
Log likelihood (convergence)	**-3677.57**	
Number of observations	**2703**	
Rho-squared w.r.t. Zero	**0.24**	

positive when they follow ATIS instructions (see for example Bonsall (1991)). The constants also show that some travelers would still leave earlier and others take public transit (compared with the RP model), probably because their alternate route has undesirable characteristics not captured in the SP model.

Prescriptive information - take public transportation constants (α_5)

When advised to take public transit in delay situations, travelers show increased propensity to do so. This indicates some potential for a pre-trip switch to transit when accurate unexpected delay information is given. Also note that there are people who prefer to leave earlier than normal to reduce the impact of unexpected congestion. Overall, there is a consistent increase in peoples' propensity to leave earlier and take public transit with pre-trip ATIS.

Restricted coefficients among RP and SP (β)

Travel time is negative and statistically significant, meaning that travelers will choose the alternative with the lowest expected travel time. Note that for computational purposes the reported travel times were rescaled from minutes to 10 hours (i.e. divided by 600).

The effect of non-reported travel times is modeled through the travel time dummy variables. These variables capture individual's lack of knowledge/experience regarding travel times. The signs are negative because, as expected, travelers are less likely to switch to unfamiliar or unused alternatives. This effect is particularly significant in the diversion to alternate route and public transportation. One explanation is that travelers who did not use a particular alternative perceive the travel time on that alternative as much longer than their usual travel time. Providing real time alternative route and transit information can be very useful. For the leave earlier and leave later alternatives we used the same dummy variable, since missing values for the two alternatives are the same, and the coefficient is positive but not significant, a result possibly related to the few non-zero values of the dummy variables.

The longer the expected delay on the usual route, the more likely travelers are to change route, leave later, take public transportation and cancel their trip, rather than leave earlier or both leave earlier and change route. The above results indicate that longer delays on the usual route reduce travelers' possibility of keeping the same travel patterns. The relative magnitudes of the coefficients also make sense. It is important to note that when large delays occur, people may switch to public transportation and may telecommute to avoid being stuck in traffic. On the other hand, the negative signs related with the departure time suggest that people would rather wait for high unexpected delays to clear than leave earlier than normal. The above finding strongly indicates that the ATIS should provide the specific amount of traffic delay to effectively switch travelers to other transportation modes or to make them alter their trips.

Perceived congestion on the alternate route reduces the possibility of taking an alternate route, as expected.

Higher expected schedule delay reduces the chance of taking the specific alternative. As expected, the magnitude of late schedule delay for fixed time workers is higher than early schedule delay, which indicates that people are less likely to take an alternative that might cause them to be late.

The existence of recurrent congestion indicated by a usual bottleneck plays an important role in travelers' reactions when they become aware of an unexpected delay on their route. Travelers that usually encounter a bottleneck are more likely to switch routes or mode, and less likely to adjust their departure time.

Specific RP model coefficients (6)

The source of delay information has a significant effect. People are more willing to change their travel patterns if they receive the information from electronic sources only or both electronic media and non-electronic sources (the base is non-electronic sources only). Also, travelers are relatively more likely to change travel patterns when they receive the delay information from the electronic media only as opposed to receiving the information from both electronic and non-electronic sources.

Specific to the SP models (γ)

The variables that capture the relationship between reported and stated behavior are highly significant. These can be capturing behavioral inertia, justification of past behavior and avoidance of cognitive dissonance and are strongly positive as expected. However, the coefficient of "do not change" category is negative, and reflects the traveler's negative RP experience, which leads them in the SP scenarios to make other decisions. The relative magnitudes indicate that the justification bias is stronger for the "change mode", "leave later" and "change route" alternatives.

The higher the difference between initially expected and actually experienced delay, the more willing travelers are to change their departure time in the SP scenarios. This indicates that people who initially expected short delays but found the actual delay longer than expected may have a higher propensity to respond to accurate information.

Scale Coefficients (θ)

The SP1 variation is explained better by the model compared with other SP scenarios. This is expected because SP1 is most similar to the current information situation in the Bay Area.

7. Applying the Model

The model is used to investigate how traveler behavior will change under 1) alternate types of ATIS and 2) different values of expected delay. Section 7.1 shows how our modeling methodology corrects for the effect of SP response bias, and Section 7.2 presents the effect of expected delay on travelers responses.

