

THE IMPACT OF SERVICE RELIABILITY  
ON WORK TRAVEL BEHAVIOR

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Submitted to the Department of Civil Engineering  
on April 10, 1980 in partial fulfillment of the  
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## ABSTRACT

The research documented in this dissertation is directed at understanding the impact of service reliability on work travel behavior. The research is focused on the impact of service reliability on commuter decisions of mode choice and trip departure time. Working with the hypothesis that service reliability is an important attribute in explaining departure time and mode choice, measures of service reliability which in many cases are tied to work arrival time considerations are proposed which capture the impact of this attribute on work travel decisions. The theory is subsequently tested empirically through the estimation of departure time and mode choice models using data collected in the San Francisco Bay Area.

Several interesting results emerged from the research effort. First, arrival time considerations are important explanatory indicators of departure time choice, and influence mode choice decisions as well. Secondly, the arrival time variables are not highly correlated with existing explanatory variables, implying that existing travel demand models may not have biased coefficients, but will still yield inconsistent forecasts where policy changes alter existing correlations between arrival time conditions and independent variables in existing models. Finally, commuter departure time and mode choice decisions appear to be interrelated in a way that suggests structuring the problem as a nested rather than a joint choice.

The implications of these results and research contributions are discussed, and directions for further research are proposed.

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## 1. INTRODUCTION

In recent years, increased attention has been focused on the importance of service reliability to the efficiency and attractiveness of transit operations. For the purpose of this research, service reliability is viewed as the consistency of transportation system performance. A more formal definition of service reliability would be the variability of service attributes which influence the decisions of travelers and transportation operators. The service attribute most often associated with reliability is travel time (wait and in-vehicle); thus, service reliability can be thought of as the travel time uncertainty for a given trip due to the variation in travel times experienced in day-to-day travel.

Unreliable service impacts both the transportation user and provider. Uncertainty associated with travel times is directly related to the traveler's concern about arriving at a destination at the intended time. While the importance of on-time arrival is more apparent for work and medical trips than for shopping or recreational trips, there is reason to believe that the reliability of service impacts travelers' trip frequency, destination, mode choice, and departure time decisions for a variety of trip purposes.

Unreliable service impacts the transportation provider both in terms of costs and revenues. As service becomes less reliable, the transportation provider must either allow increased slack time in vehicle runs in order for the vehicle to start the succeeding run on schedule, or allow the schedule to deteriorate. Increases in slack time result in longer round trip run times, which lead to the necessity of scheduling additional vehicles in service to maintain original scheduled headways. This translates directly into additional operator costs. If the schedule is allowed to deteriorate, service becomes less reliable, and travelers are less inclined to patronize the service, resulting in decreases in revenue.

While it is becoming apparent that service reliability is crucial in influencing both the demand for transit and the net cost of providing transit service (Abkowitz, et al. 1978), there has been a paucity of research directed at understanding the impacts of service reliability on traveler behavior and operator performance.

This research focuses on understanding the impact of service reliability on traveler behavior. Since the largest single group of travelers are commuters (and service reliability is hypothesized to have its most significant impact on this class of travelers), the research effort will

be restricted to a study of work travel behavior. Because work trip frequency and destination are fixed in the short run, the analysis reduces to a study of the impact of service reliability on commuters' decisions of mode choice and trip departure time.\*

In developing an understanding of the impact of service reliability on work travel behavior, a particular objective of the research is to estimate a travel behavior model which is capable of explaining the effects of service reliability on mode choice and trip departure time behavior. This should provide planners with a useful policy tool which can predict how reliability strategies affect mode choice and departure time decisions, predict peaking responses to service changes, and determine the trade-offs between policies directed at improving service reliability and those designed to improve other attributes of the system.

## 1.1 Reader's Guide

This dissertation describes the research problem; reviews past and present research related to the subject area; constructs an analysis methodology for addressing the

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\*It is assumed that route choice is not important in most instances.

problem; and describes the model estimation process, results, and implications. An example of how the models could be used in the analysis of transportation policies is also presented.

Chapter 2 presents a review of studies of travelers' attitudes towards service reliability. Study findings indicate that service reliability is an important attribute to travelers and supports the need for this research. Chapter 3 develops a theory of the role of service reliability in mode and departure time decisions, which forms the hypothesis to be tested empirically later in the research. Chapter 4 critically reviews travel behavior models which have considered the inclusion of service reliability variables. Chapter 5 discusses the methodological issues to be addressed in developing mode choice and departure time models. For each issue, a literature review is conducted to identify relevant past findings. The methodology adopted for this research effort is also described. Chapter 6 describes the data collection process and the approach used to obtain the appropriate sample needed to estimate mode choice and departure time models based on empirical data. Chapters 7 and 8 discuss the results of the estimation of the departure time and mode choice models respectively. Chapter 9 shows how the models



could be used in policy analysis. Chapter 10 summarizes the research and discusses directions for further research.

## 2. TRAVELERS' ATTITUDES ABOUT RELIABILITY\*

Studies of the preferences of actual and potential transit users have been conducted by transportation planners in efforts to improve transit service, to evaluate demonstrations, and to formulate mathematical demand models. These studies point to the importance that travelers place on reliable transportation services. In this chapter, the findings of these analyses of travelers' values are discussed, with particular emphasis on travelers' perspectives on system attributes related to reliability. Reliability is typically associated with the attribute "arrive at the intended time" or "arriving when planned".

The importance of reliability to work travelers relative to other service attributes is indicated by many studies. In a study conducted by the University of Maryland (Paine, 1976), respondents interviewed in Philadelphia were asked to rate for both auto and transit 35 listed attributes on a 1 to 7 scale of importance for the work and non-work trips, with 7 being most important. In Baltimore, the same procedure was performed for 44 attributes on a 1 to 5 scale. The system attributes for work trips, their mean value, and rank by mean importance appear in Table 2.1. Note that

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\*Much of this material appears in Abkowitz, et. al., Transit Service Reliability (1978).

Table 2.1 Rank by Importance, Work Trip for Combined  
Philadelphia, Baltimore Sample

<u>Description</u>	<u>Rank by Mean Importance</u>	<u>Mean Value</u>
Arrive without accident	1	6.49
Arrive at intended time	2	6.40
Safest vehicle	3	6.39
Avoid stopping for repairs	4	6.30
Shortest distance	5	6.14
Fast as possible	6	6.13
Avoid changing vehicle	7	6.10
Vehicle unaffected by weather	8	6.01
Protected from weather while waiting	9	5.97
Shortest time	10	5.88
Avoid waiting more than 5 min.	11	5.83
One-way cost of 25¢ rather than 50¢	12	5.66
Comfortable	13	5.62
One-way cost of 25¢ rather than 35¢	14	5.59
Clean vehicle	15	5.59
Feel independent	16	5.52
Avoid walking more than a block	17	5.48
One-way cost of 3¢ rather than 15¢	18	5.46
Cost	19	5.28
Avoid unfamiliar area	20	5.17
Travel when traffic is light	21	5.14
Uncrowded vehicle	22	5.10
Package and baggage space	23	4.70
Pride in vehicle	24	4.70
New modern vehicle	25	4.66
Friendly people	26	4.55
People you like	27	4.50
Need not pay daily	28	4.11
Avoid riding with strangers	29	4.07
Listen to radio	30	3.87
Ride with people who chat	31	3.87
Look at scenery	32	3.56
Take along family and friends	33	3.56

commuters in Baltimore and Philadelphia rated "arrive at intended time" second in importance of all the attributes. Only "arrive without accident" was viewed as more important.

The importance commuters place on travel reliability as found by University of Maryland researchers is substantiated by surveys conducted in other metropolitan areas. A commuter survey in Boston (Spear, 1976) found "arrive at the intended time" to be the most important level of service attribute ("arrive without accident" was not included in the survey). A survey of commuters conducted in Chicago (Stopher, et. al., 1974) found "arrive at the intended time" second in importance (following "easily accessible station").

Considerably less information is available with which to assess the importance of travel reliability in non-work travel. The surveys in Baltimore and Philadelphia (Paine, 1976) provide data for analyzing this question. The findings in Table 2.2 indicate that "arrive at intended time" is of lesser, albeit still considerable, importance for non-work travel. It is, perhaps, noteworthy that on-time arrival is still important relative to average travel time and cost factors, generally thought to be the most important service attributes which impact demand (although

Table 2.2 Rank by Importance, Non-Work Trip for Combined  
Philadelphia, Baltimore Sample

<u>Description</u>	<u>Rank by Mean Importance</u>	<u>Mean Value</u>
Arrive without accident	1	6.42
Safest vehicle	2	6.34
Avoid stopping for repairs	3	6.27
Protected from weather while waiting	4	6.01
Avoid changing vehicle	5	5.99
Vehicle unaffected by weather	6	5.95
One-way cost of 25¢ rather than 50¢	7	5.74
Arrive at intended time	8	5.67
Comfortable	9	5.65
Avoid walking more than a block	10	5.58
Clean vehicle	11	5.58
One-way cost of 25¢ rather than 35¢	12	5.56
One-way cost of 3¢ rather than 15¢	13	5.53
Avoid waiting more than 5 min.	14	5.40
Package and baggage space	15	5.33
Shortest distance	16	5.30
Cost	17	5.24
Fast as possible	18	5.23
Feel independent	19	5.18
Uncrowded vehicle	20	5.15
Avoid unfamiliar area	21	5.07
Travel when traffic is light	22	4.89
Shortest time	23	4.82
Friendly people	24	4.75
People you like	25	4.67
Take along family and friends	26	4.65
New modern vehicle	27	4.62
Pride in vehicle	28	4.48
Ride with people who chat	29	4.15
Look at scenery	30	4.04
Avoid riding with strangers	31	4.04
Need not pay daily	32	3.79
Listen to radio	33	3.46

socio-economic factors are often "dominant" in travel demand models).

Several studies have been conducted on user attitudes towards travel reliability on specific transit modes. Attitudinal surveys were conducted among riders of the Shirley Highway express-bus-on-freeway in the Washington, DC area (Wachs, 1976), and respondents were asked to rate attributes of the bus service which were of great importance to them. Multiple responses were permitted by the survey instrument. Ninety percent of the users cited reliable schedules, while only 29% cited a five-minute saving in travel time. This result suggests that while elapsed travel time is important to bus travelers, reliability in arrival time may be of even greater importance.

A General Motors survey of potential users of a "demand responsive jitney" system in Warren, Michigan (Golob, 1970) found "arriving when planned" to be the most essential attribute. In that survey, "arriving when planned" was found to be more important to potential users than "lower fare", "having a seat", "no transfer trip", "less wait time" or "short travel times". This result is significant in its implication that service improvements which are focused on reliability rather than speed, convenience, or reduced fare may be more successful in generating ridership. A similar

survey of dial-a-bus users and non-users in Columbia, Maryland, also found "arriving when planned" most important, with results similar to the General Motors survey in Warren, Michigan.

Park-and-ride users in Henrietta, New York (Keck and Cohen, 1976) were asked to rank thirteen level of service variables; "reliability" was cited as the second most important system attribute ("convenience" was ranked first).

User attitudes on reliability of specific modes were also examined in Haddonfield (Winchester, 1976). The Haddonfield data was separated into dial-a-ride user households, bus user households, and taxi user households to examine how these groups perceived the importance of reliability based on their experience with each mode. All user groups rated "reliability" as the most important attribute. There were only slight differences in the mean weighting of reliability for each mode, with taxi users placing the highest absolute weight on reliability, followed by bus users and then dial-a-ride users.

The results of the surveys of attitudinal response to reliability on specific modes point out the importance users place on travel reliability regardless of the mode concerned. This is a particularly significant finding

considering the vast difference in service characteristics of the different modes (e.g., dial-a-ride door-to-door service vs. express bus line-haul service).

There appears to be a distinct relationship between the demographic characteristics of travelers and attitudinal importance of reliability. The Chicago surveys of commuters (Stopher, et al., 1974) found that males ranked "arrive at the intended time" higher than females. Older riders placed a greater weight on this attribute than did younger riders. As the data is disaggregated by age group, the sample size is reduced so some doubt may be cast on the statistical significance of these results. However, a possible explanation may be that type of employment and level of position influence the importance of punctuality for the work trip and therefore the relative weighting of reliability with respect to other service attributes. These characteristics vary with age and sex.

The GM survey (Golob, 1970) also contrasted scalings for elderly, low income, and under 25 and single groups. "Arriving when planned" scored high for all groups. Only for the elderly were other attributes ranked more important ("having a seat", "no transfer trip" and "lower fares"). However, a higher weight on comfort and convenience by the elderly is not unexpected. In addition to the elderly



having a higher preference for other attributes, the lower ranking of reliability may be due in part to the diminished importance of reliability for the types of trips taken by elderly people (i.e., non-work). It is also likely that since the elderly often have fewer travel alternatives, they may be more tolerant of variations in service.

In summary, attitudinal surveys show arriving at the intended time to be among the most important service attributes for all travelers under a variety of travel conditions. For commuters its importance is paramount. For both work and non-work trips, arriving at the intended time was considered more important than average time and cost, generally thought to be dominant service attributes which impact demand. Some differences are apparent between the work and non-work trip, and between modes and demographic background. Age and sex often correlate with work type and trip purpose, however, implying that many of these other differences may also be work-related.

However, it should be noted that a serious drawback in the reported attitudinal surveys is the lack of a consistent definition for reliability. Because no formal definition of "reliability" was established in the surveys, it is likely that each respondent used his/her own judgment as to the definition of "reliability". For example, three different

people could have defined reliability as "arrive at the intended time," "vehicle unaffected by weather," and "avoid waiting more than 5 minutes" respectively.

In light of the importance that users seemingly place on reliability-related attributes, it is worth examining current levels of satisfaction users experience regarding the reliability of particular modes. The Philadelphia survey (Paine, 1976) addressed this question and helps point to the significance of reliability attributes in the attractiveness of transit service. This survey asked each respondent to express their satisfaction with both existing public transit and the automobile. Results for work and non-work trips appear in Tables 2.3 and 2.4 respectively. Among the 15 most important attributes, "arrived at the intended time" shows the fourth and sixth highest differences between satisfaction for auto and transit for work and non-work trips respectively.\* These results support the view that transit is currently considerably less reliable than auto and suggests that this performance deficiency may be a major reason for the preference for auto trips when autos are available.

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\*Part of the difference between ratings of auto and bus satisfaction may be due to cognitive dissonance on the part of auto users replying to transit attributes (i.e., many auto users who have had an opportunity to try transit, but have chosen not to, are likely to be more critical of transit attributes to support their behavior).

Table 2.3 Percentage of Satisfied Responses to Each Item for Auto Versus Public Modes with Items Ranged by Mean Importance Work Trip

Description	Importance Rank	% Satisfied with Auto	% Satisfied with Public Transit	Difference
Arrive without accident	1	89	86	3
Arrive at intended time	2	94	63	31
Safest vehicle	3	94	91	3
Avoid stopping for repairs	4	94	92	2
Shortest distance	5	97	64	33
Fast as possible	6	95	70	25
Avoid changing vehicle	7	98	69	29
Vehicle unaffected by weather	8	90	84	6
Protected from weather while waiting	9	96	54	42
Shortest time	10	92	65	24
Avoid waiting more than 5 minutes	11	98	55	43
One-way cost of 25¢ rather than 50¢	12	88	69	19
Comfortable	13	97	75	22
One-way cost of 25¢ rather than 35¢	14	88	67	21
Clean vehicle	15	92	73	19
Feel independent	16	89	58	31
Avoid walking more than a block	17	97	65	32
One-way cost of 3¢ rather than 15¢	18	84	67	17
Cost	19	91	62	29
Avoid unfamiliar area	20	93	78	15
Travel when traffic is light	21	73	64	9
Uncrowded vehicle	22	94	51	43
Package and baggage space	23	94	57	37
Pride in vehicle	24	88	60	28
New modern vehicle	25	86	68	18
Friendly people	26	91	67	24
People you like	27	93	66	27
Need not pay daily	28	82	61	21
Avoid riding with strangers	29	89	66	23
Listen to radio	30	84	44	40
Ride with people who chat	31	84	62	22
Look at scenery	32	74	72	2
Take along family and friends	33	87	57	30

Table 2.4 Percentage of Satisfied Responses to Each Item for Auto Versus Public Modes with Items Ranged by Mean Importance: Non-Work Trip

Description	Importance Rank	% Satisfied with Auto	% Satisfied with Public Transit	Difference
Arrive without accident	1	86	77	9
Safest vehicle	2	89	81	8
Avoid stopping for repairs	3	89	81	8
Protected from weather while waiting	4	95	47	48
Avoid changing vehicle	5	96	68	28
Vehicle unaffected by weather	6	90	81	9
One-way cost of 25¢ rather than 50¢	7	86	65	21
Arrive at intended time	8	93	66	27
Comfortable	9	97	69	23
Avoid walking more than a block	10	95	57	38
Clean vehicle	11	91	63	28
One-way cost of 25¢ rather than 35¢	12	85	63	22
One-way cost of 3¢ rather than 15¢	13	82	60	22
Avoid waiting more than 5 minutes	14	93	45	48
Package and baggage space	15	95	52	43
Shortest distance	16	91	55	36
Cost	17	89	54	35
Fast as possible	18	90	64	26
Feel independent	19	84	51	33
Uncrowded vehicle	20	91	48	43
Avoid unfamiliar area	21	91	72	19
Travel when traffic is light	22	67	55	12
Shortest time	23	91	55	36
Friendly people	24	92	60	32
People you like	25	91	60	31
Take along family and friends	26	86	59	27
New modern vehicle	27	84	62	22
Pride in vehicle	28	89	53	36
Ride with people who chat	29	82	56	26
Look at scenery	30	78	76	2
Avoid ride with strangers	31	91	58	33
Need not pay daily	32	76	51	25
Listen to radio	33	79	32	47

It should be recognized that although the results of these attitudinal surveys identify the importance of reliability-related attributes to the traveler, it does not imply that the same relationship exists in the traveler decision-making process. Very little is known about the relationship between attitudes and behavior, and it is inappropriate to assume that attitudinal responses are accurate indicators of behavioral response. Thus, while it is a significant finding that travelers rank reliability attributes as extremely important, the survey results are limited in that they identify the need to establish a consistent set of reliability measures and analyze the impact of service reliability on travel behavior, but are insufficient to provide an accurate assessment of this relationship.

### 3. THEORY OF THE ROLE OF SERVICE RELIABILITY IN THE CHOICE OF MODE AND DEPARTURE TIMES

This chapter proposes a theory of the role of service reliability in commuter mode choice and departure time decisions. In later stages of this dissertation, this theory is empirically tested through the estimation and analysis of departure time and mode choice models.

The theory is introduced in a three-part discussion. Section 3.1 discusses the current specification of travel time attributes in work travel behavior models. Section 3.2 proposes a measure of service reliability which could be incorporated into work travel behavior models. Finally, Section 3.3 examines the effects of omitting service reliability variables from an analysis of work travel behavior.

#### 3.1 Current Specification of Travel Time Attributes in Travel Behavior Models

For a given mode  $m$  and departure time  $d$ , each traveler will experience a particular travel time distribution for his/her commute. Assuming that a commuter leaves home to travel to work at roughly the same time each day, this

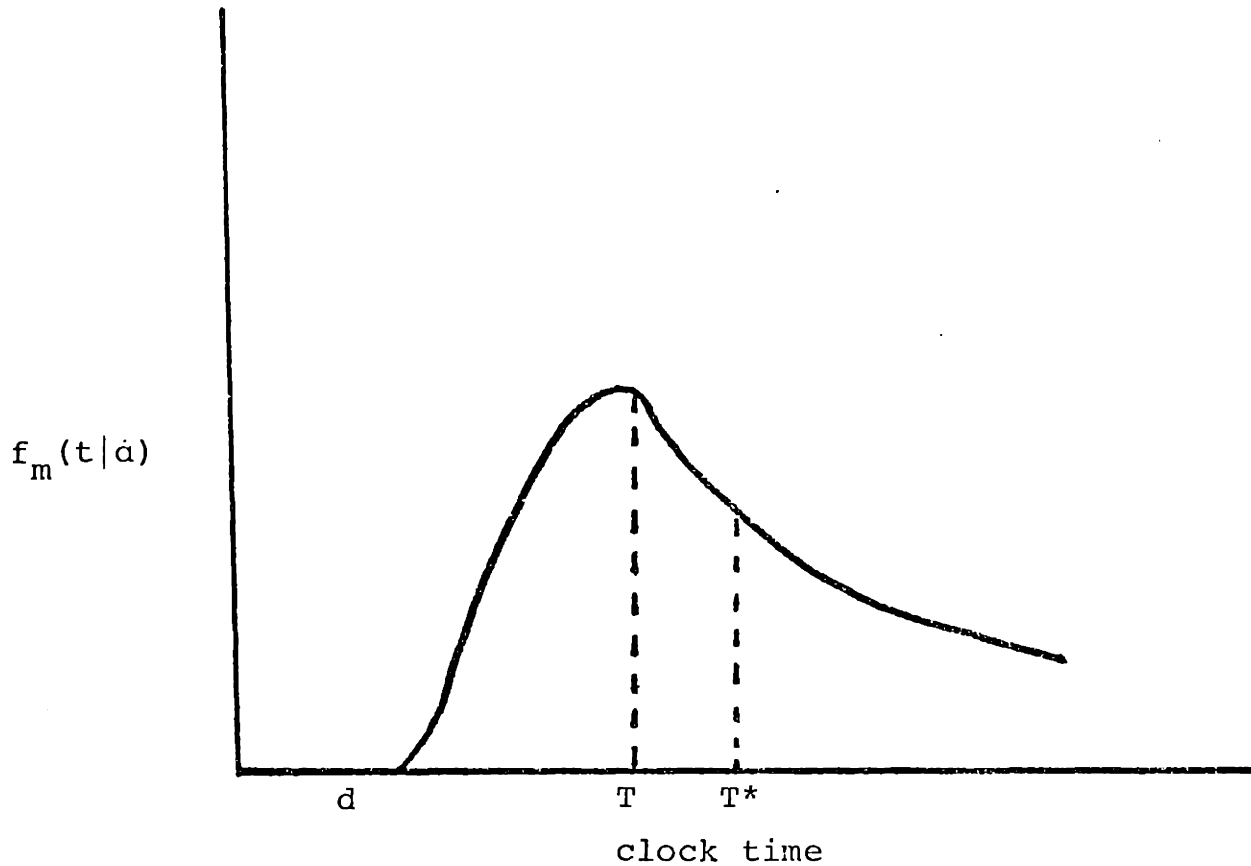
travel time distribution translates directly to an arrival time distribution at work.\* If we define  $T$  as the traveler's mean arrival time at work and  $T^*$  as the traveler's official work start time, then a typical arrival time distribution for a given mode and departure time might be similar to the distribution depicted in Figure 3.1. The figure suggests that individual commuters generally choose to arrive the majority of the time at or before their official work time, and have a usual arrival time sometime before the official work start time.\*\*

Figure 3.1 is just an example of an individual's possible distributional form for arrival time, and different commuters will experience different arrival time distributions. There would clearly be a different distribution for every mode and departure time combination facing an individual, although it is possible that while the parameters of a distribution may change, the distributional form may not vary.

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\*The study of the commute trip was restricted to a study of home-to-work travel only, due in part to the lack of available data on the p.m. return trip. This issue is discussed in more detail in Chapter 6.

\*\*This is usually true for the chosen mode and departure time, but is not necessarily true for any given mode and departure time.



where:

$f_m(t|d)$  = probability of arriving at time  $t$  given  
departure time  $d$  and mode  $m$

$T$  = mean arrival time of work

$T^*$  = official work start time

Figure 3.1 A Typical Commuter Arrival Time Distribution  
For a Given Mode and Departure Time



In current travel behavior models (which typically use the concept of utility theory and linearity in the parameters of the utility function in defining the impacts of service attributes)\*, only a measure of the mean travel time is included in the utility expression:

$$U_{md} = \alpha_{md} + \beta (T_{md} - d) + \gamma X_{md} + \epsilon_{md} \quad (3.1)$$

where  $U_{md}$  = utility for mode m and departure time d .

$\alpha_{md}$  = a constant defined for mode m and departure time d

$T_{md}$  = mean work arrival time for mode m and departure time d

$X_{md}$  = vectors of all other non-travel time attributes usually included in the utility expression for mode m and departure time d (i.e., fare, auto ownership, occupation).

$\beta, \gamma$  = scalar and vector model coefficients respectively

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\*See Ben-Akiva (1973, 1977) for a discussion of utility and choice theory as it relates to the travel decision-making process. Manski (1973) discusses the structure of random utility models in general.

$\epsilon_{md}$  = random components of the model\*

Equation 3.1 is actually a simplified expression for the travel time attributes in the utility. In application, it is common for travel time to be segmented into vectors of in-vehicle travel time and out-of-vehicle travel time (walk, wait, transfer), due to the empirically-supported belief that travelers have a higher sensitivity to out-of-vehicle travel time than in-vehicle travel time.\*\*

The major point of this discussion is to recognize that while it is apparent that there may be varying expected arrival times at work and a large amount of arrival time uncertainty about that arrival time, the specification used in current travel behavior models is not explicitly accounting for either of these effects and their implications to the traveler. By not including measures that consider arrival time implications, current models implicitly assume travelers arrive at work when they want to, and are risk neutral toward uncertainty in their arrival times. This implies that for equivalent travel times,

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\*Because of the suspected random nature of traveler decision-making, it is desirable to express alternative choices in terms of random utilities.

\*\*In empirical tests, commuters have been estimated to be more sensitive to out-of-vehicle travel time by a factor of roughly 2-3 (McIntosh and Quarmby, 1970).

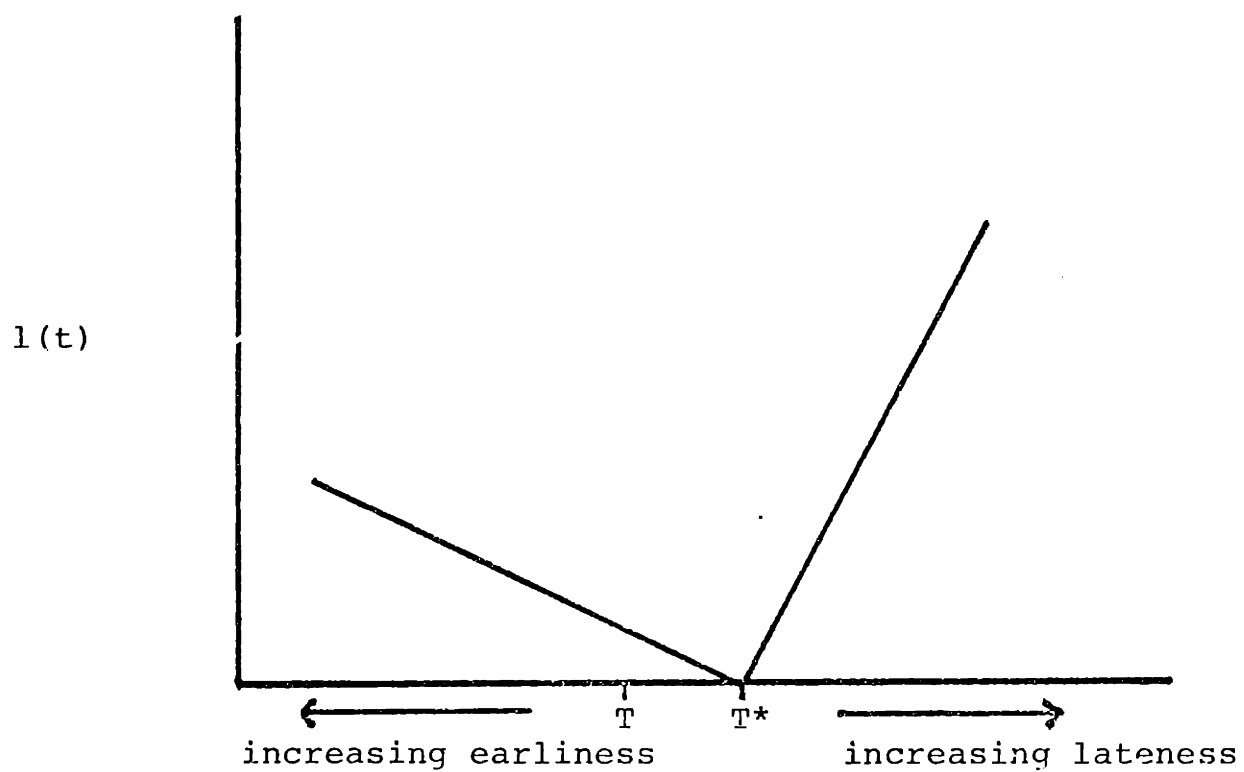
arriving at work extremely late or extremely early with equal probability is valued the same as arriving on time with certainty, which is clearly unrealistic for the majority of commuters. It also implies that travelers are indifferent between alternatives that have the same mean arrival time, but varying distributions of arrival time.

### 3.2 Defining Reliability-Related Measures

The question which arises is, "Assuming that service reliability is an important input to the traveler decision-making process, how can we model this effect on commuter choice?".

An appealing approach is to relate the arrival time uncertainty to the commuter's perceived loss associated with different arrival times, since this would be a way to represent the importance of arriving at the intended time. To represent perceived loss, the notion of an arrival time loss function is introduced.

Figure 3.2 presents a hypothetical arrival time loss function  $l(t)$ . The loss function in Figure 3.2 is based on the premise that commuters are most satisfied when they arrive to work near their official work start time. As the



where:

$l(t)$  = loss associated with arrival at time  $t$   
(expressed in utiles)

Figure 3.2 Arrival Time Loss Function

commuter arrives increasingly later than official work start time, the magnitude of the perceived loss increases, representing employment penalties which may be associated with tardiness (i.e., loss in pay, poor reputation, impact on promotion, etc). Presumably the penalties for being a few minutes late will be far less severe than arriving on the order of 15-30 minutes late.

Perceived loss is hypothesized to increase with early arrival as well, since the commuter could have utilized the extra time as leisure time at home, which is likely to be valued higher than being at the office. It is important to note, however, that the magnitude of the slope of the loss function for lateness is expected to be larger than for earliness, reflecting larger perceived penalties for late arrival to work than penalties perceived by not maximizing leisure time at home.\*

The loss function in Figure 3.2 represents just one possible functional form. While each individual has only one mean arrival time loss function,\*\* there is reason to believe that the parameters (and form) of the loss function

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\*It is assumed that overtime benefits (compensatory pay, etc.) are not available.

\*\*Individuals' loss functions may vary on a day-to-day basis due to weather, work load, etc. A mean arrival time loss function represents the average loss for an individual traveler.

will vary by individual according to their occupation (i.e., clerical, management) and work flexibility. For example, a member of the clerical staff on hourly wages will have a much higher perceived loss for late arrival than a manager who works for a firm which operates a flexitime policy.

The effect of service reliability in the commuter mode choice-departure time decision process can be defined as the expected loss for each choice alternative, through the use of a commuter arrival time loss function and by representing the uncertainty of arrival time by a probability density function of the arrival time distribution. Assuming that the mode choice decision has been resolved at the time a departure time decision is made (although the choices may be interdependent), departure time choice can be structured conditional on mode choice being fixed. The impact of service reliability on departure time could then be defined as follows:

$$E(l|d,m) = \int_d^{\infty} f_m(t|d) l(t) dt \quad (3.2)$$

The expected arrival time loss could be included in the utility specification for departure time choice, resulting in a new departure time utility specification which would be:

$$U_{d|m} = \sigma_d + \beta(T_{d|m} - d) + \gamma_d X_d + \delta E(1|d,m) + \epsilon_{dm} \quad (3.3)$$

where  $X_d$  = a vector of all non-travel time attributes that impact departure time decisions

$\gamma_d$  = a vector of model coefficients

Because of the assumed sequential structure of the mode-departure time choice problem, output from the departure time model forms inputs to the mode choice model. The information required at the mode choice level is the optimal departure time for each mode, since travelers presumably make mode choice decisions on the basis that they will choose to depart at the time that maximizes their departure time utility for each mode being considered.

For the logit model form (which will be used in this research), the optimal departure utility inclusive terms to be input in the mode choice model are derived from the departure time model, and can be expressed as (McFadden, 1977):

$$D_m^* = \text{Max}_{d=1, \dots, I} U_{d|m} = \log \left( \sum_{i=1}^I e^{U_{i|m}} \right) \quad (3.3a)$$

where  $I$  = the number of alternative departure time choices

Accepting this definition, the mode choice model specification becomes:

$$U_m = \alpha_m + \rho D_m^* + \gamma_m X_m + \theta_m T_m + \epsilon_m \quad (3.4)$$

where:

$D_m^*$  = the expected utility of the optimal departure time utility for mode m

$X_m$  = non-travel time attributes usually included in the utility expression for mode choice decisions (may include some of the same attributes used in the departure time utility)\*

$T_m$  = travel time and reliability attributes for mode m. This is because some reliability-related attributes vary across modes (e.g., inherent reliability problems with transit), not across departure times given mode.

$\alpha$  = model constants

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\*For example, high income workers may have different arrival time practices than the entire commuting market (because of their management status). They may also be more inclined to drive automobiles to work.



$\rho$  = model coefficient

$\gamma, \theta$  = vectors of model coefficients

The impact of service reliability on mode choice would be represented in attributes  $D^*$  and  $T$ , with the linkage between departure time and mode choice through  $D^*$ .

It should be noted that while Equation 3.4 includes the effect of service reliability on work arrival time, there may be cases where commuters are sensitive to travel time uncertainty even though the expected loss associated with arrival time is quite low. This situation might arise in the case of a traveler who likes to be in control of his/her own schedule. For this type of person, not knowing when the vehicle will arrive at the destination may be very upsetting, even though there is nothing pressing when the traveler reaches his/her destination.\* Furthermore, traveler exposure to infrequent but excessively long delays may also impact mode choice decisions. These effects will be represented as modal reliability attributes.

The utility structure in Equations 3.3 and 3.4 will be tested to determine what, if any, effect service reliability

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\*A view supported by Knight (1974) and Turnquist (1976).

attributes have on departure time and mode choice decisions. Several model specifications will be tested, with each specification including some measure of service reliability.

### 3.3 What Happens When Reliability Variables Are Omitted?

The previous discussion has implications for the validity of existing work travel behavior models. One obvious deficiency with current models is that they do not explicitly account for service reliability (and other arrival time considerations). Hence, the models are clearly not sensitive to policies directed at improving service reliability. For example, if a Federal agency is considering sponsoring a service reliability improvement program, there is no existing way of quantifying the expected benefits of such a program or the cost-effectiveness of supporting service reliability strategies as opposed to fare programs or programs designed to improve mean vehicle speeds.

The omission of service reliability variables, however, impacts more than just the availability of an analytical tool sensitive to service reliability policy. When reliability variables are omitted, there is reason to believe that the coefficient estimates of other independent

variables in the utility expression differ asymptotically from their true values.\* This would occur in cases where possible correlations exist between included independent variables and the omitted reliability variable (Tardiff, 1979). For example, since service reliability may be partially correlated with mean travel time, part of the explanatory effect of service reliability is perhaps being absorbed in the coefficient of mean travel time. The non-correlated impact of service reliability is likely present in the estimated constant, and partially absorbed in the error term (i.e., noise). Thus, in most cases, when reliability variables are omitted, the values of the coefficients of other independent variables in existing models are artificially higher or lower (depending on the direction of the correlation) than the true value.

If this is the case, when the omitted model is used in forecasting, errors will be present which impact the accuracy of the forecast. The portion of the constant representing reliability effects is not sensitive to different policies which affect reliability, as it should be. Furthermore, the magnitude of the mean travel time coefficient will also be artificially high (low). This will lead to overestimates (underestimates) of mode and departure

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\*A view supported by Starkie (1971).

time shifts resulting from policies directed solely at service changes other than reliability changes. Forecast errors of this nature could arise under a variety of conditions, since, for example, it would seem unlikely that expected loss would be highly correlated with mean travel time (although there will likely be some correlation between variance and mean travel time).

For the case where expected loss is perfectly correlated with mean travel time (i.e.,  $E(l|d,m) = \lambda + K(T-d)$ ) the estimated coefficient for mean travel time would be  $(\beta + \delta K)(T-d)$ . Under these circumstances, error would not be present in the forecast. However, knowledge of the value of  $k$  and  $\delta$  would be required to render the model sensitive to reliability improvement policies, as well as to understand the tradeoffs between improved reliability and improved speed investment. Since it is extremely unlikely that perfect correlation would exist, one can conclude that in general existing models are limited in their application, and are likely to produce inconsistent forecasts since they exclude variables which are correlated with omitted attributes.

### 3.4 Summary

A theory was introduced which hypothesizes that service reliability is an important component in the commuter choice process. Measures of the effects of service reliability on departure time were proposed which are related to the attribute of arrival at the intended time. Additional modal reliability attributes were defined which are independent of arrival time implications to represent the effects of travel time uncertainty independent of arrival time considerations and exposure to infrequent but excessively long service delays. It is this theory and subsequent measures which will be tested empirically as part of the research effort.

The specification currently used in travel behavior models does not explicitly account for the effects of service reliability on the choices of mode and departure time. Consideration of travel time attributes is typically restricted to modeling mean travel time; the importance of expected arrival time at work and arrival time uncertainty about that arrival time are largely ignored. The result of this omission is the development of travel behavior models which are not policy sensitive to service reliability issues and which may provide inconsistent forecasts for other policy issues.

#### 4. REVIEW OF TRAVEL BEHAVIOR MODELS WHICH HAVE CONSIDERED SERVICE RELIABILITY MEASURES

To date, few attempts have been made to model service reliability in the analysis of work travel behavior. Attempts have largely been directed at either the mode choice or departure time decision rather than considering the two decisions to be interrelated. This chapter reviews and critiques existing models of work travel behavior which have considered the impact of service reliability.

##### 4.1 Mode Choice Studies

Cambridge Systematics (Lerman, et al., 1977) attempted to incorporate both wait time and ride time variance as reliability variables in a dial-a-ride demand model estimated using the logit form. This approach met with little success; Cambridge Systematics cited three reasons for their difficulties:

- 1) there was a great deal of difficulty obtaining the proper data to accurately estimate the reliability variable. Repeated observations on an origin-destination basis were difficult to collect;

2) in the data collected, there was a high correlation between the mean and variance in ride times; and

3) the variation in wait time reliability was often so low that statistically significant coefficients for reliability variables could not be estimated.

It is important to note that the Cambridge Systematics study was conducted using zonal averages for travel time reliability. The use of aggregate measures of supply obscures the potential impact of service reliability on demand. It is also worth noting that Cambridge Systematics defined reliability variables that do not link reliability to the importance of on-time arrival at the destination.

The Urban Travel Demand Forecasting Project (UTDFP), conducted by the University of California at Berkeley, defined composite service reliability measures based on subjective rankings of the boarding characteristics at nodes and congestion characteristics on links for a passenger's trip. An example of the composite measures used in the study was the fraction of heavily congested links (as defined subjectively) for the trip.

These measures were input as explanatory variables in a logit model of mode choice. The results were rather

disappointing; the coefficients of most reliability variables either had the wrong sign or were not statistically significant (Train, 1976). Based on these results, service reliability variables were dropped from further consideration. Just recently, however, a review of the UTDFP data revealed that the service reliability data was improperly coded. Thus, the UTDFP service reliability modeling results are not a valid source of information.

Prashker (1977) estimated a multinomial logit mode choice model for commuters working in downtown Chicago, using scaled reliability measures (i.e., 1 = very reliable, 2 = fairly reliable, etc.) based on responses to a survey he conducted. Prashker tried several specifications, including omitting reliability variables from some models and including reliability variables in other models. Prashker found that inclusion of a scaled service reliability variable was statistically significant (in terms of t-statistic) and improved the predictive power of the model (in terms of percent of choices correctly predicted).

Prashker's finding demonstrates that service reliability is an important attribute in the mode choice process. Again, however, the reliability variable is defined in terms of travel time uncertainty, and an additional measure of its impact on on-time arrival is not



considered. There are also problems with the use of scaled measures. First, individuals may have different perceptions of their level of service reliability (i.e., two travelers who experience the same variability in travel time may rank their reliability differently). Secondly, it would be difficult to use the model in policy analysis since there is no metric conversion of the scaled measure (i.e., how would a planner represent a service reliability improvement if using the model to forecast?). Finally, scaled responses may include some modal bias of the individual, so the scaled reliability variables may in part be reflecting non-reliability attributes. These problems pose serious questions about the validity of transferring the model to forecast using another sample, and would also make it difficult to measure tradeoffs of reliability improvement investment versus other transit investments.

However, because objective measures of service ~~reliability are likely to be~~ monotonically related to those used by Prashker, his work can be interpreted as justification for including service reliability measures in models of mode choice, and for developing relevant objective reliability measures.

Spear (1976) also estimated a mode choice model, using a generalized convenience attribute variable (which included

reliability sub-attributes), computed as the sum of the scaled sensitivity of the user to each sub-attribute multiplied by user satisfaction for that sub-attribute. He too found a better goodness of fit with model specifications that included the generalized convenience variable than with model specifications that omitted the convenience variable. Again, for reasons cited in the Prashker discussion, it is difficult to interpret his research findings, although it does indicate that further research in defining and modeling reliability variables is appropriate.

#### 4.2 Departure Time Studies

Very little travel demand model research has been directed at understanding departure time decisions. Stephen Cosslett (McFadden, et al., 1977) estimated a multinomial logit model for the departure time decision. Using data collected for the UTDFP sample, Cosslett examined the individual's tradeoff between mean travel time, schedule delay\* and the probability of arriving late for work. Cosslett used the following utility form:

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\*Schedule delay is defined here as the difference between the actual mean arrival time and official work start time. This differs from the more classical definition of schedule delay as the difference between the desired mean arrival time and the actual mean arrival time due to discontinuities in the availability of transit service (Starkie, 1971).

$$U(T) = \alpha y(T) - \beta R(T) - \gamma L(T) \quad (4.1)$$

where:

$T$  = the time of arrival at work

$y(T)$  = the in-vehicle travel time corresponding to arrival time  $T$

$R(T)$  = the amount of earliness if  $T$  is earlier than the official work start time

$L(T)$  = the probability that the subject will arrive late for work, if he/she plans to arrive at time  $T$

The arrival time alternatives were discrete intervals of five minutes, ranging from forty minutes early to fifteen minutes late. In-vehicle travel times were obtained by interpolation from values previously computed from a congestion-corrected network. The probability of lateness was computed assuming a normal random variable with mean  $y(T)$  and standard deviation  $\sigma = a[y(T) - y(0)]$ , where  $y(0)$  is the off-peak travel time and  $(a)$  is a constant. Cosslett's justification for using this form is that simple models (in which congestion is due to queue formation at bottlenecks) suggest that the standard deviation should be approximately

proportional to excess travel time due to congestion. The results reported below are for the case  $a = 0.2$ .\*

Cosslett estimated departure time models only for auto commuters, estimating separate models for people who drive alone and those who ride-share in addition to a pooled model of all auto travelers. Because of an expected interdependence of unobserved attributes between departure time alternatives (i.e., unobserved attributes of an 8:00 a.m. departure time would be more highly correlated with those of an 8:10 a.m. departure time than with unobserved attributes of a 9:00 a.m. departure time), Cosslett assumed the IIA restriction of logit\*\* would be violated, and interpreted his result as more of an empirical fit than a choice model.

All the estimated coefficients were significant, particularly the late and early measures. Cosslett used the estimated parameters to predict the extent to which travelers would reschedule their trips when faced with increased congestion, and found that there is a small, but measurable effect, with travelers tending to schedule

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\*No justification was given for why  $a$  was set at this value.

\*\*The assumption of Independence of Irrelevant Alternatives (IIA) characterizes the logit model. The IIA assumption is a direct result of the assumption that the alternative error terms are independent and identically-distributed (Weibull).

departure times away from the peak whenever possible. Cosslett also calculated elasticities of departure and arrival times in response to changes in traffic congestion.