7.7 Effect of SP Response Bias

We illustrate the usefulness of the combined RP and SP modeling technique - as a methodology to reduce response biases, by comparing the reported and predicted choice frequencies. Table 6 presents the choice frequencies of the responses for the ATIS scenarios and Table 7 presents the predicted frequencies. The rows of the tables represent the frequencies of travel responses and the columns represent the ATIS scenarios.

In order to investigate the effect of response bias we:

1. Applied the models on the RP data;
2. Used the relative coefficients of SP constants, instead of the RP constant coefficients, for each ATIS scenario. The SP constants represent the effect of ATIS scenarios on travel behavior, after correcting for the SP biases and the scale difference between the SP and RP models.
3. Included the justification bias variables to account for inertia effects on travelers' choices;
4. Excluded the variables related to the current information sources (such as radio or television) in the ATIS scenarios.
5. Excluded all other variables used in the. SP models assuming that these variables capture the response biases of the respondents.

Tables 6 and 7 allow us to compare the performance of our model in terms of correcting for the effects of response bias.

Clearly the respondents, when set in a hypothetical ATIS scenario, are more prone to reply that they will change the usual travel pattern when in reality they would not. The model corrects this over responsiveness by predicting that fewer people will actually change travel pattern. Note that the predicted frequencies of the "do not change" category for all the ATIS scenarios presented in Table 7 are higher than the reported frequencies for the "do not change category" in Table 6.

The qualitative information (delay on the usual route) is similar to information obtained by the current information sources (radio, television, own observation), although now this information is accurate. Therefore, we anticipate a reported switching behavior for the qualitative scenario close to that of the actual one when individuals obtain information through current information sources. However, we observe an overreaction to the qualitative information scenario (compare second with third column of Table 6). The model corrects for this overreaction predicting that the choice frequencies under the current information sources and the qualitative ATIS have similar magnitude (compare second with third column of Table 7). Furthermore, as expected, the model predicts that under qualitative information less travelers will not change travel plans, than under current information sources.

Similarly, in the case of the quantitative and predictive information scenarios, the model reduces the over responsiveness for the departure time alternatives. Finally, in the case of prescriptive information, the model predicts that more travelers will comply with the suggested alternative route or mode.

Table 6: Reported *Choice* Frequencies (%)

	Current Sources	Qualitative	Quantitative	Predictive	Prescriptive Route	Prescriptive Mode
Do not Change	39.92	21.68	12.01	13.05	18.46	21.41
Change Route (CR)	16.77	13.29	12.84	13.68	44.02	19.27
Leave Earlier (LE)	22.75	45.19	45.96	46.11	24.54	26.34
Leave Later (LL)	10.78	14.11	22.98	21.26	7.51	10.06
Change Mode	2.2	5.73	6.21	5.89	5.48	22.91
CR and LE	6.39					
Cancel Trip	1.2					

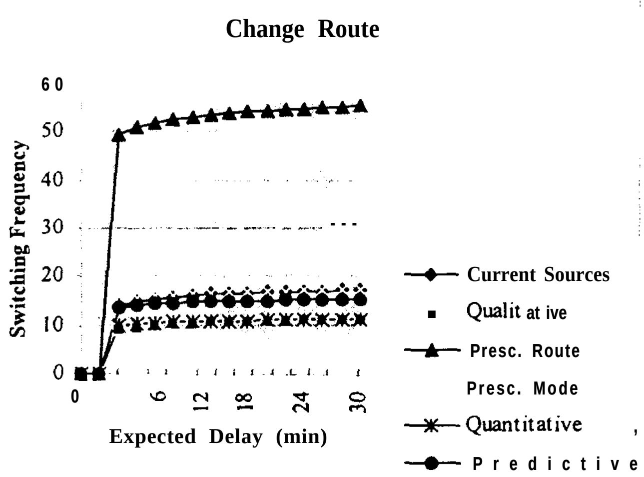
Table 7: Predicted Choice Frequencies (%)