Cosslett's research contributes several important innovations in attempts to understand work departure time behavior. Cosslett's work represents one of the first attempts to model departure time choice, and identifies the importance of uncertainty associated with commuter departure decisions. Cosslett takes account of possible losses associated with early and late arrival, and notes the difference in sensitivity to loss due to earliness from loss due to lateness.

There are, however, several drawbacks to Cosslett's approach. First, Cosslett's model does not explicitly consider a loss function; his specification assumes a linear loss function for earliness, with expected arrival time loss proportional to the difference between the expected arrival time and the official work start time. The problem with this formulation is that it assumes, for example, that twice as much loss is perceived for arriving 10 minutes early than 5 minutes early, etc. This may be unrealistic. The earliness loss variable is also constructed with the assumption that a traveler's perceived arrival time loss is minimized by arriving exactly on time, rather than arriving

slightly earlier than the official work start time. Cosslett's lateness variable does take account of uncertainties in travel time, but the late variable definition is somewhat inconsistent with the early variable definition.

Cosslett also considers only time-related attributes in the departure time utility expression. Realistically one would expect departure time choice might be impacted by age, sex, income, occupation type, flexitime policies, and a variety of other socio-demographic considerations. Furthermore, Cosslett does not attempt to model the potential interdependencies of the mode choice and departure time decisions, preferring instead to estimate separate departure time models for each mode. Finally, by not explicitly including a constant in the utility expression, Cosslett is making a questionable assumption that the departure time decision is fully explained by the variables included in the model.

Following Cosslett's effort, Ken Small (1978) also conducted a study of the scheduling of work trips, using the same UTDFP data set. Small estimated a departure time model using discrete time periods and assuming mode choice as fixed. He estimated only a departure time model for auto trips using UTDFP data, but also estimated departure time

models for auto, motorcycle, and bus travelers using data collected in Singapore by the World Bank.

Small found that commuters do indeed perceive a tradeoff between traveling under uncongested conditions and traveling at their preferred time of day. He also found the departure time decision is impacted by the worker's official work hours, occupational and family status, work-hour flexibility, and car occupancy.

Small recognized the drawback of using discrete time periods, but argued that the use of discrete time periods is plausible because people generally respond to questions about departure or arrival times by rounding off to the nearest 5 minutes. Small estimated a logit model, recognizing that the IIA property might be violated. However, he argued that even when departures from independence can be demonstrated at statistically significant levels, the coefficient estimates by logit may not be badly biased. For his estimated models, Small conducted three tests for departures from independence and found the logit estimates were reasonable.

Small compared his results with earlier work conducted by Cosslett and McFadden, who found that for commuters driving alone to work, they are willing to incur 0.62

minutes of travel time to avoid arriving one more minute early, and 2.14 minutes of travel time to avoid a 10% increase in the probability of arriving late. In place of the frequency of arriving late variable, Small defined a schedule delay\* late variable which would have a different coefficient than schedule delay early; he also defined a late dummy variable to model additional effects which account for late arrival behavior.

Small's final formulation for the model based on UTDFP data was:

$$W(s) = \beta_1 RPTR15(s) + \beta_2 RPTR10(s) + \beta_3 TIM(s) + \beta_4 SDE(s) + \beta_5 SDL(s) + \beta_6 DIL(s) \quad (4.2)$$

where:

$W(s)$	=	utility for time period s
$RPTR15(s),$	=	round-off bias variables for reporting
$RPTR10(s)$		of intervals of 10 and 15 minutes of
		schedule delay (1 if round-off present;
		0 otherwise)
$TIM(s)$	=	mean travel time
$SDE(s)$	=	schedule delay early (schedule delay
		if early arrival; 0 otherwise)

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\*As defined by Cosslett.





fixed and people have reported their flexibility level to justify their arrival time as dictated by their mode. He concluded the bias can only be assessed by estimating more complete models which include the behavioral determinants of mode choice and of survey response to the flexibility question, something he did not attempt. Small also attempted to model quadratic schedule delay functions but noted the effects of collinearity between a term and its square.

Small's Singapore modeling efforts were somewhat constrained due to limited data on travel time for different time periods (travel times were only calculated on a dichotomous peak and off-peak basis). He defined only three departure time alternatives (before peak, peak, after peak), and defined early and late schedule delay variables as the minimum schedule delay which a commuter would have to suffer in order to travel during the period in question. These schedule delay variables are similar, but not identical, to those defined in the San Francisco models. The grouping of alternatives is quite different than the San Francisco alternatives.

Small estimated separate departure time models for auto, motorcycle, and bus travelers as well as a model of the entire Singapore sample using a specification containing

only mean travel time, schedule delay early, and schedule delay late variables. Some of the estimation differences between the San Francisco and Singapore models are difficult to identify since there are differences in the level of detail of the information available from the surveys, model formulations and the cultures of the travel markets. One counter-intuitive result of the Singapore model was that the schedule delay lateness coefficient was smaller than the schedule delay earliness coefficient (the difference being significant for all models which included both variables).

Small's research has several strong points. As in Cosslett's work, he notes differences in workers' sensitivity to early and late arrival. Small also defines consistent measures for early and late variables, as well as recognizing that there are additional effects which account for late arrival behavior. Small also explored the impact of work flexibility and occupation on the departure time decision. Furthermore, he explicitly accounts for round-off bias in the reporting of travel times. Finally, Small attempted to examine departure time decisions faced by Singapore bus commuters, although the nature of the data was such that the model specification was necessarily simple and the departure time choices were essentially peak vs. off-peak rather than selection among various peak departure times.

The most serious weakness in the Small research is the lack of consideration of variation of travel time in the utility specification. His methodology assumes that a traveler can arrive at work with certainty at the chosen time. The only decision facing the traveler is the tradeoff of longer travel times in order to arrive at the preferred time. Clearly this assumption simplifies his analysis, but it also creates an unrealistic situation. Part of the schedule delay experienced by travelers is in response to travel time uncertainty, and this effect is not captured in the Small model. Small also made no attempt to consider the interdependencies of the mode choice-departure time decision. Finally, Small's early and late variables suffer from the same assumptions used by Cosslett to define his early variable.

#### 4.3 Summary

A review of the limited empirical work which has been directed at understanding the impact of service reliability on work travel behavior has revealed some interesting findings. To date, the departure time decision has been modeled conditional on mode choice, and the impact of service reliability has been examined separately for each decision level.

Early attempts to include objective service reliability measures in mode choice models ran into difficulty due to problems encountered in collecting accurate data. The inclusion of scaled reliability variables in mode choice models have resulted in statistically significant coefficients for the reliability variables, and have improved the predictive power of the models. However, the use of scaled variables poses serious questions about the validity of transferring the model for forecasting in other areas, and also makes it difficult to evaluate reliability improvement policies and measure tradeoffs of reliability investment versus other transit improvement strategies. However, because objective measures are likely to be monotonically related to scaled measures, past research provides motivation for developing relevant objective measures of service reliability, and measuring their impact on work travel decisions.

Departure time research has examined more closely the tradeoff between travel times and work arrival times. Empirical work has been restricted primarily to auto travelers, but important advances have been accomplished in differentiating between traveler sensitivities to early and late work arrival, and recognizing the impact of work flexibility and occupation on perceived tradeoffs between travel time and schedule delay. While the use of logit

forms of models and the structuring of departure time choices into discrete time periods may appear inappropriate on theoretical grounds, the errors introduced may not be critical issues in practical applications.

Despite these accomplishments, there remain several obstacles which must be overcome. Although the significance of the tradeoff between mean travel time and work arrival time has been demonstrated to some degree, the effect of travel time uncertainty has not been properly considered. In addition, the potential interdependency of the mode choice and departure time decisions has been virtually ignored. Finally, past research has been restricted primarily to a study of auto travelers. The effect of service reliability on transit use and user departure time decisions has not been examined.

The research proposed herein is aimed at extending the study of service reliability and work travel behavior by considering the interdependencies of the mode and departure time decisions, explicitly accounting for travel time uncertainty in these travel choice decisions, improving the definition of arrival time loss measures, and expanding the choice set to include a study of automobile, transit, and carpool commuters. Issues to consider in designing an analysis methodology to study the above problems are

identified in Chapter 5, including a review of relevant literature pertaining to each issue.

## 5. METHODOLOGICAL ISSUES IN DEVELOPING MODE AND DEPARTURE TIME CHOICE MODELS

This chapter presents a discussion of the methodological issues which should be addressed in developing mode and departure time choice models. Within each issue, a literature review is conducted to identify past findings which are relevant to the research topic.

Section 5.1 describes the model structure adopted for this research and the estimation technique selected for model estimation. Section 5.2 examines previous literature in an attempt to define relevant moments and functional forms for auto, transit, and carpool travel time distributions. Section 5.3 presents a discussion of the procedure used to estimate arrival time loss functions. Collectively, Sections 5.2 and 5.3 provide the necessary information for computing the expected loss variable.

### 5.1 Model Structure and Estimation Technique

This section examines structural issues and estimation procedures considered in defining a model for this research. It includes discussions relating to formulating the choice process, selecting a feasible set of departure time and mode



choice alternatives, and selection of the most appropriate model estimation technique.

The major structural issue is how to treat the interdependency of the mode choice and departure time decisions. Ben-Akiva and Lerman (1975) hypothesize that if a hierarchical decision structure is used, it should be based on explicit behavioral hypotheses about household or individual behavior with specific models having appropriate linkages to other components of a choice hierarchy.

Recall from the discussion in Chapter 3 that mode and departure time appear to be interdependent choices, but the departure decision is likely to be made after a mode choice decision has been reached. Thus, it makes sense to structure the problem as a sequential decision, where departure time is chosen conditional on the mode having been selected. The hypothesized structure would be:

$$U_{d|m} = f_1( tt_{d|m}, E(l|d,m), X_{d|m} ) + \epsilon_{dm} \quad (5.1)$$

$$U_m = f_2(D_m^*, T_m, X_m) + \epsilon_m \quad (5.2)$$

where:  $U_{d|m}$  = utility for departure time  $d$  given mode  $m$   
has been chosen

$tt_{d|m}$  = mean travel time for the chosen mode  $m$  at

departure time  $d$

$E(l|d,m)$  = expected loss associated with work arrival for  
departure time  $d$  given mode  $m$  has been chosen

$X_{d|m}$  = other travel costs and socio-economic  
considerations that impact departure time  
 $d$  for mode  $m$

$U_m$  = utility for mode  $m$

$D_m^*$  = maximum value of  $U_{d|m}$  for mode  $m$

$T_m$  = travel time and reliability attributes for  
mode  $m$

$X_m$  = other travel costs and socio-economic  
considerations that impact mode  $m$  (may  
include attributes in  $X_{d|m}$ )

$\epsilon_m, \epsilon_{dm}$  = random components of the model

The linkage between the departure time and mode choice models is through  $D_m^*$ , the expected value of the maximum departure time utility for each mode (McFadden, 1977). These maximum utilities are estimated from the departure time models, and serve as an input to the mode choice models.

It should also be noted that the attribute vector  $X$  in the mode choice specification may include variables which also appeared in the departure time specification. For example, older travelers may be more inclined to arrive

earlier than the rest of the general population because of their established work ethic. These same travelers may also be more likely to commute by automobile since they are likely to have more established incomes and higher levels of auto ownership.

The formulation in Equations 5.1 and 5.2 are based on the following assumptions: (1) the commuter has a continuous choice of departure times so that the possibility of schedule delay\* does not arise; (2) for any departure time and mode, the commuter has perfect knowledge of the journey time distribution; (3) with the exception of in-vehicle travel time (and transit and carpool wait time), all other time components are known and have zero variance; and (4) the commuter has a fixed starting time at work.

These assumptions are all plausible with the exception of the first assumption and perhaps the fourth assumption. The fourth assumption could be violated if a commuter's place of employment has a flexible arrival time policy. However, even in the case of allowable flexible arrival times, the employer is still likely to have an official work start time which is known to employees and outside businesses.

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\*As defined by Starkie (1971).

The first assumption presents a problem for transit users, since transit vehicles serve stops at fixed intervals rather than continuously. Thus, situations can easily arise where transit commuters may not have a continuous range of arrival times to consider, although this problem is less severe during peak periods when transit service is more frequent. However, there is no systematic way to deal with this problem, since different people are faced with different official work start times and service intervals, resulting in a different reduction of feasible arrival time choices for each individual. For the purposes of this research, transit choice will be represented as continuous choice, with the hope that each departure time choice interval is sufficiently large that a transit user would be able to arrive by transit at least once within each interval. A more indepth examination of this issue is warranted in future research.

The issue of selecting a feasible set of alternatives requires the determination of a feasible range of alternative departure times (based on a feasible range of expected arrival times) and modes. The range of expected arrival times used in the UTDFP studies (42.5 minutes before official work start time to 17.5 minutes after) is reasonable since most commuters typically expect to arrive

within that time frame. Since the UTDFP data set is the only available data set with such detailed information on departure times during the peak period, the same arrival time range was adopted for this research to conform with available data.

The most appropriate estimation technique is dependent in part on whether the departure time decision is modeled as a continuous choice or as a set of discrete choices. Koenker (1978) argues that discrete periodizations are rather unsatisfactory for empirical analysis of demand because there is the lack of any natural periods. With continuously varying time parameters, he feels that the structure of the demand model is preserved while still being able to work with parametric models. Cosslett (McFadden, et al., 1977) modeled departure time using different discrete interval lengths, and concluded that "the size of the time interval selected is not critical." Cosslett's finding implies that discrete alternatives can be used without upsetting the structure of demand models or introducing unnatural periodizations. However, since departure time is a continuous choice over time, it would be desirable to model departure time as a continuous choice process.

The departure time model selected for this study is "continuous logit" (Ben-Akiva and Watanatada, 1978), a model

which can be estimated based on discrete approximations of a continuous choice process, with the model subject to the standard assumptions of a logit formulation. The model is explained in more detail in the following discussion.

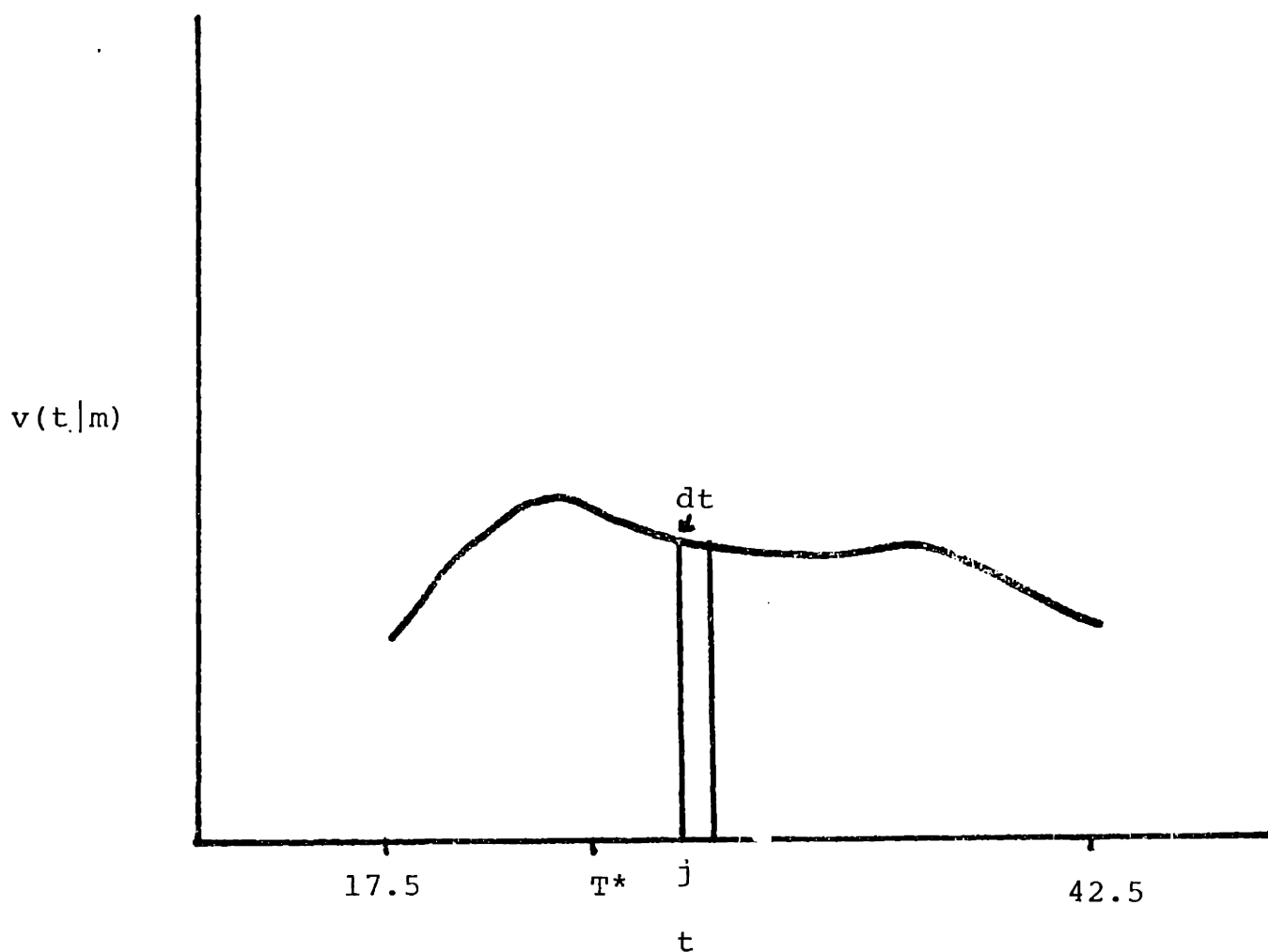
Consider a feasible range of arrival times from 42.5 minutes before official work start time to 17.5 minutes after official work start time (see Figure 5.1), corresponding to the arrival time outcome of a range of feasible departure times. The utility for arriving at a time  $t$  in this range can be expressed as  $V(t|m)$ , the systematic component of the utility  $U(t|m) = V(t|m) + \epsilon$ .\*

To find the probability of arriving at a point  $j$  in  $t$ , one can define a thin slice of arrival time of width  $dt$ , and the probability of arriving at point  $j$  can be expressed as follows:

$$dP(j) = P(j \leq t \leq j + dt) \quad (5.3)$$

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\* $V(t|m)$ , the systematic component of the utility expression, contains the observed attributes (i.e., travel and socio-economic information) relevant to the alternative.  $\epsilon$  represents the random component of the utility expression.



where:  $v(t|m)$  = observed utility of arriving at time  $t$   
 (corresponding to departing at time  $d =$   
 $t$ -average travel time for a departure  
 time of  $d$ )  
 assuming mode  $m$  has been chosen

Figure 5.1 Departure Time Represented as a Continuous Choice

Using continuous logit, this becomes:

$$dP(j) = e^{V(j)} dt / \int_{-17.5}^{42.5} e^{V(j)} dt \quad (5.4)$$

A continuous logit model can be defined using discrete inputs, provided that the size of the discrete increment is small enough. In the case of this research, the increment will be set at five minutes.\* Thus, for example, the probability of arriving between 12.5 and 17.5 minutes early could be computed as:

$$\begin{aligned} \Pr (12.5 \leq t \leq 17.5) &= \frac{\int_{12.5}^{17.5} e^{V(j)} dt}{\int_{-17.5}^{42.5} e^{V(j)} dt} \approx \frac{e^{V(15)} \cdot 5}{\sum_{t=0}^{11} e^{V(-15+5t)} \cdot 5} \\ &= \frac{e^{V(15)}}{\sum_{t=0}^{11} e^{V(-15+5t)}} \quad (5.5) \end{aligned}$$

This model uses discrete inputs for the dependent variable, making the estimation of this continuous logit model the same as the estimation of a discrete logit model since discrete approximations are used to represent

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\*Linearity of  $V(t)$  is assumed within each five minute interval.



continuous intervals of choice. However, the estimated continuous logit model can have an advantage over discrete logit models in application. Since the continuous logit model inputs represent a discrete approximation of a continuous choice process, the estimated continuous logit model can be used to forecast at any point over a continuous range of choice (not restricted to the discrete approximation choices). The discrete logit model is restricted to forecasting only for the discrete choices initially defined in the model.\*

However, continuous logit is not free from the IIA properties implicit in logit formulation. Since there is the possibility of correlation among departure time alternatives, diagnostic tests (McFadden, Train and Tye, 1977) of departures from the IIA assumption will be conducted. (Small, in his departure time work (1978), found that the true departure time choice model departed from the independence assumption implicit in his model, but that the magnitude of the departure was small enough to justify considerable confidence in the estimated coefficients.) Thus, continuous logit over the full range of departure times will be used, and estimation results will be subjected

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\*In cases where alternatives contain alternative-specific constants, there is less of a distinction between continuous and discrete logit models used in forecasting.

to diagnostic tests for departure from the IIA assumption. If problems arise, alternative specifications will be estimated and tested, where appropriate.

Another possible departure time estimation technique is probit modeling (Daganzo, Bouthelie, and Sheffi, 1977), which is based on the assumption that the error terms in each alternative are distributed normal. In probit, the utility functions have additive disturbances, but the error terms do not have to be independent nor do they necessarily have identical variances. Until recently, multinomial probit was not used because of computational problems with its estimation and application. This has been largely overcome for small choice sets (Daganzo, et al. 1977). The advantages of probit over logit are that the error terms can be correlated and the probit form permits measurement of random taste variation. Unfortunately, probit is still too costly an estimation technique for the size of the choice set under consideration in this research.

The estimation of a mode choice model can probably be accomplished through the use of logit on discrete alternatives (i.e., multinomial logit). One would expect there to be less correlation between the mode choice alternatives than in the case of correlation among departure time alternatives. Thus, the IIA assumption may not be

violated. Nevertheless, diagnostic tests will be conducted to determine if the IIA assumption can be rejected.

## 5.2 Moments and Distributions for Travel and Wait Times

In order to construct service reliability variables, knowledge of the moments and functional form of various travel and wait time distributions are necessary. For auto users, it is assumed that wait and walk times are known and have zero variance; only in-vehicle travel time is subject to variation. For transit and carpool travel, there exists variation in both wait time and in-vehicle travel time. It is also important to note that the moments of all the distributions (and possibly functional form) will vary for each mode and each departure time (see Figure 5.2). For example, as depicted in Figure 5.2, wider travel time distributions may accompany longer travel times. This necessitates the development of a generalized structure for computing auto, transit, and carpool travel time moments and distributions.

The discussion below explores these issues; it is assumed that the mean in-vehicle travel times and headways are known. The organization of each sub-heading begins with a discussion of the mean (where appropriate) and standard

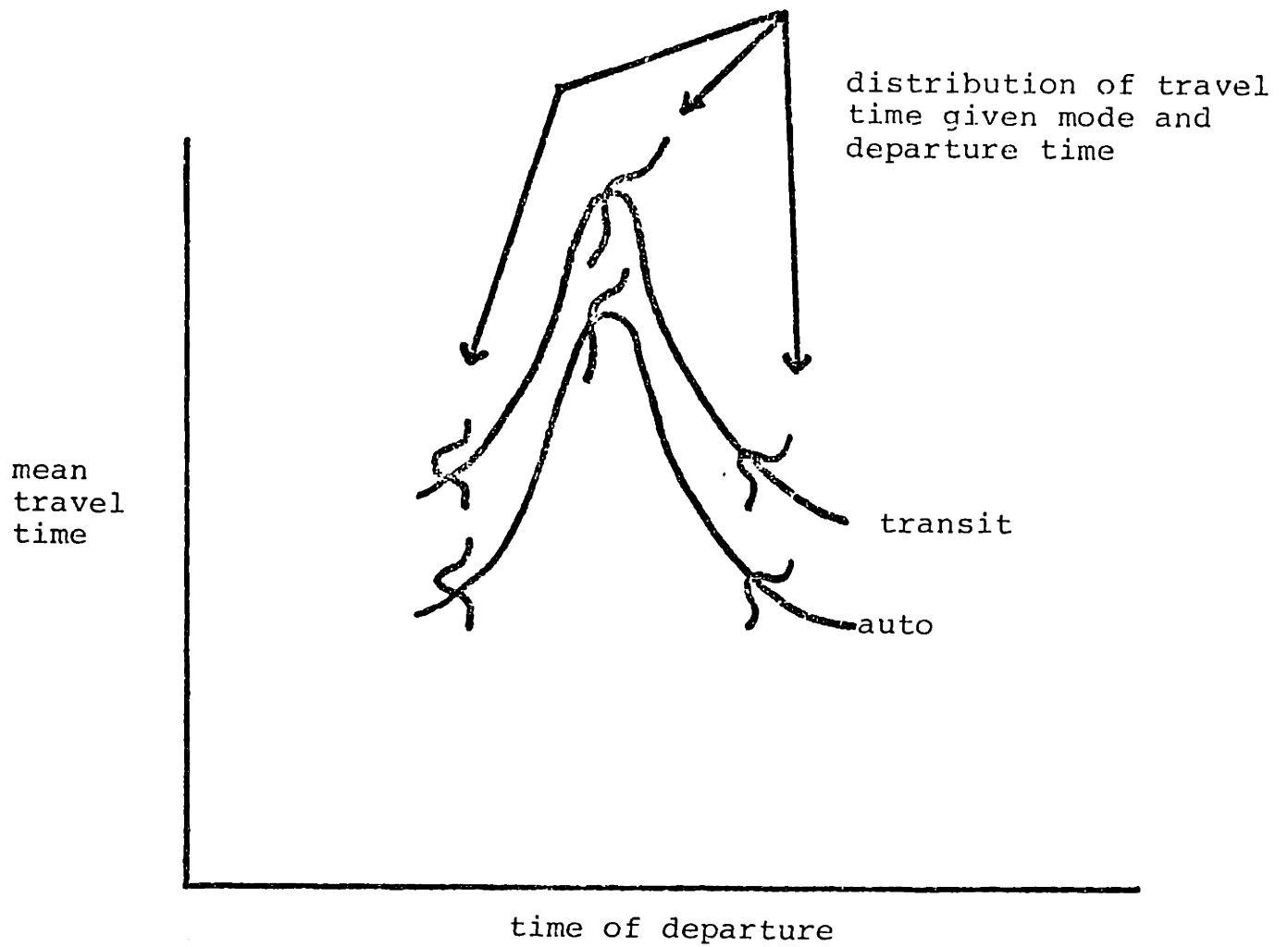


Figure 5.2 Hypothetical Moments and Distributions for Various Modes and Departure Times

deviation of the travel time component, followed by a presentation of material related to the distributional form of the travel time component.

#### 5.2.1 Auto In-Vehicle Travel Time

A study of the relationship between the mean and standard deviation of auto in-vehicle travel times was conducted by Herman and Lam for journeys to and from work, based on data collected on individuals across several days of auto travel in Detroit (1974). They estimated this relationship using power function and linear specifications. The power function result for journeys to work was:

$$S = 0.36\bar{t}^{0.49} \quad (5.6)$$

where  $S$  = standard deviation of trip time for each individual (in minutes)

$\bar{t}$  = mean trip time for each individual (in minutes)

This result closely resembled estimates made by Turner and Wardrop (discussed in Herman and Lam, 1974) for their central London study in 1947:

$$S = 0.52\bar{t}^{0.68} \quad (5.7)$$

However, Herman and Lam found that the power function only fit the data well for mean travel times up to 30 minutes. They felt their linear estimate offered a better overall fit. The estimated linear relation was:

$$S = 0.59 + 0.0456\bar{t} \quad (5.8)$$

The data collected by Herman and Lam is quite good because they were able to trace trip characteristics of the same individual over several days. Since the power function breaks down for mean travel times over 30 minutes, and because many commuters are likely to experience average journey times in excess of 30 minutes, the linear estimate in Equation 5.8 was selected for this research.

Several studies have been conducted on the distributional form of auto journey times. Smeed and Jeffcoate (1971) found the distribution of the standardized variable,  $X = (t - \bar{t})/S$ , is usefully approximated by the normal distribution. Turner and Wardrop found the distribution of the standardized variable follows the normal distribution only in the lower 75% of their distribution. The upper 25% was found to have a much longer tail than the normal distribution. Herman and Lam's analysis supports the

Turner and Wardrop finding. This agreement in finding is particularly significant in terms of transferability when one considers that the two studies took place 26 years apart and were based on data from different cities in different countries.

Richardson and Taylor (1978), in their study of private car commuter journeys in Melbourne, Australia, concurred with findings reported by Herman and Lam and by Turner and Wardrop. The domain of the distribution of the standard deviate was approximately  $(-.2.0, + 3.5)$  standard deviations about the mean. They decided to test some other distributions which could model the observed skew. They tested the fit of a lognormal distribution by defining a standardized log-transformed travel time and testing its fit to a normal distribution. Richardson and Taylor found that the lognormal distribution provided a much better fit to the data than the normal distribution.

Polus and Schofer (1976) conducted an analytic study of freeway reliability, noting the difference between freeway and arterial travel. Using Chicago data, they tested for the best fit to a distribution of lane occupancies. Of the distributions tested (normal, gamma, beta), the gamma distribution demonstrated the best fit. The parameters of the gamma distribution were estimated via regression

equations using link length, mean lane occupancy, and number of lanes as independent variables. Although it is possible to convert a lane occupancy distribution to a travel time distribution (Smeed, 1968), difficulties in obtaining disaggregate data on the independent variables mentioned above, plus the need to model the arterial distribution and combine its effects with freeway travel, present a number of barriers to using this research result. Polus (1975) did estimate a separate distribution for arterials, and although the gamma distribution exhibited the best fit, the procedure Polus used to estimate gamma parameters did not yield statistically significant results.

The review of auto travel time distributions indicates that the lognormal distribution for auto travel time is a slightly better form than the normal distribution. The Polus and Schofer model requires complex data and only considers the freeway portion of the auto journey. Thus, the lognormal distribution was selected as the most appropriate distributional form for auto in-vehicle travel time for this research.



### 5.2.2 Transit Wait Time

The quality of the research conducted on transit travel (wait and in-vehicle) times is not nearly as good as the auto travel time research. Much of this is due to the lack of appropriate data for analysis. Transit data typically consists of several observations on a given day, rather than observations on the same individual across several days. Recent data collection activities associated with the UMTA Service and Methods Demonstration project in Minneapolis have focused on collecting more appropriate transit operations data for examining service reliability. Hopefully, this will stimulate future research interest in this area. Thus, in the following discussion and in Section 5.2.3, an effort was made to select plausible results from available research, recognizing the shortcomings of this approach. The wait time discussion is based on the assumption that only mean scheduled headway data is available.

Regression analyses have been conducted by several researchers interested in examining the relationship between average wait time and mean (scheduled) headway. Holroyd and Scraggs (1966) measured mean headways ( $\bar{h}$ ) and mean wait times ( $\bar{w}$ ) in Central London, and estimated the following equation:

$$\bar{w} = \frac{(\bar{h}^2 + 70)\bar{h}}{2\bar{h}^2 + 70} \quad (\text{minutes}) \quad (5.9)$$

Unfortunately, the sample they used was for off-peak travel, where it is likely that average headways were quite a bit higher than during peak conditions. Thus, the use of their estimate might be of questionable validity if applied to a study of peak period commuters.

Kulash (1971) estimated the following relationship in his simulation study using MBTA data:

$$\bar{w} = \frac{.58v(h)}{\bar{h}} + .48\bar{h} + .53 \quad (\text{min.}) \quad (5.10)$$

where  $v(h)$  is the variance of the headway.

Seddon and Day (1974), in their study of bus passenger waiting times in Greater Manchester, found:

$$\bar{w} = \frac{.5v(h)}{\bar{h}} + .285\bar{h} + 1.71 \quad (\text{min.}) \quad (5.11)$$

The problem with using either of these models is that detailed information on headway distributions is not readily available. Thus, it would be difficult to obtain a reliable estimate of the headway variance. It is possible to infer the headway variance from existing studies linking the headway standard deviation to transit travel time (Polus, 1975; Fulchino and Graves, 1976), but such an indirect

approach may introduce additional errors, and this technique should be considered only as a last resort.

Fortunately, there exist some English studies of transit wait time which have considered peak period transit travel and which developed simple models of wait time. Seddon and Day (1974) collected data from Greater Manchester on routes ranging in scheduled headways from 4 to 30 minutes. The data was collected for varying times of the day. The resulting regression estimate was:

$$\bar{w} = 2.34 + .25668\bar{h} \text{ (min.)} \quad (5.12)$$

They also estimated regressions on  $\bar{w}$  which required observations of the headway for each bus on the route, clearly too detailed a level of information to be considered for this research effort (among these was Equation 5.11).

O'Flaherty and Mangan (1970) collected peak (evening) and off-peak data in Leeds, and estimated the following relationship based on peak data only:

$$\bar{w} = 1.79 + 0.14\bar{h} \text{ (minutes)} \quad (5.13)$$

Since the O'Flaherty and Mangan estimation sample is based solely on peak period observations, and because information

on individuals' mean scheduled headway is readily available, Equation 5.13 is a possible candidate for use in this research.\* However, the coefficient for mean headway is much lower than one would expect. Typically, under conditions of peak headways and peak period congestion, it is not uncommon for mean wait times to be much closer to half the headway, with wait times increasing as service regularity deteriorates (i.e., increase in headway variation). The only justification for expecting a low mean headway coefficient would be for cases where headways are sufficiently high and service sufficiently predictable that travelers can time their arrivals at bus stops to ensure catching a bus rather than incurring longer wait times by arriving randomly at the bus stop.

There have been some recent, more sophisticated, attempts to model expected wait time. Turnquist (1976) assumed a lognormal bus arrival time distribution, developed an equation for computing the percentage of random and non-random arrivals, and computed the expected wait time for each group of passenger arrivals. His expression for mean passenger wait time is:

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\*It is assumed that evening peak conditions are similar to morning peak conditions. The mean headway coefficient is much lower than the estimate in Equation 5.12, presumably due to better knowledge of schedule during peak travel only as compared to a mix of peak and off-peak travel examined in the Seddon and Day study.

$$\bar{w} = aE(w_n) + (1-a)E(w_r) \quad (5.14)$$

where  $a$  = percentage of non-random passenger arrivals

$w_n$  = non-random passenger arrival wait time

$w_r$  = random passenger arrival wait time

Although Turnquist appropriately identifies the presence of two segments of commuters who experience different expected wait times, the techniques required to estimate  $a$ ,  $E(w_n)$ , and  $E(w_r)$  would make this approach somewhat cumbersome.

Bowman (1979), developed a logit model for predicting passenger arrival time at a stop, given headway and vehicle arrival time distributions. Validation was reasonably successful using Chicago data. The problem is that the model output is expressed in terms of expected passenger arrival time, not expected passenger wait time. It is possible to infer expected wait time from knowledge of passenger and vehicle arrivals, but again the level of information required to use this technique is not typically contained in existing surveys.

In the absence of any definitive model of transit wait time, for the purposes of this study mean transit wait time was assumed to be one-half the scheduled transit headway. This assumption is based on the notion that transit service is characterized by short headways but large variabilities during the peak period, and is also based on the desire to represent traveler schedule delay usually incurred since bus service is not actually available on a continuous basis as assumed in the structure of alternative departure time choices for this research. The transit wait time literature review presented here clearly identifies the need to conduct extensive transit travel time research based on data collected across several days of transit operation on the same set of individuals.

More limited research has been conducted on the standard deviation of wait time. Joliffe and Hutchinson (1975) studied arrivals of passengers and departures of buses at ten stops in suburban London on each of eight different days. They found the standard deviation of observed waiting times is strongly related to the mean, being about 15 percent less than the mean. This implies:

$$\begin{array}{lcl} \text{standard deviation} & & \\ \text{of wait time} & = & .85\bar{w} \end{array} \quad (5.15)$$

Friedman (1975), based on data generated from a simulation study, estimated regression equations of the mean and standard deviation of wait time. For the standard deviation model, the independent variables included headway standard deviation, mean travel time from route terminal to the stop in question, and the coefficient of variation of travel time; these are rarely available in most data sets. Furthermore, validation attempts were not very successful. Thus, Friedman's work is not appropriate for this research.

Since the Joliffe and Hutchinson finding (Equation 5.15) is based on data collected across several days, their results may hold more validity than the mean transit wait time research reviewed earlier. However, if Equation 5.15 is applied to mean wait time when mean wait time is defined as one half the headway, it is quite likely that the estimated standard deviation of wait time will be much higher than one would intuitively expect. This would be due to the additional effects of schedule delay which were considered in determining mean wait time for this research. Since the standard deviation of wait time should not be affected by schedule delay, the approach taken to compute transit wait time standard deviation was to use Equation 5.15, but applied to mean wait times computed from Equation 5.13 rather than mean wait time defined as one half the headway.

Little is known about the form of the wait time distribution. Normality will be assumed for this research, since it makes intuitive sense and allows for compatibility of transit wait and in-vehicle travel times (see Section 5.2.5). Tests were conducted to determine the impact of assuming a normal wait time distribution if the actual distribution is not normal (i.e., bi-modal). These tests are described in Appendix A, and indicate that the normal approximation is acceptable.

### 5.2.3 Transit In-Vehicle Travel Time

The literature review did not uncover any previous research directed at the relationship between transit in-vehicle travel time and its standard deviation. In order to obtain insight into this relationship, an analysis was conducted using data collected in Portland, Oregon by Tri-Met.\*

For a five day period in October 1977, a person was stationed at a street corner in the Portland CBD, recording the time of each bus arrival for the entire day. Thus, there exists five observations on each bus run. The

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\*Furnished by Bob Prowda of Tri-Met.



scheduled start times of each bus run were also made available. Assuming that the bus began its run on schedule, then the actual transit in-vehicle travel time from the starting point on the route to the CBD can be computed. Since there are five observations on each bus run, mean in-vehicle travel time and its standard deviation can be computed for each bus run.

Since this research is directed at morning, peak period work trips, the period of study was restricted to all buses departing between 6 a.m. and 9 a.m., traveling in-bound. This yielded a data set of 276 bus runs, with up to five observations for each run.\*\* For each of the 276 bus runs, the travel time mean and standard deviation were computed.

Using this data, a regression equation of the following form was estimated:

$$S = a_1 + a_2 \bar{t} \quad (5.16)$$

where  $S$  = standard deviation of in-vehicle travel time

$\bar{t}$  = mean in-vehicle travel time

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\*This assumption is based on the assumption that most of the peak period runs are the first and/or second runs for each vehicle, thus limiting the probability that propagated delays have caused buses to begin runs behind schedule.

\*\*Bus runs with less than four observations were omitted from the sample.

This specification was selected to maintain consistency with the Herman and Lam specification selected for the standard deviation of auto in-vehicle travel time.\*

The estimated result was:

$$S = 0.95696 + 0.02562\bar{t} \quad \text{corrected } R^2 = 0.055 \quad (5.17) \\ (3.83) \quad (4.13)$$

The figures in parentheses are t-statistics. Although the percent of variation explained by the regression estimate is quite low, the coefficients are significant. For typical transit in-vehicle travel times (i.e., 30 minutes), this result compares quite favorably with results from a Multisystems (1979) study of bus transit (they suggest standard deviation = .06 x mean travel time). It is also interesting to note that Equation 5.17 is of the same order of magnitude as Herman and Lam's estimate for the standard deviation of auto in-vehicle travel time. The estimate of the standard deviation of bus in-vehicle travel time has a higher constant and lower coefficient of mean travel time than the Herman and Lam auto estimate. This makes intuitive sense, since one would expect that the inherent variation in

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\*Several other specifications which considered variables  $\bar{t}^2$  and  $\bar{t}^3$  were also estimated. In all cases, the corrected  $R^2$  was lower than the specification in Equation 5.17.

transit service is higher than for auto, and perhaps less affected by trip distance.

Because of the need to identify a generalized expression for computing the standard deviation of in-vehicle travel time, and considering that the estimate based on Portland data makes intuitive sense, is supported by the Multisystems study and compares favorably with earlier auto travel studies, the transit standard deviation regression estimate was adopted for this research effort.

Fortunately, research has been conducted on the form of the transit in-vehicle travel time distribution. Jenkins (1976) conducted a study of simulation models of bus routes and ways in which they have been used to represent various aspects of routes. One area of interest was bus link travel times, and Jenkins presented a gamma distribution of the following form based on 120 observations:

$$f(t_1) = 158 (t_1 - 0.76) \exp(-3.6(t_1 - 0.76)) \quad (5.18)$$

where  $t_1$  = bus travel time between two points

It should be noted that the data used by Jenkins had a mean travel time of 1.3 minutes and a standard deviation of 0.4. This demonstrates that Jenkins' model is primarily

oriented to travel time distributions on shorter links. It would be inappropriate to use these results for the magnitude of in-vehicle travel times experienced by morning commuters. Furthermore, Jenkins' work is based on repeated observations on one link, so his estimates may not even be transferable to other links of similar size.

Turnquist and Bowman (1979) reason that the shifted gamma function yields the best explanation for observed transit vehicle travel behavior. The amount shifted can be determined by assuming the maximum legal speed over the length of the link, with the gamma distribution modeling the additional time as the sum of delays due to congestion, lights, etc. Turnquist and Bowman estimated shifted gamma distribution parameters for two separate data sets, Evanston and Cincinnati. The hypothesis tests confirmed that the shifted gamma distribution is a good model of transit vehicle travel times. Turnquist and Bowman also estimated equations for determining the shifted gamma distribution parameters as a function of average total boarding and alighting passengers, and number of signalized intersections.

While clearly the level of detail required to obtain the gamma parameters using the Turnquist and Bowman estimates would not be available, it would be possible to

use the unshifted gamma distribution, obtaining the parameters by assuming a maximum legal bus speed for most urban travel, and estimating the gamma parameters since the travel time mean is known and the variance can be computed using Equation 5.17. However, this would require some knowledge of the maximum transit vehicle speed at the site where the travel survey was conducted, and knowledge of distance traveled by each individual while on the vehicle; this would be a cumbersome task.

Polus (1975) studied bus travel time, and examined the potential of normal, beta, and gamma distributions to represent the bus travel time distribution. Based on a preliminary review, he selected the beta distribution for further study. His estimated beta distribution of travel time for the peak period was:

$$f_y(y) = \frac{y^{28.104} (C-y)^{13.552}}{B \cdot C^{28.104}} \quad (5.19)$$

where:

$$B = \frac{\Gamma(29.104) \Gamma(14.73)}{\Gamma(43.656)} \quad 0 \leq y \leq C$$

$$C = 1.5 \cdot m(y) \quad \text{where } m(y) = \text{mean travel time}$$

Polus' work was never validated using data other than the data he used for estimation. Turnquist and Bowman, commenting on Polus' work, felt that the resulting first and second moments estimated adequately represent the corresponding moments of the observed travel times, but the shape of the probability density function did not conform well to the shape of the observed histograms.

Each of the studies of the bus travel time distribution has some undersirable qualities. Jenkins' research is directed at link travel times. Turnquist's efforts yielded reasonable results, but the level of detail required to use his results or to use the shifted gamma and estimate the parameters by the method of moments makes the technique quite cumbersome. Polus' work was never validated, but it has the advantage of being easy to use given knowledge of the mean and variance. On this basis, the Polus model was selected for this research effort.

#### 5.2.4 Carpool Travel Times

There was no available information on the moments and distributional form for carpool in-vehicle and out-of-vehicle travel time. Intuitively, carpool travel is subject to in-vehicle travel time considerations which are similar

to the single occupant auto, and wait time considerations which are similar to transit.

The major distinction between carpool and single occupant auto in-vehicle travel time is the additional collection time incurred by carpool commuters. In the absence of any empirical information, it was assumed that the mean carpool collection time is three minutes. Equation 5.8 was used to compute the standard deviation of carpool in-vehicle travel time, with mean carpool in-vehicle travel time set at three minutes greater (due to three minute collection time) than single occupant auto mean in-vehicle travel time. This was based on the assumption that single occupant autos and carpools experience similar line-haul travel characteristics, which seems quite plausible. The carpool in-vehicle travel time distribution was similarly assumed to be approximated by a lognormal distribution.