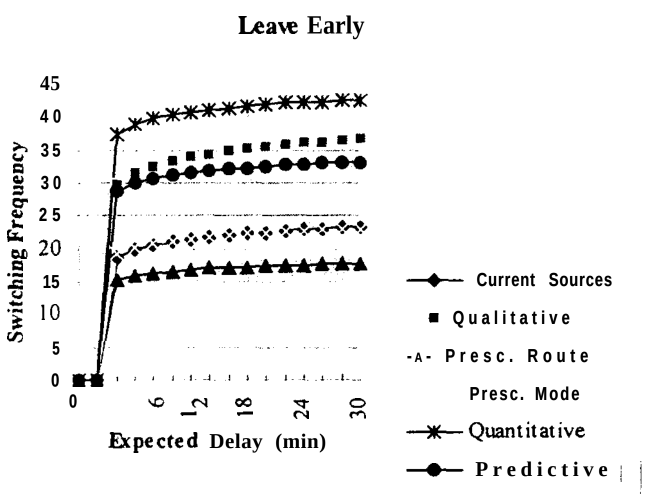
	Current Sources	Qualitative	Quantitative	Predictive	Prescriptive Route	Prescriptive Mode
Do not Change	**39.92**	39.04	25.77	23.76	27.89	29.95
Change Route (CR)	**16.77**	12.72	13.38	14.13	46.72	17.56
Leave Earlier (LE)	**22.75**	28.69	33.02	35.87	17.39	19.19
Leave Later (LL)	10.78	11.22	20.04	19	4.09	6.58
Change Mode	**2.2**	8.32	7.79	7.23	3.89	26.71
CR and LE	6.39					
Cancel Trip	1.2					

7.2 Effect of expected delay on pre-trip travel choices

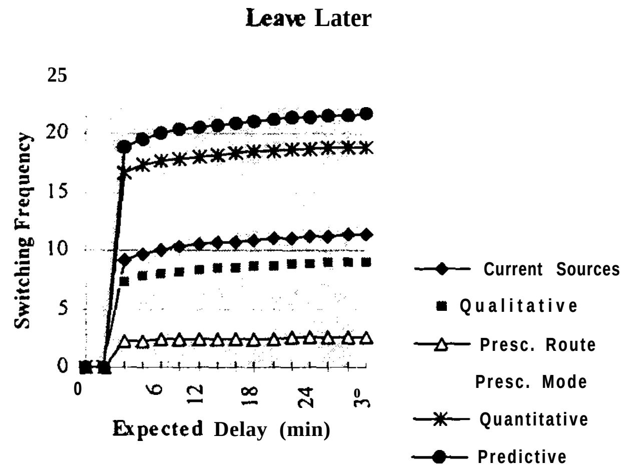
The following graphs present travelers pre-trip decisions under each ATIS scenario, when the expected delay varies from 5 minutes to 30 minutes. In our data delays less than 2 minutes do not cause any traveler to divert.

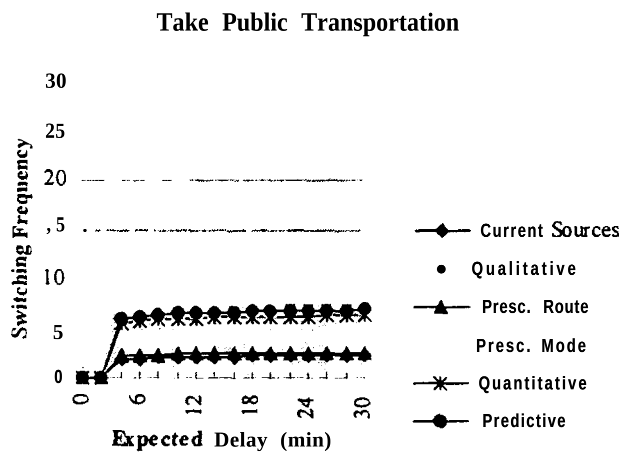
We can see that under all ATIS scenarios, as the expected delay increases the probability of usual travel pattern decreases. Under the current information acquisition situation, the probability of switching route or changing departure time increases, while the probability of changing mode or canceling trip remains stable and minimal. Qualitative information





favors the "leave earlier" alternative, while it also increases the probability of changing route. Quantitative and predictive information favor the departure time alternatives. This result is expected since travelers now have a concrete idea of the amount of delay and can adjust their departure time to meet their travel needs. Prescriptive information regarding taking the alternate route increases the probability to change route, while travelers barely consider the "leave later" and "change mode" alternatives.





Finally, prescriptive information to take public transportation increases the probability of changing mode as well as "leave later", while the "change route" and "leave earlier" alternatives become less attractive.

Overall, the results show a strong captivity of travelers to their choices. When travelers become aware of the delay, they tend to switch immediately to their available alternatives. When delay increases over 20 minutes no changes in the behavior are observed. Beyond a certain threshold travelers seem to become indifferent to delay increases.