Carpool wait time assumptions were based on the premise that commuting carpools have established schedules and are not subject to the inherent variabilities which are common in transit systems. Carpoolers were assumed to have average wait times of two minutes, and the carpool wait time standard deviation was assumed to be one minute per passenger. Since the average carpool size was assumed to be 2.5 people (1.5 passengers), carpool wait time standard

deviation was set at 1.5 minutes. As in the case of transit wait times, individual carpool wait times were assumed to follow a normal distribution.

#### 5.2.5 Computing Expected Loss for Auto, Transit and Carpool Travel

The moments and distributional form for auto in-vehicle time and transit and carpool wait and in-vehicle times are used to compute expected loss. For auto travel, the arrival time distribution is directly inferred from the auto in-vehicle time distribution. Thus, the auto arrival time distribution should be lognormal; however, using a lognormal distribution in the integral to compute expected loss introduced some computational problems. Tests were run to see if a normal approximation of the lognormal distribution would yield similar computed expected loss results (see Appendix B). For all cases tested, the magnitude of the error introduced by using a normal approximation was less than 1%. Since the normal approximation closely resembles results using the lognormal distribution, and because computing the expected loss integral under normality is computationally feasible, normal approximations for auto and carpool in-vehicle times were used in the expected loss computations in place of the lognormal distribution.



The arrival time distribution for transit travelers depends on both the wait time distribution and the in-vehicle travel time distribution. Normality was assumed for the transit wait time distribution. Based on research conducted by Polus, the transit in-vehicle travel time distribution is of the beta form. The problem which arises is how to convolute beta and normal distributions to form an arrival time distribution for transit travelers. One possible simplification is to compare expected loss computed using a normal distribution to expected loss computed using a beta distribution. If the normal approximation is good, then a normal distribution can be used to represent the in-vehicle travel time distribution, and the arrival time distribution would be normal (the sum of two normally distributed variables is a normal).

Such tests were conducted, and are described in Appendix C. The results indicated that using an unrestricted normal distribution in place of a restricted beta distribution would not alter the outcome of the analysis. Based on these results, it was assumed that both the transit wait and in-vehicle travel time distributions could be represented as normals. Thus, the arrival time distribution would also be normal.

The normal approximation of a lognormal distribution was introduced previously in the auto discussion, a result which also applies to the carpool in-vehicle time distribution. Since normality was assumed for the carpool out-of-vehicle travel time distribution, the carpool arrival time distribution is also a combination of two normal distributions. The moments for the transit and carpool arrival time distributions are defined below.

If  $x$  is the transit (carpool) wait time distribution and  $y$  is the transit (carpool) in-vehicle travel time distribution, then the total travel time distribution (and therefore the arrival time distribution),  $z = x + y$ , has the following first and second moments:

$$E(z) = E(x) + E(y) \quad (5.20)$$

$$V(z) = V(x) + V(y) + 2 \text{ cov } (x,y) \quad (5.21)$$

Because data does not exist to estimate the covariance of an individual's wait and in-vehicle travel times, and because intuitively one would expect this term to have a negligible value relative to  $V(x)$  and  $V(y)$ , the expression for the transit (carpool) total travel time variance can be approximated by:

$$V(z) = V(x) + V(y)$$

(5.22)

This implies that the transit and carpool arrival time distributions will be normal, being a function of the mean wait time, mean in-vehicle travel time, and the traveler's departure time from home, with a variance consisting of the sum of the wait time and in-vehicle travel time variances.

### 5.3 Estimating the Arrival Time Loss Function

#### 5.3.1 Methodology

A review of previous research provides some insight into the nature and shape of the arrival time loss function. It has been shown that people are more sensitive to lateness than to earliness, and that they perceive higher degrees of loss with increasing amounts of earliness or lateness. This suggests a loss function which has its lowest value near the official work start time, with a monotonically decreasing loss for earliness as arrival approaches official work start time, and a monotonically increasing loss for lateness as arrival occurs further from the official work start time. The slope of the lateness curve will be higher than the slope of the earliness curve. Figure 5.3 describes the hypothesized loss function.

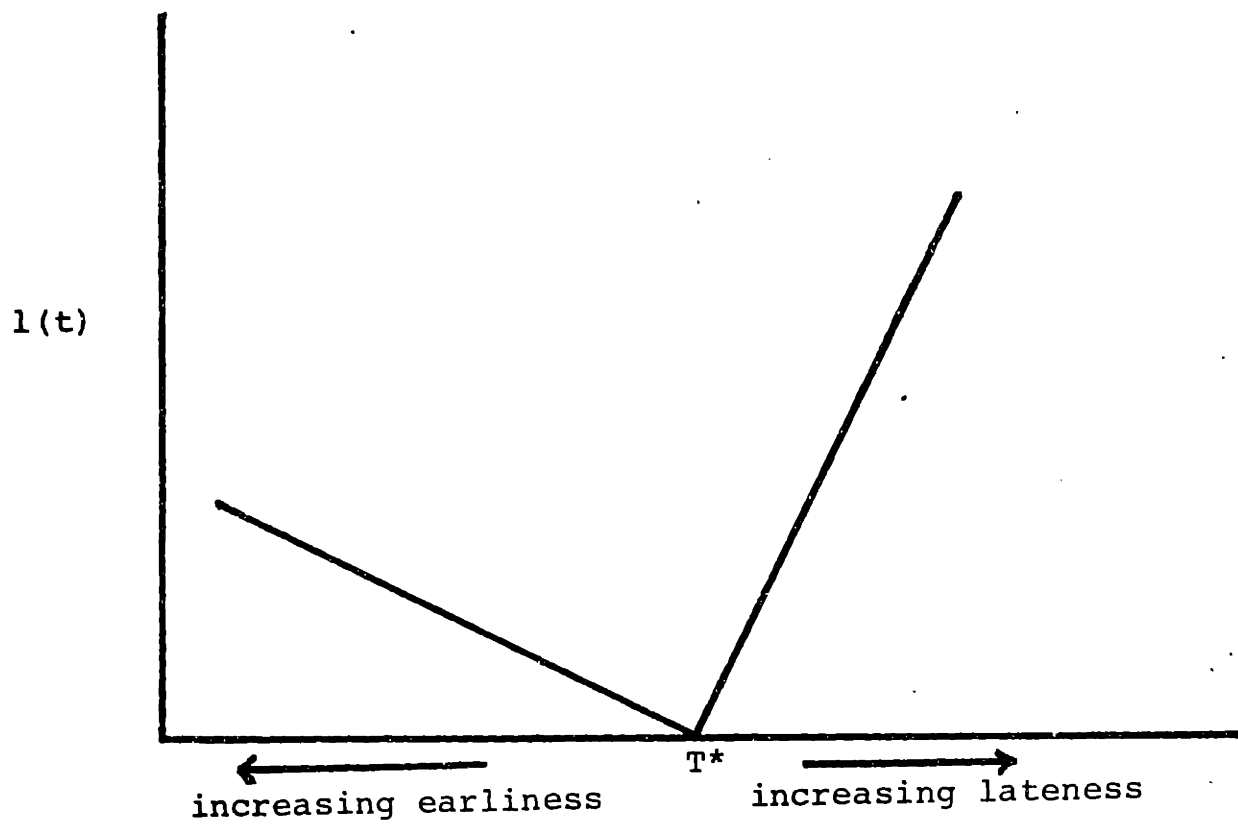


Figure 5.3 Hypothetical Arrival Time Loss Function

The loss function in Figure 5.3 represents just one possible functional form. Each individual is assumed to have a specific arrival time loss function, and it is possible that the parameters and form of the loss function might vary by individual according to their occupation and work flexibility. It is also not clear that a bi-linear loss function is appropriate. However, for computational reasons (in computing expected loss), linear loss functions are desirable, providing they have an acceptable statistical fit to the empirical data.

The concept of loss as discussed here is rather similar to the concept of disutility. Direct estimation of a uni-attribute disutility function for arrival time is identical to estimating an arrival time loss function; direct disutility assessment is the technique proposed for loss function estimation.

The proposed methodology for direct disutility assessment is based on von Neumann-Morgenstern utility theory (Hauser and Urban, 1977). The theory is axiomatically based, specifies functional forms and explicitly measures risk aversion. Individually specified preference parameters are directly calculated from "indifference" questions based on lotteries and tradeoffs with respect to attribute levels.

The utility assessment methodology proposed herein is comprised of five steps: 1) establishing bounds; 2) establishing monotonicity; 3) determining if the respondent is risk averse, risk neutral, or risk prone; 4) determining if the respondent is increasingly, decreasingly or constantly risk (prone, neutral, averse); and 5) based on steps 2-4, selecting the appropriate class of parametric forms, and estimating the utility function. Each step is described in detail in the following discussion.

The arrival time bounds should be set such that the traveler has a choice of a wide range of possible arrival times, yet the choice set is limited to relevant alternatives. For this survey, the arrival time bounds were set from 20 minutes earlier to 45 minutes later than a respondent's official work start time.\*

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\*It should be noted that the range of loss function estimation differs from the range of departure time choices available in the UTDFP data set (see Section 6.1). This was due in part to the fact that the searches for appropriate data with which to estimate the choice models and loss function surveys were conducted simultaneously, and in part due to a desire to extend the late arrival range to allow for more information in modeling late arrival loss, which was expected to be a more difficult estimation problem. In retrospect, this approach may have produced some bias in the model, since early arrival loss was extrapolated beyond the estimation range to accommodate departure time choices available in the UTDFP data.

Although a priori monotonicity has been assumed, the survey should address this issue. If the respondent prefers arriving closer to his/her official work start time than arriving earlier or later, then monotonicity (decreasing for earliness, increasing for lateness) has been established.

Risk tendencies (averse, neutral, prone) are determined by asking the decision-maker whether he/she prefers a lottery with equal chances of arriving at  $(x+h)$  or  $(x-h)$  vs. arriving at  $x$  with certainty. This test should be done separately for earliness and lateness. The question should also be repeated two or three times, varying  $x$  and  $h$  over the range being considered. A decision-maker is risk averse if he/she prefers the expected consequence of the lottery ( $x$  with certainty) to that lottery. A decision-maker is risk prone if he/she prefers the lottery to the expected consequence of the lottery. Indifference implies risk neutrality.

Risk tendencies (increasing, decreasing, constant) are determined by posing a series of separate questions for earliness and lateness. Each question offers the respondent a choice between a lottery with equal chances of two different arrival time outcomes and asks for the respondent's certainty equivalent (expected consequence) such that the respondent is indifferent between the

certainty equivalent and the lottery. A decision-maker is decreasingly (increasingly) [constantly] risk averse if (1) he/she is risk averse, and (2) his/her risk premium (difference between expected consequence of the lottery and the certainty equivalent) for any lottery  $x$  decreases (increases) [remains constant] as the reference amount  $x$  increases. An additional question of this nature is asked where one of the lottery outcomes is an early arrival and one is a late arrival. The certainty equivalent to this lottery provides information for computing the tradeoffs in sensitivities to earliness and lateness, and this is used to transform the arrival time loss function to one scale for the entire bounded range.

Responses to the above steps establish the class of parametric forms which should be considered. For example, if the respondent is constantly risk averse, possible forms might be (Pratt, 1964):

$$u(x) = x \quad (5.23)$$

$$u(x) = -e^{-cx} \quad (5.24)$$

$$u(x) = e^{-cx} \quad (5.25)$$

The response to the certainty equivalent questions provide data for estimating the function parameters.



For this research, alternative functional forms were examined, including the estimation of linear disutility functions using linear regression. For the arrival time problem, a reasonable approach is to assess one disutility function,  $U_1(x)$ , monotonically decreasing in  $x$  for earliness and another,  $U_2(x)$ , monotonically increasing in  $x$  for lateness.

The remaining problem is to scale  $U_1$  and  $U_2$  correctly. This is accomplished using the trade-off questions posed in step 4. By setting  $U$  (arriving 45 minutes late) = 1, and  $U$  (preferred arrival time) = 0, the certainty equivalent responses permit the transformation of  $U_1(x)$  to the same scale as  $U_2(x)$  (rather than on separate scales which would have no comparability).

A sample survey form appears in Figure 5.4. Questions 1-3, 11, and 12 address employment responsibilities and employer arrival time policies. Question 4 is used to establish monotonicity. Questions 5-10 determine whether the respondent is risk averse, neutral, or prone. Questions 13-19 provide data for utility estimation and are also used to determine whether the decision-maker has increasingly, decreasingly or constant risk tendencies.

1. Do you have to be at work at a particular time?  
\_\_\_\_yes  
\_\_\_\_no  
If yes, what is that time?\_\_\_\_\_
2. Is it a strict requirement that you arrive by that time?  
\_\_\_\_yes  
\_\_\_\_no  
If no, how long a grace period do you have?\_\_\_\_\_minutes
3. I usually arrive:  
\_\_\_\_earlier than my official work start time  
by\_\_\_\_\_ (how many) minutes  
\_\_\_\_at my official work start time  
\_\_\_\_later than my official work start time  
by\_\_\_\_\_ (how many) minutes
4. Do you prefer arriving as close as possible to the official work start time? Yes\_\_\_\_\_ No\_\_\_\_\_

Please answer questions 5-10 by selecting one response for each question. These questions are designed to see how uncertainty affects your preferences. If the questions do not appear to make sense, please try to answer them anyway.

5. Suppose you had a choice of the options below, which would you prefer:  
\_\_\_\_arriving to work exactly on time for certain  
\_\_\_\_taking a chance of arriving either 5 minutes late or 5 minutes early
6. Suppose you had a choice of the options below, which would you prefer:  
\_\_\_\_arriving at work exactly on time for certain  
\_\_\_\_taking a chance of arriving either 20 minutes late or 20 minutes early
7. Suppose you had a choice of the options below, which would you prefer:  
\_\_\_\_arriving to work 10 minutes late for certain  
\_\_\_\_taking a chance of arriving either 15 minutes late or 5 minutes late

Figure 5.4 Sample Survey Form for Arrival Time Loss Function Estimation

8. Supposing you had a choice of the options below, which would you prefer:
- \_\_\_\_\_ arriving to work 10 minutes late for certain
- \_\_\_\_\_ taking a chance of arriving either 20 minutes late or on time
9. Supposing you had a choice of the options below, which would you prefer:
- \_\_\_\_\_ arriving to work 10 minutes early for certain
- \_\_\_\_\_ taking a chance of arriving either 15 minutes early or 5 minutes early
10. Suppose you had a choice of the options below, which would you prefer:
- \_\_\_\_\_ arriving 10 minutes early for certain
- \_\_\_\_\_ taking a chance of arriving either 20 minutes early or on time
11. I am employed:
- \_\_\_\_\_ Full-time \_\_\_\_\_ Part-time
12. My employment position would be classified as:
- |                                 |                                    |
|---------------------------------|------------------------------------|
| _____ Professional or technical | _____ Administration               |
| _____ Sales                     | _____ Service-Related              |
| _____ Clerical                  | _____ Crafts-related               |
| _____ Management                | _____ Other (please specify _____) |

Figure 5.4 (continued)

Please answer questions 13-19 by placing a number in each blank which best describes your view. Take time to read the entire sentence before making your decision. This set of questions is designed to determine the amount that uncertainty affects your behavior.

13. I would be just as happy arriving\_\_\_\_\_minutes late for certain as I would taking a chance of arriving either 45 minutes late or on time.
14. I would be just as happy arriving\_\_\_\_\_minutes late for certain as I would taking a chance of arriving either 45 minutes late or the number of minutes late I answered in question 13.
15. I would be just as happy arriving\_\_\_\_\_minutes late for certain as I would taking a chance of arriving either the number of minutes late I answered in question 13 or arriving on time.
16. I would be just as happy arriving\_\_\_\_\_minutes early for certain as I would taking a chance of either arriving on time or 20 minutes early.
17. I would be just as happy arriving\_\_\_\_\_minutes early for certain as I would taking a chance of either arriving on time or the number of minutes early I answered in question 16.
18. ~~I would be just as happy arriving\_\_\_\_\_minutes early for certain as I would taking a chance of arriving either the number of minutes early I answered in question 16 or arriving 20 minutes early.~~
19. I would be just as happy arriving\_\_\_\_\_minutes early/late (circle one) for certain as I would taking a chance of arriving either 10 minutes late or 10 minutes early.

Figure 5.4 (continued)

This form of direct utility assessment has only recently been used in application (Hauser and Urban, 1977; Menhard, 1976). Based on limited applied experience, the nature of the questions (presenting lotteries, etc.) requires a direct interface between the interviewer and respondent. Thus, surveys must be personally conducted, which is a costly approach both in terms of time and resources.

While it would have been desirable to estimate separate loss functions for different employment classifications (because of an a priori belief that perceived arrival time loss varies by job responsibilities), a number of constraints precluded conducting enough personal surveys to assemble a large enough data set for that purpose.\* What was undertaken instead was to conduct a set of personal interviews (10), estimate a generalized arrival time loss function, and capture the effects of employment classification by including dummy variables for various

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\*A primary constraint was due to the fact that the research was Federally-sponsored. Federal regulations are quite strict regarding the size of a survey which can be conducted by Federal employees without Office of Management and Budget (OMB) approval. It should also be noted that even in the case where a larger sample could have been collected, there would be serious questions about the feasibility of using this technique because of the time and resources required to explain the survey instrument so that respondents could elicit appropriate responses to the survey questions.

classifications and work policies in the utility specification for departure time and mode choice.

Only Menhard (1976) has applied von Neumann-Morgenstern utility theory to a transportation problem. His research concerned the estimation of user preference utilities for dial-a-ride (DAR) service based on data he collected in Rochester, New York. Immediate request users were asked to respond to a series of lottery questions pertaining to bus fare, pickup reliability, wait time, consistency of wait time, and travel time. Advance request dial-a-ride users responded to lottery questions concerning attributes of trip time, reliability of pickup and delivery, and fare. Multi-attributed utility functions were estimated based on responses to the lotteries.

In employing this technique, Menhard found that most respondents had no difficulty responding to the questions as posed, and that respondents answered consistently and felt sure of their tradeoffs in most cases. On the other hand, Menhard reported some responses were inconsistent with previously stated preferences, and that care should be taken to describe alternatives clearly.

Functional measurement is another form of direct utility assessment which has been used in transportation

(Meyer, et al., 1978; Lerman and Louviere, 1977). In this approach, individuals are confronted with alternative combinations of attributes and attribute levels (i.e., fare, in-vehicle travel time, out-of-vehicle travel time). The respondent is asked to evaluate the alternatives by ranking them or associating a utility with each option (i.e., on a scale from 0 to 100). These preferences can then be used to estimate either uni-attribute or multi-attribute utility functions. Functional measurement is considered a flexible analytic tool since it can be used to estimate a variety of functional forms.

Another possible approach might be to estimate the parameters of the loss function directly in the choice model estimation process through the use of revealed preferences of choice based on travel and household surveys. If a closed form solution for computing expected loss is available, the loss function parameters can be estimated and expected loss computed simultaneously (as might be possible in Equation 5.32). However, there is no existing model estimation program with this capability, although development of such a program would be an interesting direction for future research.

### 5.3.2 Data Collection and Loss Function Estimation

Personal interviews were conducted with ten selected individuals in an attempt to estimate a generalized arrival time loss function. One observation was omitted from the sample because of an arrival time preference outside the scope of the analysis. The limitations of the sample size precluded the development of complex and disaggregate loss functions. However, it was felt that the estimation of an aggregate function could achieve some degree of statistical credibility.

The entire sample consisted of individuals employed in either a professional/technical or management/administration capacity. This selection was made intentionally because the nature of the survey required the respondent to be reasonably comfortable with the concepts of lotteries and probability. However, the specific employment positions of the sample had sufficient variation to be representative of the population as a whole (i.e., sample included school teachers, Federal employees, private sector employees, project managers, consultants, etc.).

Eight of the nine respondents had to be at work at a particular time, yet only four had a strict requirement that they arrive by that time. A rather interesting finding was



that only five members of the sample preferred arriving as close as possible to the official work start time, while the other four people actually preferred arriving earlier than the official work start time. Of those that preferred arriving earlier, the average preferred arrival time was approximately 15 minutes early.

Although not all of the respondents preferred arriving closer to the official work start time than arriving earlier or later, all the respondents appeared to have monotonic loss functions about their preferred arrival time.

The sample responded in a rather inconsistent manner concerning their risk tendencies for various certainty equivalents. Six respondents were consistently risk averse, two were consistently risk prone, and one provided inconsistent responses for cases concerning on-time certainty equivalents. For questions considering a certainty equivalent of 10 minutes late, three people responded in a consistently risk averse manner, five were consistently risk prone, and one respondent was inconsistent. This result makes intuitive sense since many people, when faced with a late certainty equivalent, may risk the possibility of being even later for the chance of arriving on-time or only slightly late. For cases concerning a certainty equivalent of 10 minutes early, two

people were consistently risk averse, two respondents were consistently risk prone, and five provided inconsistent responses. This result indicates the sample has a more passive attitude towards earliness. The respondents appear to be less concerned about the implications of earliness and in many cases have not formulated a particular risk approach to earliness.

These results suggest that there is no dominant functional form for arrival time loss that characterizes the population as a whole. This led to a decision to estimate and evaluate both linear and quadratic functional forms.

Loss function estimation consisted of separate attempts to model lateness and earliness loss functions. The lateness function was estimated first; the earliness coordinates were scaled to the lateness coordinates and then the earliness function was estimated.

Computing disutility (loss) coordinates was not a straightforward process. On the lateness side,  $U(45 \text{ minutes late})$  was set equal to one for the entire sample. If the respondent preferred arriving as close as possible to his/her official work start time,  $U(\text{on-time})$  was set equal to zero; otherwise,  $U(\text{usual arrival time to work})$  was set equal to zero. For the cases where  $U(\text{usual arrival time to$

work) = 0,  $U(\text{on-time})$  was interpolated based on the knowledge of  $U(\text{usual arrival time to work})$  and  $U(45 \text{ minutes late})$ . The rest of the lateness utility coordinates were derived from responses to the lateness lottery questions and the prior knowledge described above.

Computing earliness utility coordinates was more difficult because in a certain range of earliness, loss is decreasing for those who prefer arriving and usually arrive early, while loss is increasing for respondents who prefer arriving on-time. The response to question 19 (see Figure 5.4) provides enough information to derive  $U(10 \text{ minutes early})$ , and this coupled with knowledge of the time point for which the individual's utility is zero, is sufficient information to compute additional earliness utility points based on responses to the earliness lotteries.

There were two additional problems to consider in estimating the earliness function. First, inconsistent responses to earliness questions on the part of several individuals resulted in the derivation of inconsistent utility coordinates for earliness (in some cases an individual had two different utility values for the same time coordinate). A second problem arose because different respondents had different minimum disutility points (some being on-time while others were considerably early). As a

result, the computation of the utility coordinates for each lottery had to be handled on a case by case basis depending upon whether the lottery consequences were on the same side or different sides of the minimum utility time point (i.e., for a respondent with a preferred arrival time of 15 minutes early, selecting between consequences of 10 minutes early and 20 minutes early is different than for a respondent who has a preferred arrival time of on-time selecting between those consequences).

Each individual's lateness responses were input as five data points. Therefore, lateness loss function estimation was performed on a data set consisting of 45 observations. Both linear and quadratic forms were estimated, and the results appear in Table 5.1.

An analysis of the estimation results shows that all function estimates explain most of the variation in the data (in terms of corrected  $R^2$ ). The coefficient estimates are all significant, with the exception, perhaps, of  $\beta_3$  in case 3. This may be due in part to the potential for multicollinearity between  $x$  and  $x^2$ .

All coefficients have the proper signs.\* Cases 1 and 3 have functional forms which fit the data better (in terms of corrected  $R^2$ ) than case 2. There are only slight differences in the coefficient estimates for cases 1 and 3.

Given the clear superiority of cases 1 and 3 over case 2, and the negligible difference between case 1 and case 3 coefficient estimates, the case 1 specification was selected because of its linearity.

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\*Lateness is expressed in terms of negative values (i.e.,  $x=-10$  represents the point  $x = 10$  minutes late).

Table 5.1. Lateness Loss Function Estimation

Case 1

$$U(X) = \beta_1 + \beta_2 X$$

# of variables = 2, # of observations = 45

corrected  $R^2 = .85731$

$F(1,43) = 265.365$

<u>Coefficient</u>	<u>Value</u>	<u>Standard Error</u>	<u>T-Statistic</u>
$\beta_1$	0.16329	0.03020	5.40
$\beta_2$	-0.01757	0.00108	-16.29

Case 2

$$U(X) = \beta_1 + \beta_2 X^2$$

# of variables = 2, # of observations = 45

corrected  $R^2 = .72268$

$F(1,43) = 115.661$

<u>Coefficient</u>	<u>Value</u>	<u>Standard Error</u>	<u>T-Statistic</u>
$\beta_1$	0.219	0.040	5.446
$\beta_2$	$3.986 \times 10^{-4}$	$3.706 \times 10^{-4}$	10.754

Case 3

$$U(X) = \beta_1 + \beta_2 X + \beta_3 X^2$$

# of variables = 3, # of observations = 45

corrected  $R^2 = .8587$

$F(2,42) = 134.701$

<u>Coefficient</u>	<u>Value</u>	<u>Standard Error</u>	<u>T-Statistic</u>
$\beta_1$	0.161	0.0301	5.3578
$\beta_2$	-0.015	0.0023	-6.5112
$\beta_3$	$6.83 \times 10^{-5}$	$5.72 \times 10^{-5}$	1.1931

Using the case 1 specification, lateness loss is expressed as:

$$U(X) = 0.16329 - 0.01757X \text{ for } X \leq 9.29 \text{ minutes early (5.26)}$$

A graph of this function appears in Figure 5.5. It is interesting to note that the intercept at the x-axis is at  $x=9.29$  minutes early, indicating that the population as a whole considers about a 5-10 minute early arrival to be the most desirable work arrival time. This makes some intuitive sense, since it can be argued that employees feel most comfortable arriving shortly before official work start time, so that they can obtain coffee, read the paper, or chat a little bit before settling down to work.

The estimation procedure used to derive an earliness arrival loss function was similar to the lateness estimation approach. Each individual's earliness responses were input as five data points, resulting in a sample of 45 observations. Estimation results for a variety of functional forms appear in Table 5.2.

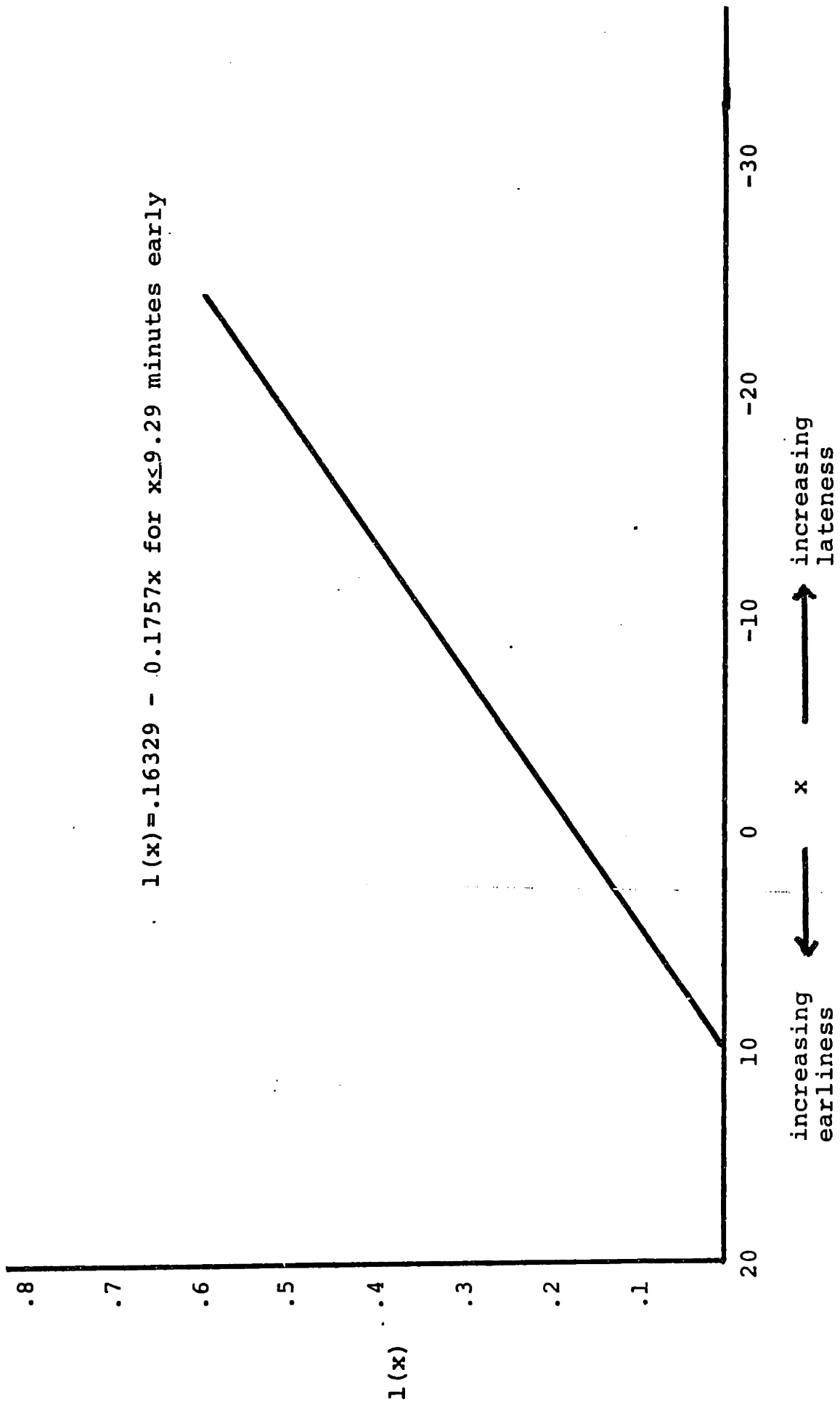


Figure 5.5 Lateness Arrival Time Loss Function



Table 5.2 Earliness Loss Function Estimation

Case 1

$$U(X) = \beta_1 + \beta_2 X$$

# of variables = 2, # of observations = 45

corrected  $R^2 = .00139$

$F(1,43) = 1.061$

<u>Coefficient</u>	<u>Value</u>	<u>Standard Error</u>	<u>T-Statistic</u>
$\beta_1$	0.03787	0.03935	0.96241
$\beta_2$	0.00301	0.00293	1.03026

Case 2

$$U(X) = \beta_1 X$$

# of variables = 1, # of observations = 45

corrected  $R^2 = .00307$

$F(0,44) = 0.135$

<u>Coefficient</u>	<u>Value</u>	<u>Standard Error</u>	<u>T-Statistic</u>
$\beta_1$	0.00545	0.00147	3.70556

Case 3

$$U(X) = \beta_1 X^{1/2}$$

# of variables = 1, # of observations = 45

corrected  $R^2 = .03198$

$F(0,44) = 1.453$

<u>Coefficient</u>	<u>Value</u>	<u>Standard Error</u>	<u>T-Statistic</u>
$\beta_1$	.02247	.0572	3.9313

Case 4

$$U(X) = \beta_1 X^{1/4}$$

# of variables = 1, # of observations = 45

corrected  $R^2 = .04256$

$F(0,44) = 1.956$

<u>Coefficient</u>	<u>Value</u>	<u>Standard Error</u>	<u>T-Statistic</u>
$\beta_1$	.04417	.011	4.014

The earliness function estimates are all statistically much weaker than the lateness estimates. In Case 1, close to nothing is "explained" by the specification, and the coefficients do not statistically differ from zero. Case 2 results are more promising, with slight improvements in corrected  $R^2$ , and with a statistically significant coefficient estimate for the lone parameter in the specification. Cases 3 and 4 are non-linear specifications; both cases exhibited much improved results, particularly in terms of corrected  $R^2$ , with case 4 being a slightly better estimate.

The choice of the most appropriate earliness specification reduces to selection between the best linear form (Case 2) and the best non-linear form (Case 4). Both functions are plotted in Figure 5.6. While the non-linear form is a better estimate from a statistical standpoint, Figure 5.6 shows that there is little difference between the two specifications when used to assign loss associated with varying early arrival times. What is somewhat disturbing about the non-linear model is its asymptotic behavior beginning at an arrival time of 15 minutes early. Acceptance and use of the non-linear form for travelers who might arrive much earlier than the official work start time (i.e., 40 minutes) could result in inaccurate measures of perceived loss in that arrival time range. For that reason,

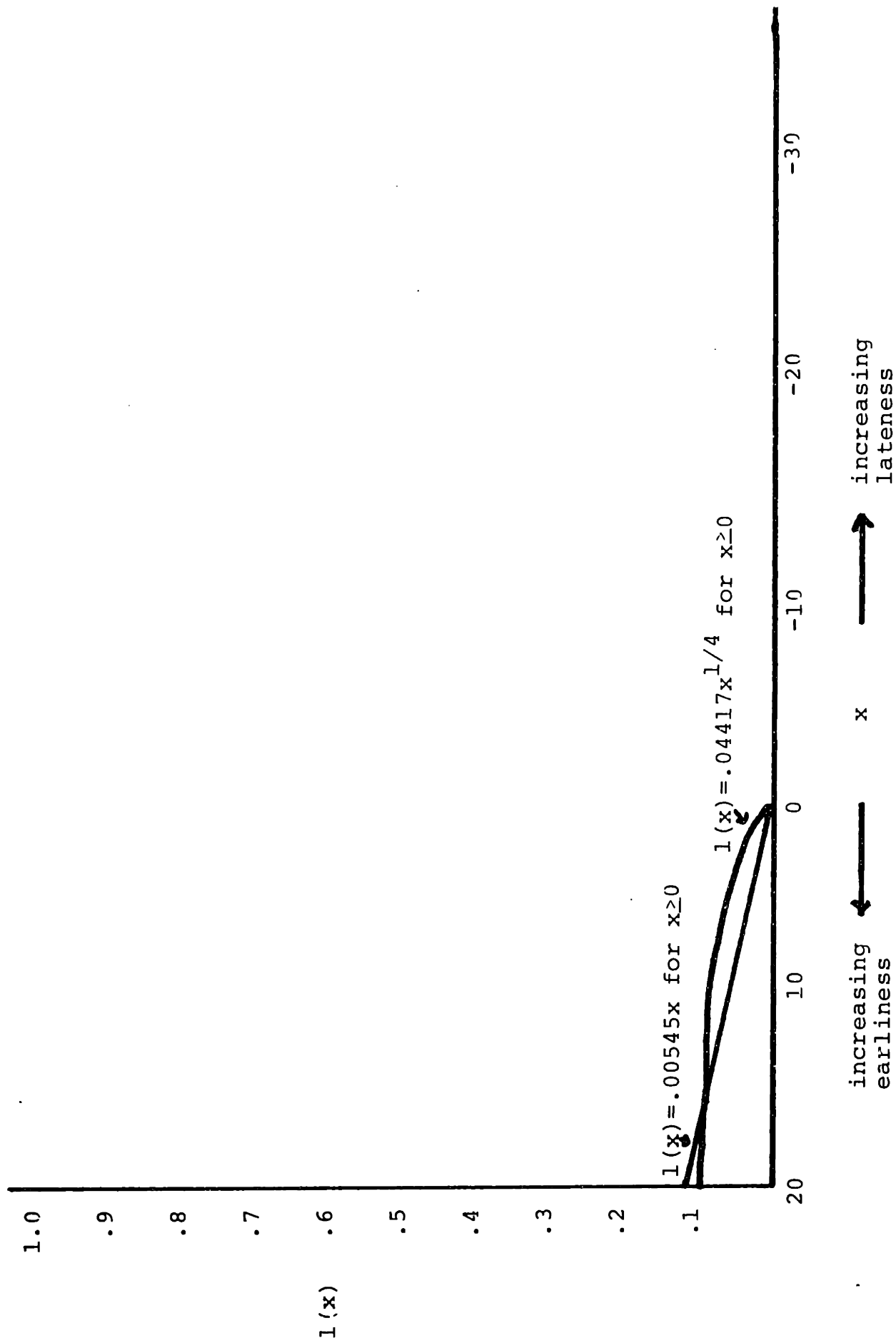


Figure 5.6 Earliness Arrival Time Loss Functions

and because the use of a linear form is more desirable from a computational standpoint, the linear form was selected to represent early arrival time loss. Thus, early arrival time loss is expressed as:

$$U(X) = .00545X \text{ for } X \geq 0. \quad (5.27)$$

The complete arrival time loss function appears in Figure 5.7. It is interesting to note that the slope of the lateness function is roughly three times greater than the slope of the earliness function. This finding agrees with a priori expectations that individuals view late arrival much more onerously than early arrival to work. It also compares quite favorably with Small's research (1978) where he found the marginal rate of substitution between schedule delay (as defined by Cosslett) early and schedule delay late to be about 4.

It is important to note that the selected earliness and lateness functions intersect the x-intercept at different points, resulting in some question as to which function is appropriate to use in the overlapping range. The reason for the overlapping functions is due to the fact that different individuals have different preferred arrival times, and that when this information is aggregated, the aggregate estimations produce overlapping functions. In actuality,

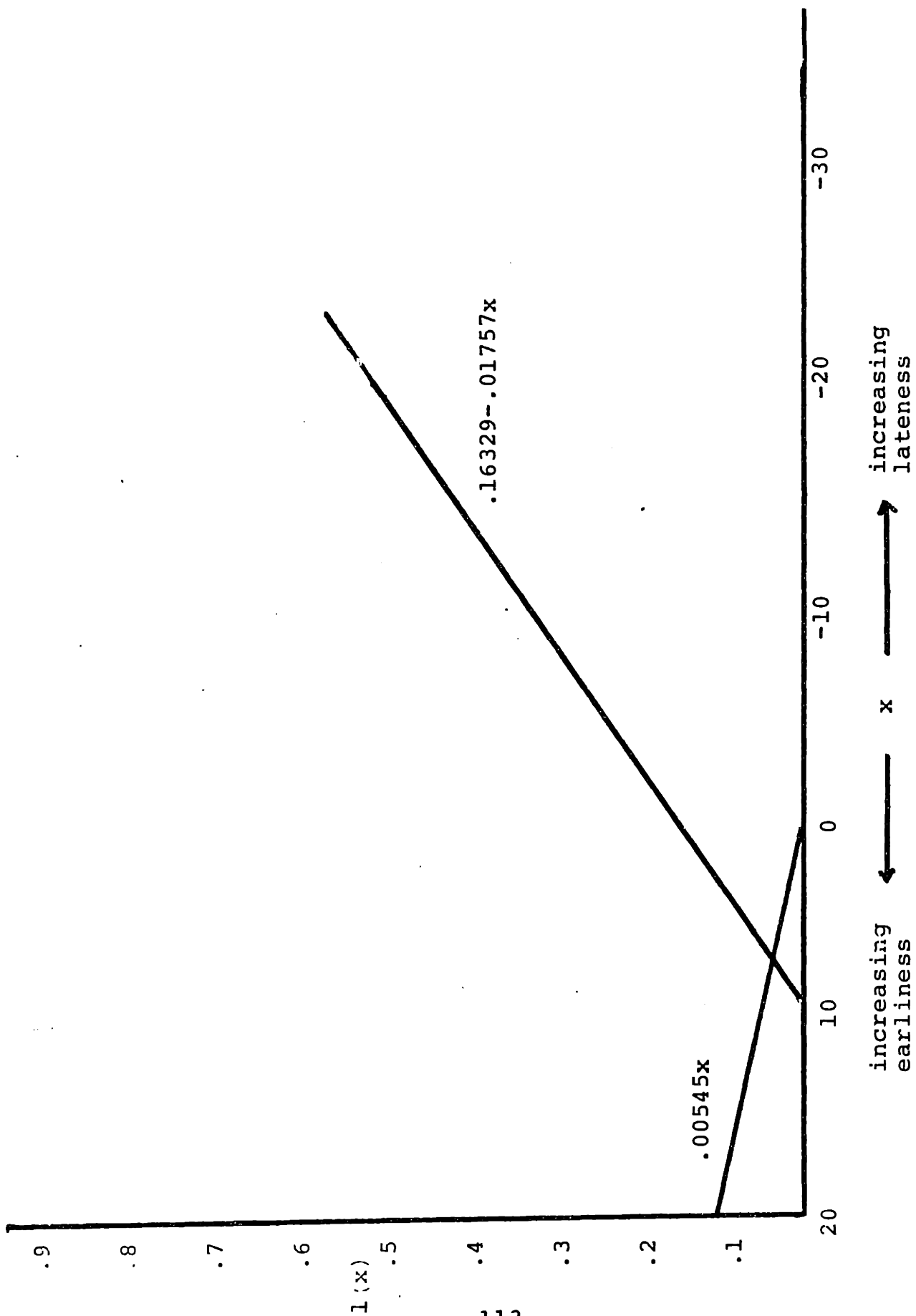


Figure 5.7 Complete Arrival Time Loss Function

each individual does not face an overlapping range; furthermore, it is possible to assume that the estimated slopes of both the earliness and lateness functions are reasonable indicators of loss perceived at both the aggregate and individual levels, and that the issue which has to be addressed is identification of the point at which each individual moves from one function to the other (i.e., their preferred arrival time). The following discussion relates to this issue.

If we define  $p$  as the preferred arrival time, then arrival loss is defined as:

$$L(t|p) = \begin{aligned} &.00545(t-p) \text{ if } t > p \\ &-.01757(t-p) \text{ if } t < p \end{aligned} \quad (5.28)$$

Each individual in the population will have a different  $p$ , depending on their employment circumstances (it is assumed that the entire population has the same slope for earliness loss and the same slope for lateness loss, as explained in Section 5.3.1).

Let us assume that for the population,  $p$  is normally distributed:

$$p \sim N(p, \sigma^2)$$

where  $p$  and  $\sigma^2$  are the population mean and variance respectively. The individual expected loss can then be computed by treating  $p$  as a random variable as follows:

$$E(\text{loss}) = \int_{-\infty}^{\infty} [\int L(t|p)f(t)dt]f(p)dp \quad (5.29)$$

The formulation in Equation 5.29 was used to compute expected loss in this research. Based on the limited data from the survey, the computed mean and variance of  $p$  are\* :

---

\*For practical reasons, an integral interval of three sigma bounds can be used, since such an interval captures 99% of the area under the normal distribution. The expression becomes:

$$\int_{-17.73}^{30.51} [\int L(t|p)f(t)dt]f(p)dp \quad (5.31)$$

It is also interesting to note that since total travel time for all modes is being approximated as a normal distribution, and because the arrival time loss functions are linear, a closed form solution can be derived for the inside integral of Equation 5.29. Suppose that the arrival time  $t$  is distributed normal, with mean  $\mu$  and variance  $\sigma^2$ . For a given value of  $p$ , the expected loss can be expressed as:

$$E[l(t)] = (1 - \Phi(\frac{p-\mu}{\sigma}))E[.00545(t-p)] + \Phi(\frac{p-\mu}{\sigma})E[-.01757(t-p)] \quad (5.32)$$

where:

$$E[.00545(t-p)] = .00545[\mu + \sigma \frac{\phi(\frac{p-\mu}{\sigma})}{1 - \Phi(\frac{p-\mu}{\sigma})}] \quad (5.33)$$

$$E[-.01757(t-p)] = -.01757[\mu - \sigma \frac{\phi(\frac{p-\mu}{\sigma})}{\Phi(\frac{p-\mu}{\sigma})}] \quad (5.34)$$

$p = 6.39$  minutes

$\sigma^2 = 64.63$  ( $\sigma = 8.04$ )

(5.30)

#### 5.4 Summary

This chapter has addressed the issues considered in structuring the analysis methodology. Based on a review of previous research, and through the design and implementation of additional analyses, the final analysis methodology was defined. The methodology is multi-staged, with examination of service information and loss function analysis combining to form arrival time variables (that include reliability effects) which, in turn, are studied in the estimation of a departure time model. Results from the departure time model are then utilized in the estimation of the mode choice model.

A sequential modeling structure will be used, with departure time choice conditional on mode choice. Separate models will be estimated for mode and departure time choice. This structure was selected because of a behavioral belief that the decisions are interdependent, with the departure time decision made conditional on a mode choice decision having been reached.