8. CONCLUSIONS

We have explored automobile commuters' pre-trip decisions and switching in response to unexpected congestion. The major aspects of the research should be emphasized:

- The model developed comprehensively addresses the pre-trip response to traffic information.
- The use of advanced modeling techniques permitted combining reported and stated preference data. The application of the model demonstrated the usefulness of this technique to reduce the response biases inherent in the SP choice experiment.
- The modeling framework can be directly implemented in traffic simulation models to estimate and predict the impacts of ATIS in a transportation network.

Our estimation results show that with accurate quantitative delay information, commuters may overcome their behavioral inertia when faced with unexpected delays. This may lead to a more dynamic re-adjustment, with travelers willing to change from their habitual travel patterns. Furthermore, commuters indicate an a priori willingness to take ATIS advice on taking alternate modes and routes in unexpected delay situations. Of course their real life experience with specific ATIS technologies will influence the day-to-day travel decisions.

We found that *lack* of experience with alternate modes and routes was a critical factor in travelers' willingness to divert. Thus, real-time information about alternate modes and routes will surely support travelers decisions to divert.

The challenge faced by ATIS designers is to predict the extent of delays on an individual basis and allow users to explore the implications of changes in their travel decisions. ATIS designers may consider the possibility of predicting and informing users on how these changes would affect them. Although with ATIS each individual commuter may be more willing to alter his/her travel behavior, the overall system impacts/benefits still need to be evaluated. The true test of validity will come from ATIS field tests.

References

[1] M. Abdel-Aty, K. Vaughn, R. Kitamura, and P. Jovanis. Survey of Route Choice Behavior: Empirical Results from Southern California and their Implications for Advanced Traveler Information Systems. Partners in Advanced Transit and Highways (PATH) Research Report Draft No. 93-l 8, Institute of Transportation Studies, University of California at Davis, 1993.

[2] M. Abdel-Aty, K. Vaughn, R. Kitamura, P. Jovanis, and F. Mannering. Models of Commuters' Information Use and Route Choice: Initial Results Based on a Southern California Commuter Route Choice Survey. Preprint number 940474. Presented at TRB

73rd Annual Meeting. Institute of Transportation Studies, University of California at Davis, 1994.

[3] M. Abkowitz. An Analysis of the Commuter Departure Time Decision. Transportation, Vol. 10, 198 1.

[4] S. Abu-Eisheh, and F. Mannering. Discrete/Continuous Analysis of Commuters' Route and Departure Time Choices. Transportation Research Record 1138, 1987.

[6] M. Ben-Akiva, A. de Palma, and I. Kaysi. Dynamic Network Models and Driver Information Systems. Transportation Research, 25A(5), 1991.

[7] M. Ben-Akiva, I. Kaysi, A. Polydoropoulou, H. Koutsopoulos, and P. Whitworth. Design of an Integrated Data Collection Program to Support Modeling for User Response to ATIS Services. Proceedings of the 1994 IVHS America First Annual Meeting, 1994.

[8] M. Ben-Akiva, I. Kaysi, A. Polydoropoulou, H. Koutsopoulos, and P. Whitworth. Public Acceptance and User Response to ATIS Products and Services: Modeling Framework and Data Requirements. Massachusetts Institute of Technology. Report Prepared for Economic Analysis Division, John A. Volpe National Transportation Systems Center and Office of Policy Development , Federal Highways Administration, 1993.

[9] M. Ben-Akiva, and S. Lerman. Discrete Choice Analysis. The MIT Press, Cambridge, MA, 1985.

[10] Bonsall and T. Parry. Using an Interactive Route-Choice Simulator to Investigate Drivers' Compliance with Route Guidance Advice. Transportation Research Record, 1306, 1991.

[11] M.A. Bradley, and A.J. Daly. Hague Consulting Group. Estimation of Logit Choice Models Using Mixed Stated Preference and Revealed Preference Information. Proceedings 6th International Conference on Travel Behavior, International Association for Travel Behavior. Quebec, Canada, 199 1.

[12] E. Daniels, M. Levin, and J. McDermott. Improving Commercial Radio Traffic Reports in the Chicago Area. Transportation Research Record 600, 1976.

[13] C. Dudek, G. Weaver, D. Hatcher, and S. Richards, Field Evaluation of Messages for Real-time Diversion of Freeway Traffic for Special Events. Transportation Research Record 682, 1978.