Departure time will be modeled as a continuous choice, using a logit model formulation. Since alternative departure times may not be free of the IIA assumption implicit in logit, diagnostic tests of IIA violation will be conducted, and the model respecified if appropriate.

Multinomial logit will be used to estimate discrete alternatives of mode choice; one would expect there to be less correlation between error terms of the alternative modes than in the case of departure time choice, although diagnostic tests of IIA violation will be conducted on the mode choice model as well.

The range of departure time choice will be such that expected arrival times vary from 42.5 minutes earlier than the official work start time to 17.5 minutes later than the official work start time, to conform with available departure time data. Mode choice will be restricted to single occupant auto, transit, and carpool alternatives.

Travel time moments were defined for auto, transit, and carpool in-vehicle travel times, and for transit and carpool wait times. Under the assumption that average auto and transit in-vehicle times, and average scheduled headway are available from existing data, equations for standard deviations of the above attributes as well as for mean

transit and carpool wait times were defined. The Herman and Lam linear function was selected for computing the standard deviation of auto and carpool in-vehicle travel times; the transit in-vehicle travel time standard deviation equation was derived by analyzing data on morning peak period bus travel in Portland, Oregon. Transit mean wait time will be defined as one-half the scheduled headway; a Joliffe and Hutchinson finding is being used to compute the standard deviation of wait time, using inputs of mean wait time computed from an expression derived by O'Flaherty and Mangan. Carpool mean wait time was assumed to be two minutes per passenger, with a standard deviation of wait time of 1.5 minutes.

Auto and carpool in-vehicle travel times will be modeled as normal approximations for lognormal distributions (Richardson and Taylor) (see Appendix B); transit in-vehicle travel time is being represented as a normal approximation for a beta distribution (Polus)(see Appendix C). Since there is no literature on distributions of transit or carpool wait times, normality is being assumed (see Appendix A) in each case.

Much of the travel time data used in this research was derived from previous studies of auto, transit, and carpool travel, or assumed due to the lack of available literature

on the subject. In many cases, previous studies were based on data which did not adequately represent day-to-day service levels experienced by travelers. As a result, the data used in this research suffers from these problems and a future research priority should be to collect better reliability data.

The problem of representing the combined effects of transit and carpool wait time and in-vehicle travel time uncertainty was overcome based on the acceptance of the normal approximation for the beta and lognormal distributions for in-vehicle time respectively. Since transit and carpool wait times and in-vehicle travel times can both be represented as distributed normal, their joint distribution can also be represented as normal, and transit and carpool arrival time distributions can be derived.

Finally, a procedure for estimating arrival time loss functions was defined and utilized on a very limited sample which responded to personal interviews. While it would have been desirable to estimate separate arrival time loss functions for different employment categories and employer arrival time policies, a number of constraints precluded collecting a sample large enough to accomplish this objective. Rather, the sample was used to estimate a generalized arrival time loss function, and the effects of

job classification and employer work policies will be modeled separately in the utility specifications for departure time and mode choice.

The linear specification was selected to represent both earliness and lateness arrival time loss. The estimation results revealed that the population perceives loss due to late arrival as more severe than early arrival loss, the difference in the slopes for early and late arrival loss being a factor of three. The early and late arrival loss functions, when combined to represent a continuous loss function, produced an overlapping region, which it appears is due to variations in preferred arrival times for different individuals. A technique was proposed and will be utilized to correct for this problem in order to represent continuous individual arrival time loss functions when computing expected loss.

## 6. DATA COLLECTION AND REDUCTION

This chapter examines existing data sets which provide mean service attribute information and contain other relevant data needed for this research. In particular, travel information for various possible departure times is a necessary input to defining the attributes of departure time alternatives. Following selection of the most appropriate existing data set, there is a discussion of the reduction process used to pare down the data to the relevant sample. The chapter concludes with a description of additional data and variable construction generated to complete the information needed for model estimation.

### 6.1 Selecting the UTDFP Sample

The only available data sets which contain travel data for varying times of the day, as well as information on official work start time, are from Singapore and the San Francisco Bay Area (UTDFP data set). These data sets are reviewed in the subsequent discussion.

The Singapore data consists of a pair of surveys conducted by the World Bank before and after the institution of a peak-hour toll on highways leading into the central business district. Commuters were asked the time of day at

which they took their trip, their official work start time, and flexibility of their work hours. In addition, calculations of mean peak and off-peak travel times were made for each commuter. The sample consists of 850 observations.

The major shortcoming of this data set is that the existence of only two sets of travel times (and only one peak travel time) is not the level of segmentation needed for defining peak period departure time alternatives. It appears that the Singapore data set is more useful for modeling the difference between peak and off-peak travel rather than the effects of day-to-day variability experienced under specific departure times during the morning commute.

The San Francisco Bay Area data set was collected by the Urban Travel Demand Forecasting Project (UTDFP) under the direction of Professor Daniel McFadden at the University of California at Berkeley. This sample of 991 commuters in the San Francisco Bay Area under 1972 conditions was used by Cosslett and Small in their studies. Included in this data set of traveler behavior, attitudes, and socio-economic characteristics is information on official work start time, actual arrival time, and work schedule flexibility. In addition, the UTDFP data set contains calculations (for each

individual) for auto in-vehicle travel time for twelve alternative time periods during the peak period. This was produced by interpolating between peak and off-peak network values; a similar effort can be applied to produce bus travel times for various time periods during the peak period.

The UTDFP data set has clear advantages over the Singapore data set for departure time research. While both data sets contain travel behavior and socio-economic data, the detailed level of service data for various modes and departure times which exists in the UTDFP data is a primary input to the departure time model. For this reason, the UTDFP sample was selected for use in this research, and the reliability service attributes will be computed using the mean travel time and scheduled headways reported in the UTDFP data.

## 6.2 Data Reduction

The data reduction process was designed to accomplish five basic objectives: 1) omit park-and-ride users, 2) omit observations where the respondent's official work hours begin outside the a.m. peak (7:00 a.m. - 9:30 a.m.), 3) omit non- and part-time workers, 4) omit observations where the

respondent has an expected work arrival time of more than 40 minutes earlier or greater than 15 minutes later than his/her official work start time, and 5) omit incomplete observations. The motivation for establishing these objectives is presented in the following discussion.

Park and ride users were omitted from the sample because it was felt that although their level of service differs from auto drive alone or transit service, the sample size would not be large enough for estimation purposes. Furthermore, the variation in daily park and ride service resulting from variations in auto in-vehicle, transit wait, and transit in-vehicle travel time might be difficult to represent in the model inputs.

Respondents whose official work start times begin outside the a.m. peak were omitted because of the research objective of studying the morning peak period commute trip. These respondents would not typically commute during the morning peak period.

Non- and part-time workers were not included in the research sample for different reasons. Non-workers were omitted because the research is directed only at work trips.



The issue concerning part-time workers arises over a problem of how to represent the reliability of the return p.m. trip home. The UTDFP data does not include information on flexibility of arrival time at home, nor does it include detailed travel time data for various p.m. work departure times. Thus, a decision was made to consider only home-to-work travel, recognizing that by not treating p.m. reliability, it is implicitly assumed that home arrival time loss in the evening peak is some linear function of work arrival time loss in the morning peak. This could be plausible for some travelers, but is not likely for all. A study of p.m. reliability and its implications would be a useful direction for further research.

Part-time workers were omitted because although part-time workers might be commuting inbound during the a.m. peak, they would be commuting outbound during the off-peak. Even though p.m. reliability is not being considered in the study, part-time workers would not be subject to the same return trip travel time and reliability considerations as full-time workers (i.e., one problem would be that transit headways outbound during the p.m. peak for full-time workers would be quite different than off-peak headways that part-time workers would face on the outbound trip). To maintain consistency within the sample, part-time workers were omitted.

Respondents with expected work arrival times more than 40 minutes earlier or greater than 15 minutes later than their official work start time were thought to have regular non-work activities (i.e., medical trip, chaffeur-ing children, etc.) which resulted in this extreme arrival time behavior. Because their work travel decisions would be based partially on non-work considerations and also since detailed departure time data was only available for the restricted period, these people were omitted from the sample.

Observations which contained incomplete data were omitted on the basis that the missing data was needed to conduct the research and that furnishing subjective inputs for the missing data would introduce potential biases into the data.

Table 6.1 presents a tabulation of data reduction activities. The table shows that the omission of park and ride users affects a very small share of the total UTDFP sample. Respondents whose official work start times begin outside the a.m. peak or for which there is incomplete data on official work start time comprise 29% of the sample. Unfortunately, the number of incomplete observations was not separated from the observations which were complete and which had start times outside the a.m. peak. Non- and part-

Table 6.1 Tabulation of Data Reduction Activities

	<u># affected in sample</u>	<u>% of sample affected</u>
Park and Ride Users	38	3.8
Official Work Hours Outliers: for those whose hours begin before 7:00 am and after 9:30 am, and those for which there is no reported data	283	28.6
Non- and Part-Time Workers	112	11.3
People whose expected arrival is more than 40 minutes earlier or 15 minutes later than official work start time	191	19.3
<u>Incomplete Data</u>		
auto chosen mode	2	0.2
transit chosen mode	2	0.2
drive alone cost	16	1.6
transit cost	18	1.8
carpool cost	16	1.6
drive alone on-vehicle time*	16	1.6
transit on-vehicle time*	125	12.6
# of workers in household	1	0.1
minutes can be late to work	74	7.5
reported time to work by usual mode	31	3.1
walk time at home end*	91	9.2
walk time at work end*	104	10.5
line-haul time at official work start time (drive alone)*	16	1.6
line-haul time at official work start time (transit)*	104	10.5
initial transit headway, midday*	128	12.9
initial transit headway, peak*	52	5.2
cumulative transfer headway, midday*	145	14.6
cumulative transfer head., peak*	52	5.2
cumulative walk to trans., mid*	99	10.0
cumulative walk to trans., peak*	104	10.5
age	3	0.3
actual work arrive time	21	2.1
no chosen modes	66	6.7
<hr/>		
TOTAL OBSERVATIONS OMITTED FROM SAMPLE	566	57.1

\* Network values

time workers comprised 11.3% of the sample, while people whose expected arrival time is more than 40 minutes earlier or more than 15 minutes later than their official work start time comprised a surprising 19.3% of the sample. Of the data required for the research, the most common incomplete observations pertained to transit data computed from network programs. There is no clear explanation for the omitted data in the UTDFP literature. One problem might be that transit network data was not computed for the seventy respondents whose chosen mode was not auto, carpool, or transit. It is also likely that other transit observations were left undefined because computed values exceeded or were lower than critical values in the program.

Many of the observations were omitted from the sample based on multiple criteria (i.e., part-time worker, transit data not available). The total number of observations omitted was 566, or 57.1% of the sample. This caused some concern about whether the remaining sample of 425 respondents would be too small for departure time model estimation and whether mode choice model coefficients estimated using the reduced sample would be biased.

Table 6.2 presents a breakdown of the actual mode and departure time choices for the reduced sample. For the mode choice situation, all modes have an adequate number of

Table 6.2 Actual Mode and Departure Time Choices of Reduced Sample

<u>Mode</u>	<u># in reduced sample</u>	<u>% of reduced sample</u>	<u>% of full sample</u>
Auto	223	52.5	53.5
Transit	95	22.4	15.7
Carpool	107	25.2	20.2
Other	<u>0</u>	<u>0.0</u>	<u>10.6</u>
TOTAL	425	100.1	100.0

Departure Such That \*  
Expected Arrival Is:

40 minutes early	18	4.2
35 minutes early	9	2.1
30 minutes early	39	9.2
25 minutes early	11	2.6
20 minutes early	22	5.2
15 minutes early	63	14.8
10 minutes early	48	11.3
5 minutes early	43	10.1
On Time	149	35.1
5 minutes late	5	1.2
10 minutes late	6	1.4
15 minutes late	<u>12</u>	<u>2.8</u>
TOTAL	425	100.0

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\* Based on individuals' reported arrival times.

sample observations to facilitate model estimation. It is interesting to note that the single occupant auto mode split for the reduced sample differs only slightly from the single occupant auto mode split for the full sample. However, transit and carpool mode share in the reduced sample are 43% and 25% higher respectively than their mode share in the full sample. Thus, the estimated mode choice model will be somewhat biased toward transit and carpool use, but not at the expense of single occupant auto use.

Departure time choices are concentrated on expected arrival times near the official work start time, with fewer observations for very early and late expected arrivals. However, since there are at least five observations of actual choice for each alternative, it was determined that departure time model should be estimated on the sample and analyzed for acceptable statistical qualities.

### 6.3 Additional Data and Variable Construction

With the existing UTDFP data reduced to the appropriate sample, the next step in the data refinement process generated additional relevant departure time and mode choice data, including reliability-related information. The additional departure and mode choice data would complete the

sample, enabling the research effort to enter a model estimation phase, beginning with the departure time model.

Additional departure time data consisted of computing in-vehicle travel times, out-of-vehicle travel times, standard deviations of travel times, and expected loss for each of twelve departure time periods. This data was derived for each mode using expressions discussed in Chapter 5.

It was mentioned previously in Section 6.1 that the UTDFP data contains auto in-vehicle travel time for twelve alternative time periods (five minute intervals) ranging from an expected arrival forty minutes before official work start time to an expected arrival 15 minutes later than the official work start time. The UTDFP data set also contains the derivative of auto in-vehicle travel time with respect to expected time of arrival for each of the expected arrival time alternatives. The use of this information will be described subsequently.

The standard deviation of auto in-vehicle time was computed using UTDFP auto in-vehicle travel times and Equation 5.8. Auto out-of vehicle time was assumed to be 5 minutes, allocated for walking from the parking lot to the

destination at the work end; auto out-of-vehicle time standard deviation was assumed to be zero.

Carpool line-haul travel time corresponding to each of the departure time periods was assumed to be identical to auto for the in-vehicle portion of the trip; carpool collection times were also treated as in-vehicle travel time. Carpool in-vehicle time standard deviation was computed using Equation 5.8. The walk time for carpoolers at the work end was assumed to be three minutes, slightly less than in a single occupant auto, due to assumed preferential parking for carpoolers; carpool walk time standard deviation was also assumed to be zero. Carpool wait time moments were defined as discussed in Section 5.2.4.

Transit in-vehicle travel times corresponding to each of the departure time periods were derived by using the transit in-vehicle time for an expected arrival time at the official work schedule (available in UTDFP data set), and the derivative of auto in-vehicle travel time with respect to expected time of arrival for each of the expected arrival time alternatives. By multiplying the transit in-vehicle travel time for an alternative by the derivative for that alternative, the transit in-vehicle time for the adjacent alternative can be computed. If the process is repeated a



number of times, the entire range of alternative transit in-vehicle times can be computed. Thus, transit in-vehicle travel time is always a constant differential from auto in-vehicle travel time. This procedure required the assumption that transit in-vehicle time is subject to the same congestion effects as auto in-vehicle time. Since all transit vehicles in the UTDFP study area at the time of the survey were buses, this assumption is reasonable. Transit in-vehicle time standard deviations were calculated using Equation 5.17.

Transit access and egress times were available from the UTDFP data. Transit wait times were computed from headway information in the existing UTDFP data. If the departure time for an alternative was later than 7:00 a.m. or earlier than 9:00 a.m., then the peak headway was assigned to the alternative. If the departure time was earlier than 7:00 a.m. or later than 9:00 a.m., the average of peak and midday headways was used for the alternative, the assumption being that departures of this nature would be offered curtailed peak service (but probably better than midday service). For transfer trips, cumulative headways were used to compute the

wait time mean and standard deviation.\* Transit wait time moments were defined as described in Section 5.2.2.

Expected loss terms were computed for each mode-departure time combination. The expected loss formulation (see Equation 5.31) varied for each combination since the arrival time distribution varied by both mode and departure time.\*\*

The actual inputs into the departure time model were the travel time attributes and expected loss for each departure time alternative computed for the actual mode choice (recall departure time choice is conditional on mode having been selected). The reason for computing data for all mode-departure time combinations is because this data is necessary for calculating  $D^*$  for each mode in order for it

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\*The use of cumulative headways to compute the standard deviation of wait time for transfer trips rather than computing separate standard deviations of wait time for each transfer leg results in the derivation of slightly higher wait time standard deviations. For the one transfer trip, a study of headways ranging from 10 minutes to 30 minutes results in an overbias ranging from 2% in the 10 minute initial headway, 10 minute transfer headway case to 21% in the 30 minute initial headway, 30 minute transfer headway case.

\*\*In computing expected loss terms, the estimated loss functions were extended linearly beyond the range of arrival time used for estimation. In doing so, it was assumed that the slope of the loss functions remains unchanged for extremely early and late arrivals. The plausibility of this assumption would be questionable in cases where people have different reactions to extreme situations.

to be used as an input to the mode choice model (see Section 5.1).

Additional mode choice data included  $D^*$  for each mode. Once the departure time model was estimated, the travel time and expected loss for each departure time-mode combination was used along with the other departure time variables to compute the utility for each departure time-mode combination. All the departure time utilities were exponentiated, then summed by mode, and the log of the resulting value produced  $D^*$  by mode, which served as an input to the mode choice model.

The sample mean and standard deviation for many of the data elements discussed in this chapter appear in Appendix D. Relevant socio-demographic information used in travel demand model estimation is also included in this Appendix.

#### 6.4 Summary

This chapter has discussed the data collection and reduction process used to develop the appropriate sample for departure time and mode choice model estimation.

The UTDFP data set collected in the San Francisco Bay Area was selected for this research effort, primarily because it contains detailed level of service data for various modes and departure times in addition to more traditional travel behavior and socio-economic data. The UTDFP sample of 991 observations was reduced for this study by omitting park-and-ride users, observations where the respondent's official work hours begin outside the morning peak, non- and part-time workers, observations where the respondent has an expected work arrival time of more than 40 minutes earlier or greater than 15 minutes later than his/her official work start time, and observations for which there was incomplete data. The remaining sample of 425 observations was examined on the basis of actual mode and departure time chosen, and it was determined that the reduced sample would be adequate for mode choice model estimation (although variable coefficients may be biased toward transit and carpool alternatives), and that the departure time model should be estimated on the sample and analyzed for acceptable statistical qualities.

For the reduced sample, additional departure time and mode choice data were generated and new variables constructed in order to complete the information required for departure time and mode choice model estimation.

## 7. DEPARTURE TIME MODEL ESTIMATION

This chapter describes the departure time model estimation process, including model specification, estimation results, and an analysis of the model results. Diagnostic tests conducted on the estimated model concerning possible violation of logit's IIA property are also reported.

### 7.1 Model Specification and Estimation Results

Twelve departure time alternatives were defined for the departure time model. Each alternative represented a five minute departure time interval, and the data input for each alternative represented a discrete approximation of departure attributes for the continuous interval. Since the departure time period of study ranged from an expected arrival of 42.5 minutes earlier than the official work start time to an expected arrival of 17.5 minutes later than the official work start time, and since the discrete observation for each interval consisted of information at the mean point of the interval, the discrete alternatives were defined as follows:

- 40E - departure such that the expected arrival is 37.5 to 42.5 minutes earlier than official work start time
- 35E - departure such that the expected arrival is 32.5 to 37.5 minutes earlier than official work start time

•  
•  
•

- 15L - departure such that the expected arrival is 12.5 to 17.5 minutes later than official work start time.

A two-phased approach was used to select the most appropriate departure time model. The initial phase consisted of selecting independent variables which, a priori, made intuitive sense as explanatory variables of departure time. The variables were generically specified and were introduced one at a time into the departure time specification. For the addition of each new variable, a model was estimated, and the results were examined for statistical significance, proper signs, and for the possibility of different independent variables explaining similar effects in the model (by comparing the magnitude and statistical significance of the suspected variables when both are included in the same specification). This process was repeated several times until all variables had been considered. During the initial phase, variables were only entered into alternatives where a priori one could justify their presence.

In the second phase, the variables in the final Phase 1 model were individually tested in alternative specific

specifications in an effort to refine the model specification. Because of counterintuitive signs and high standard errors for the coefficient of the expected loss variable in Phase 1, alternative specifications of expected loss as well as other reliability variables were also defined and tested through model estimation in Phase 2. The selected departure time model is presented at the end of the Phase 2 discussion.

The variables a priori considered for inclusion in the departure time model included work arrival time flexibility, occupational characteristics, income, actual mode chosen, age, sex, location of where the respondent lives and works, travel time, and expected loss.. Variable definitions, the justification for considering these variables and the expected results are presented in the following discussion.

Work arrival time flexibility was considered as a potential explanatory variable since a person who has a flexible job can arrive late without large perceived penalties. The variable was defined as a Boolean variable with a value of 1 if a respondent could be late to work and a value of 0 otherwise. This variable was included in the expected on-time arrival and expected late arrival alternatives, and was expected to have a positive coefficient value.

The occupational characteristics variable was also defined as a Boolean variable. A value of 1 indicated that a respondent was employed in a professional/technical or management/administrative capacity; a value of 0 implied the respondent did not have these occupational characteristics. The motivation for defining this variable was to examine potential differences in departure time behavior between salaried and hourly employees. It was felt that people employed in a professional/technical-management/administration capacity might plan to arrive at the official work start time in order to oversee the performance of subordinates. Consequently, the occupational characteristic variable was initially placed only in the expected on-time arrival alternative, and a positive coefficient sign was expected.

Income was hypothesized to be an explanatory variable which might serve as a proxy for employee characteristics that would affect departure time decisions. An examination of various income groups and their actual departure time choices revealed that the only significant behavioral difference was that workers earning less than \$5000 a year (1972 conditions) had a higher than proportionate share of expected on-time arrivals. It was reasoned that this income level might be representative of blue collar workers, which would explain the importance of arriving exactly on time.



Based on this information, a Boolean variable was defined with a value of 1 if annual income was \$5000 or less and a value of 0 otherwise. This variable was entered only into the expected on-time arrival alternative, with an expected positive coefficient sign.