[14] M. Haselkom, J. Spyridakis, L. Conquest, and W. Barfied. Surveying Commuter Behavior as a Basis for Designing Motorist Information systems. Paper Presented at the

first Vehicle Navigation and Information Systems Conference, IEEE, Toronto, Canada, 1989.

[15] C. Hendrickson, and E. Plank. The Flexibility of Departure Times for Work Trips. Transportation Research A. Vol. 18 A, No. 1 ., Pergamon Press, 1984.

[16] R. Jou and H. Mahmassani. Comparability and Transferability of commuter Behavior Characteristics Between Cities: Departure time and Switching Decision. Preprint No. 940878, Presented at the 73rd Annual Meeting of Transportation Research Board, Washington, DC 1994.

[17] A. Khattak, Driver Response to Unexpected Travel Conditions: Effect of Information and Other Factors. Ph.D. Dissertation, Civil Engineering Department, Northwestern University, Evaston, Illinois, 199 1.

[18] A. Khattak. Behavioral Impacts of Recurring and Incident Congestion and Response to Advanced Traveler Information Systems in the Bay Area. Working Paper, California PATH, UCB-ITS-P WP-93- 12, 1993.

[19] A. Khattak and A. de Palma, “Commuters’ Propensity to Change Transportation Decisions in Adverse Travel conditions: some Results from a Behavioral Survey in Brussels. Research Report, UCB-ITS-RR-94- 12, Institute of Transportation Studies, University of California, 1994.

[20] A. Khattak, J. Schofer, F. Koppelman, “Effect of Traffic Reports on Commuters Route and Departure Time Changes.” Journal of Advanced Transportation, Vol. 29, No. 2, 1995.

[21] Koutsopoulos H., A. Polydoropoulou, and M. Ben-Akiva. Travel Simulators for Data Collection on Driver Behavior in the Presence of Information. Transp. Res.-C, vo1.3. 1995.

[22] J. Polak, and P. Jones, Assessing Traveler responses to road Pricing Options. In Proceedings 6th International Conference on Travel Behavior, International Association for Travel Behavior. Quebec, Canada, 1991.

[23] F. Mannering. Poisson Analysis of Commuter Flexibility in changing routes and departure times. Transportation Research, Vol. 23 B, No. 1, 1989.

[24] T. Morikawa. Incorporating Stated Preference Data in Travel Demand Analysis. Ph.D. Thesis, Massachusetts Institute of Technology, 1989.

[25] D. McFadden. A. Talvitie, S. Coslett, L. Hasan, M. Johnson, F. Reid, and K. Train. Demand Model estimation and Validation. Vol. 5 of Urban Travel Demand Forecasting

Project Phase I. Final Report series. Special Report UCB-ITS-SR-77-9, Institute of Transportation Studies, University of California, Berkeley, 1977.

[26] Polydoropoulou, A., M. Ben-Akiva, and I. Kaysi. Revealed Preference Models of the Influence of Traffic Information on Drivers Route Choice Behavior. Transp. Research Record, No. 1453, 1994.

[27] Polydoropoulou, A., M. Ben-Akiva, A. Khattak, and G. Lauprete. Modeling Revealed and Stated En-Route Travel Response to ATIS. Paper Presented at the 75th Annual Meeting, Transportation Research Board, Washigton D.C., 1996.

[28] E. Shirazi, S. Anderson, and J. Stensey. Commuters' Attitudes Toward Traffic Information Systems and Route Diversion. Transportation Research record, 1168, 1988.

[29] J. Schofer, A. Khattak, and F. Koppelman. Behavioral Issues in the Design and Evaluation of Advanced Traveler Information Systems. Transportation Research, Part C, Vol. 1, No. 2, 1993

[30] K. Small. The Scheduling of consumer Activities: Work Trips. American Economic Review, 72, 1982.

[31] M. Vaziri, and T. Lam. Perceived Factors affecting Driver Route Decisions. Journal of Transportation Engineering. Vol. 109, No. 2, 1983.

[32] P.H.J. Van der Mede and E.C. Van Berkum. Modeling Route Choice, Inertia and Responses to Variable message Signs. In Proceedings 6th International Conference on Travel Behavior, International Association for Travel Behavior. Quebec, Canada, 199 1.

[33] M. Wachs. Relationship Between Driver's Attitudes Toward Alternate Routes and Driver and Route Characteristics. Highway Research Record 197, 1967.