Since departure time was being modeled conditional on mode choice, the actual chosen mode is known. There was some reason to believe that the mode selected might affect people's departure time decisions. For example, auto travelers might be more likely to depart with an expected on-time arrival than bus travelers, since they might feel more in control of their arrival pattern by relying on their own form of transportation. It was also expected that transit users might not try to arrive too early since they might be facing off-peak transit schedules, where the lack of accessible routes or the unavailability of express buses might create problems should they commute that early. Thus, two variables were defined: 1) an auto dummy variable (1 if auto user; 0 otherwise) used only in the expected on-time arrival alternative with an expected positive coefficient, and 2) a generic transit dummy variable (1 if transit user; 0 otherwise) entered into the extremely early departure time alternatives (40E, 35E, 30E, 25E, 20E) with an expected negative coefficient sign.

Age was considered because of the possibility that older workers might have different departure time patterns than younger workers. Since older people have been in the work force for a longer period of time, they may have adjusted their departure times to having expected arrival times earlier than the sample as a whole in response to the work ethic they may have adopted. A Boolean variable was defined as 1 if over 50 years of age and 0 otherwise. This variable was entered into the extremely early departure time periods, and a positive coefficient sign was expected.

Sex was considered as a possible explanatory variable, since there could potentially be differences in male and female departure time behavior. Although there was no a priori causal explanation for differences in departure time behavior, an examination of males and females in the sample and their actual time choices showed a slight trend toward a higher share of women selecting expected late arrival times. This is perhaps due to women feeling less of a constraint to arriving by the official work start time. A Boolean sex variable (1 if female; 0 otherwise) was included in the expected late arrival alternatives, and a positive coefficient sign was expected.

Location of where the respondent lives and works was considered due to an awareness that transit users who

commuted over the Bay Bridge (live in East Bay, work in San Francisco) had the benefit of an exclusive transit lane on the Bridge. It was felt that Bay Bridge transit users may be subject to different trip reliability than other transit users, so a separate variable was defined to pick up the bias in their expected loss, since their expected losses were computed based on the same reliability assumptions as other transit travelers. A Boolean variable equal to 1 if Bay Bridge transit trip, 0 otherwise was defined. This variable was entered only into the slightly early (15E, 10E, and 5E) departure time alternatives, because nearly all Bay Bridge travelers chose to arrive during that period. A positive estimated coefficient sign was expected.

The travel time for the chosen mode was entered into every departure time alternative. Initially, plans were made to segment travel time into out-of-vehicle travel time and in-vehicle travel time to reflect an a priori view that travelers are more sensitive to out-of-vehicle travel time. However, because there is little variation in out-of-vehicle travel time across alternative departure times (particularly for auto and carpool modes), a total travel time variable was defined instead. This variable was expected to have a negative sign.

The expected loss for the chosen mode also entered every departure time alternative. In general, the largest computed expected losses were for alternatives with expected late arrivals, followed by the expected arrival extremely early alternatives. A negative coefficient sign was anticipated.

A number of constants were also specified in the model to represent omitted effects. Because of the size of the departure time choice set, departure time alternatives were assigned group constants. Expected arrival extremely early alternatives (40E, 35E, 30E, 25E, 20E) were assigned one constant, expected arrival slightly early alternatives (15E, 10E, 5E) were assigned another constant, and a third constant was defined for the expected on-time arrival alternative. This grouping was selected because of the view that travelers quite possibly consider macro-choices of either arriving very early, slightly early, on-time, or late.

The final Phase 1 specification and model estimation results are presented in Tables 7.1, 7.2 and 7.3. Almost all of the variables described in the previous discussion,

Table 7.1 Phase I Departure Time Model Specification:  
Variable Definition

DEPARTURE TIME ALTERNATIVES: Discrete Approximations of Five Minute Intervals of Expected Arrival Time, Ranging from 42.5 Minutes Early to 17.5 Minutes Late

INDEPENDENT VARIABLES:

TIME = total travel time

ELOSS = expected loss

FLEX = 1 if can be late to work  
0 otherwise

ADUM = 1 if auto drive alone is chosen mode  
0 otherwise

BDUM = 1 if transit is chosen mode  
0 otherwise

BRIDGE = 1 if transit user and crosses Bay Bridge to get to work  
0 otherwise

INCOME = 1 if earning \$5000 or less (1972 dollars)  
0 otherwise

AGE = 1 if over 50  
0 otherwise

OCC = 1 if professional/technical or management/administration  
0 otherwise

ONTIME = 1 if arrival between 2.5 minutes before and 2.5 minutes after official work start time  
0 otherwise

EARLY1 = 1 if arrival earlier than 17.5 minutes before the official work start time  
0 otherwise

EARLY2 = 1 if arrival between 17.5 minutes early and 2.5 minutes early;  
0 otherwise

Table 7.2 Phase I Departure Time Model Specification: Alternative Definition

Alt.	TIME	ELOSS	FLEX	ADUM	BDUM	BRIDGE	INCOME	AGE	OCC	ONTIME	EARLY1	EARLY2
40E	x	x			x			x			x	
35E	x	x			x			x			x	
30E	x	x			x			x			x	
25E	x	x			x			x			x	
20E	x	x			x			x			x	
15E	x	x				x						x
10E	x	x				x						x
5E	x	x				x						x
On Time	x	x	x	x			x		x	x		
5L	x	x	x									
10L	x	x	x									
15L	x	x	x									

Note: an 'x' denotes that the attribute listed on the top of the table is entered into the utility for the alternative listed in the left-hand column of the table.

Table 7.3 Phase I Departure Time Model Estimation Results

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic Standard Error</u>	<u>Asymptotic T-Statistic</u>
TIME	-0.037	0.032	-1.184
ELOSS	-0.016	1.959	-0.008
FLEX	1.259	0.214	5.890
ADUM	0.652	0.226	2.884
BDUM	-0.474	0.320	-1.482
BRIDGE	1.303	0.565	2.305
INCOME	0.873	0.470	1.858
AGE	0.659	0.278	2.371
OCC	0.334	0.222	1.506
ONTIME	2.443	0.406	6.020
EARLY1	1.454	0.415	3.507
EARLY2	2.423	0.496	4.886

log likelihood = -841.815

L(0) = -1056.082

# of observations = 425

# of cases = 5100

when input into the model, were statistically significant,\* had the proper sign and improved the overall statistical significance of the model. The sex variable had a small and insignificant coefficient value, implying a negligible explanatory effect on choice, and was subsequently dropped from further consideration.

The expected loss coefficient had the proper sign but was low in magnitude and was statistically insignificant. This prompted a serious examination of the variable, as well as consideration of alternative specifications of expected loss and definition of other reliability variables. These considerations are discussed later in this section.

At the beginning of the second phase, the variables defined in Table 7.1 were individually tested in alternative-specific specifications in an attempt to refine the model specification. This was done to identify additional explanatory effects in the departure time model

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\*Statistical significance is defined here as having a t-statistic with an absolute value of 1. If this is the case, then we are 68% confident that the actual coefficient value differs from zero. In more conservative studies, statistical significance is often defined as having a t-statistic greater than 1.65 (90% confidence) or 1.96 (95% confidence). A less conservative definition of significance was adopted for this work because of a willingness to accept larger Type I error in exchange for smaller Type II error.



that could be justified, but which were not considered on an intuitive basis in Phase 1.

In addition to a bus dummy variable in the expected early arrival alternative, separate alternative specific bus dummy variables were defined for the slightly early alternative set and for the on-time alternative. Both of the estimated coefficients for the new variables had small values and were insignificant, so the initial bus dummy specification was retained.

A similar attempt was made for the auto dummy variable. In addition to the existing auto dummy variable in the on-time alternative, separate variables were defined for the extremely early alternative set and the slightly early alternative set. Again, the new variables had small estimated coefficient values and were statistically insignificant, and the initial auto dummy variable specification was retained.

The results were quite different when experimenting with the work arrival time flexibility variable. The flexibility variable initially appeared in both the expected on-time and late arrival alternatives. In this phase, separate flexibility variables were defined for the on-time alternative and the late alternative set, to see if there

was a distinct difference in traveler sensitivity to this variable depending on the alternative choice being considered. A separate flexibility variable was also defined for the slightly early alternative. The estimated flexibility coefficients for this specification were\*:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
FLEX in 15L, 10L, 5L	3.141	4.059
FLEX in On-time	1.017	3.606
FLEX in 5E, 10E, 15E	-0.052	-0.180

The results show that work arrival time flexibility does indeed have a separate and significant positive impact on expected on-time arrival and expected late arrival. Because the coefficient for the flexibility variable in the slightly early alternative set is insignificant and small in magnitude, it was dropped out of the model. Separate on-time and late arrival flexibility variables were, however, retained in the model specification.

Tests run on the occupation variable yielded even more surprising results. Recall that in the initial specification the occupation variable appeared only in the expected on-time alternative. Separate variables were also

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\*Only the estimated coefficients for the variable of interest are reported in this discussion.

defined for the extremely early and slightly early alternative sets, with the following estimation results:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
OCC in 40E-20E	-0.897	-1.888
OCC in 15E-5E	-0.713	-1.451
OCC in On-time	-0.362	-0.785

Because of the significance of the occupation variable in the extremely early and slightly early alternatives, and the lower coefficient value and statistical insignificance of the occupation variable in the on-time alternative given the presence of the other occupation variables, the on-time arrival occupation variable was dropped from further consideration while the other variables were retained. The sign and significance of the early arrival occupation variables indicates that, everything else being equal, professional/technical-management/administration employees are less likely to arrive earlier than the official work start time relative to the population as a whole.

Alternative specific definitions for the income variable were also tested. The only important finding occurred when a separate income variable for the slightly early alternative set was specified in addition to the existing variable in the expected on-time arrival alternative. The estimation results on the variables of interest were:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
INCOME in 5E, 10E, 15E	1.898	1.780
INCOME in On-Time	2.285	2.164

Both coefficient estimates are significant. Because of the similarity in the magnitude of these coefficients, a combined income variable was defined and tested, with the following result:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
INCOME in 5E, 10E, 15E, On-Time	2.097	2.031

This specification was adopted in the model. The result implies that low income workers are more likely to arrive slightly earlier or at their official work start time in comparison to the entire sample.

Initially, the Bay Bridge variable only appeared in the slightly early alternative set. When a separate bridge variable was also defined for the extremely early alternative set, the estimation result was:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
BRIDGE in 40E-20E	2.567	2.160
BRIDGE in 15E-5E	2.748	2.579

As in the case with the income variable, a combined variable was defined, which resulted in the following estimation result:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
BRIDGE in 40E-5E	2.710	2.564

The combined variable was used in the model, and the coefficient sign reflects that Bay Bridge transit travelers have better level of service than the transit population as a whole (this interpretation is based on the fact that most all Bay Bridge Transit travelers in the sample have chosen early arrival times).

In addition to the age variable defined in the Phase 1 specification, separate age variables were defined in the slightly early alternative set and the on-time alternative. The estimated coefficients were:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
AGE in 40E-20E	0.973	1.419
AGE in 15E-5E	0.768	1.136
AGE in On-Time	-0.272	-0.398

The on-time age variable was dropped from the specification; the other two age variables were redefined into one variable, with the following estimated coefficient:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
AGE in 40E-5E	1.091	3.545

By combining the age variables, a statistically more reliable age variable was defined whose positive sign implies that older workers do tend to arrive earlier than younger workers. The combined variable was selected for inclusion in the departure time model.

With the specification of the departure time model nearly complete, the research effort focused on the expected loss variable. The coefficient for expected loss in the Phase I model (see Table 7.3) was insignificant, yet there appeared to be a sound theoretical basis for including the variable in the model. One possibility was that expected loss is a relevant variable, but its impact might be correlated with an omitted variable which affected the magnitude and statistical significance of the estimated coefficient.

A decision was made to take a closer look at this problem by separating expected loss into four alternative specific variables (extremely early set, slightly early set, on-time, late set), and to examine the estimated coefficients. This approach was taken, and yielded the following estimation result:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
ELOSS in 40E-20E	-2.40	-0.868
ELOSS in 15E-5E	-11.63	-1.643
ELOSS in 0n-Time	-68.90	-1.006
ELOSS in 5L-15L	5.52	1.716

The most alarming result is that the ELOSS variable for the late alternative set not only has the wrong coefficient sign, but the estimated coefficient is also significant! The other three ELOSS variables have the proper sign, with coefficients of varying magnitudes and statistical significance.

The immediate conclusion based on this result is that the late alternatives are misspecified, and there is likely an omitted variable whose effects are sufficiently correlated with expected loss that the expected loss coefficient is being seriously affected.

An effort was made to identify variables not already in the model that might be correlated with the selection of late arrival times. The travel and socio-economic characteristics of commuters who actually arrive late to work were compared to the sample as a whole, but no obvious explanatory indicators (outside of the explanatory variables already in the model) were found.

The problem was subsequently addressed by specifying separate constants for the 5L and 10L alternatives to represent omitted alternative-specific lateness effects. It was recognized that this approach would allow for the proper estimation of the coefficient for the expected loss variable, but that further research should examine other explanatory indicators of expected late arrival time choice.

The estimated coefficient for expected loss, with the addition of the lateness constants, was:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
ELOSS (in all alternatives)	-3.757	-1.463

With the additional constants in the model, the expected loss variable has the proper sign and is statistically significant.

The next step in the research was to determine whether other reliability variables should be included in the departure time model in place of or in addition to the expected loss variable. The following three variables were defined and tested in the departure time model: 1) fixed loss, 2) separate expected early loss and expected late loss variables, and 3) the probability of late arrival.



The fixed loss variable was defined as the expected loss for each alternative under the assumption that the variance in travel time is zero. In effect, fixed loss is the expected loss for a given departure time alternative, knowing with certainty that you will arrive at the expected time. A comparison of the magnitude and significance of the fixed loss and expected loss coefficients provides insight into loss derived from arriving at a particular time and loss derived from uncertainty about arriving at that particular time. An attempt was made to estimate a model with both variables in the specification; however, the high correlation between the two variables resulted in insignificant coefficient estimates for both variables. The variables were then entered into separate specifications and the estimation results were compared. The results were:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>	<u>Log Likelihood</u>
FIXED LOSS	-3.499	-1.364	-821.781
ELOSS	-3.757	-1.463	-821.639

The results show both variables have similar coefficient values and statistical significance. A comparison of log likelihood values implies that the expected loss model has a slightly better statistical fit. Thus, it makes sense to retain the expected loss variable. However, the coefficient for fixed loss definitely suggests that the effect of expected loss on departure time consists

primarily of loss derived from arriving at a particular time, and much less so from the uncertainty of arrival about that time. This result is somewhat surprising, but may perhaps be due to the quality of the UTDFP data and reliance on previous studies which used inadequate data, either of which might lead to the lack of variation in the reliability data (see Appendix D), or methodological problems rather than an indication that reliability is truly of marginal importance.

The notion behind defining separate early and late expected loss variables was to isolate travelers' sensitivities to early and late arrival. As in the previous case, the correlation between these variables and the ELOSS variable did not permit estimation using a model specification that included all three variables. This resulted in the estimation of two separate models and a comparison of the results. Denoting early expected loss as EARLOSS and late expected loss as LATELOSS, the comparative results were:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
EARLOSS	-3.168	-1.380
LATELOSS	-25.728	-1.099
ELOSS	-3.757	-1.463

These results reveal a dramatic difference in travelers' sensitivity to loss associated with early and late arrival.

The relative difference in coefficient values for early expected loss and late expected loss also suggests that the loss function is only partially representing traveler's sensitivities to early and late arrival times. Because both EARLOSS and LATELOSS have the proper sign and the coefficients are significant, a decision was made to use separate loss variables, and to drop ELOSS from the model specification.

The probability of late arrival was considered as a substitute for late expected loss. A model was estimated using a specification that included both lateness and probability of late arrival variables, but the high correlation between the two variables resulted in insignificant coefficient estimates for both variables. The variables were subsequently used in separate models, yielding the following comparative results:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
Prob(late)	-3.11	-0.70
LATELOSS	-25.728	-1.09

The coefficient values of the two variables differ considerably, likely explained by the difference in the units of measurement used to define the variables. Since the coefficient for probability of lateness is not statistically significant, it was dropped from further

consideration and LATELOSS was retained in the model specification. This completed the Phase 2 effort.

Tables 7.4, 7.5, and 7.6 present the selected departure time model specification and estimation results.\* The results are discussed in more detail in the following section.

## 7.2 Further Discussion

This section discusses the model estimation results, validation tests conducted on the departure time model, sensitivity analyses of the loss function assumptions, and a comparative study of estimated models with and without reliability-related arrival time variables in the model specification. Finally, a comparison is made between the selected departure time model and a departure time model using Cosslett's departure time specification.\*\*

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\*In general, throughout the departure time model estimation process (and also for the mode choice model estimation process) the values of the coefficients for the other variables in the model did not change appreciably as the variable of interest was tested and ultimately left in or deleted from the model.

\*\*The Cosslett specification was chosen for comparison since his work is the only other departure time research which has considered travel time uncertainty in the model specification.

Table 7.4 Selected Departure Time Model Specification:  
Variable Definition

DEPARTURE TIME ALTERNATIVES: Discrete Approximations of Five Minute Intervals of Expected Arrival Time, Ranging From 42.5 Minutes Early to 17.5 Minutes Late

INDEPENDENT VARIABLES:

TIME	=	total travel time
EARLOSS	=	early arrival expected loss
LATELOSS	=	late arrival expected loss
FLEXON	=	1 if can be late to work (on time alternative) 0 otherwise
FLEXLATE	=	1 if can be late to work (late alternatives) 0 otherwise
ADUM	=	1 if auto drive alone is chosen mode 0 otherwise
BDUM	=	1 if transit is chosen mode 0 otherwise
BRIDGE	=	1 if transit user and crosses Bay Bridge to get to work 0 otherwise
INCOME	=	1 if earning \$5000 or less (1972 dollars) 0 otherwise
AGE	=	1 if over 50 0 otherwise
OCC 1	=	1 if professional/technical or management/adminis- tration (extremely early alternatives) 0 otherwise
OCC 2	=	1 if professional/technical or management/adminis- tration (slightly early alternatives) 0 otherwise
ONTIME	=	1 if arrival between 2.5 minutes before and 2.5 minutes after official work start time 0 otherwise
EARLY 1	=	1 if arrival earlier than 17.5 minutes before the official work start time 0 otherwise
EARLY 2	=	1 if arrival between 17.5 minutes early and 2.5 minutes early 0 otherwise

Table 7.4 Selected Departure Time Model Specification:  
Variable Definition (Cont'd)

INDEPENDENT VARIABLES:

LATE 1      =    1 if arrival between 2.5 and 7.5 minutes after  
                      the official work start time  
                      0 otherwise

LATE 2      =    1 if arrival between 7.5 and 12.5 minutes after  
                      the official work start time  
                      0 otherwise

Table 7.5 Selected Departure Time Model Specification: Alternative Definition

ALT.	TIME	EARLOSS	LATELOSS	FLEXON	FLEXLATE	ADUM	BDUM	BRIDGE	INCOME	AGE	OCC1	OCC2	ONTIME	EARLY1	EARLY2	LATE1	LATE2
40E	x	x	x				x	x		x	x			x			
35E	x	x	x				x	x		x	x			x			
30E	x	x	x				x	x		x	x			x			
25E	x	x	x				x	x		x	x			x			
20E	x	x	x				x	x		x	x			x			
15E	x	x	x				x	x	x	x		x			x		
10E	x	x	x					x	x	x		x			x		
5E	x	x	x					x	x	x		x			x		
On																	
Time	x	x	x	x		x			x				x				
5L	x	x	x		x											x	
10L	x	x	x		x												x
15L	x	x	x		x												

Note: an 'x' denotes that the attribute listed on the top of the table is entered into the utility for the alternative listed in the left-hand column of the table.

Table 7.6 Selected Departure Model Estimation Results

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic Standard Error</u>	<u>Asymptotic T-Statistic</u>
TIME	-0.041	0.032	-1.279
EARLOSS	-3.168	2.296	-1.380
LATELOSS	-25.728	23.411	-1.099
FLEXON	1.084	0.227	4.780
FLEXLATE	3.162	0.756	4.184
ADUM	0.496	0.269	1.846
BDUM	-0.794	0.319	-2.487
BRIDGE	2.764	1.063	2.600
INCOME	2.042	1.032	1.979
AGE	1.104	0.308	3.583
OCC 1	-0.492	0.277	-1.774
OCC 2	-0.575	0.250	-2.304
ONTIME	-3.606	6.894	-0.523
EARLY 1	-6.483	8.734	-0.742
EARLY 2	-5.874	8.717	-0.674
LATE 1	-5.211	4.018	-1.300
LATE 2	-2.880	2.062	-1.397

log likelihood = -820.974

L(constants) = -875.846

L(0) = -1056.082

# of observations = 425

# of cases = 5100



Table 7.6 presents the selected departure time model estimation results. As discussed previously, all the independent variables have the expected sign and are significant (as defined in Section 7.1) with the exception of some of the constants. The reliability-related arrival time variables (EARLOSS and LATELOSS) appear to lend additional explanatory power to the model. This implies that measures which capture the impacts of arriving to work at a particular time and the uncertainties associated with arriving at that particular time are significant explanatory factors in determining departure time choice. However, uncertainty of arrival time has a considerably smaller effect on departure time choice than arrival away from the official work start time. It is also interesting to note that the flexibility variables, which are also related to arrival time implications, are also significant variables in the model. Based on these results, it is fair to say that a primary departure time consideration is the implications of when the traveler will arrive at work and the uncertainty associated with it, and the perceived penalties for arriving at that particular time.

In evaluating the model results, it is often interesting to examine the marginal rates of substitution for different sets of independent variables in the model specification. When all the variables of interest are

included in the same specification, the marginal rates of substitution between two variables are simply the ratio of the variable coefficients (expressed in terms of the corresponding units). For the departure time model, the issue of how travelers tradeoff travel time and loss is rather interesting. Based on the model results, a prototypical commuter in the sample would be willing to incur a one minute increase in travel time to reduce his/her early expected loss by .013 utiles, or to reduce his/her late expected loss by .0016 utiles. Travelers are more sensitive to late expected loss than to early expected loss by a factor of over 8. It is difficult to interpret the marginal rates of substitution between time and loss, because the units of loss are somewhat dimensionless. However, the comparison of early and late expected loss shows a much higher traveler sensitivity to late expected loss. This result is somewhat surprising, since it was anticipated that most of the difference in sensitivity between early and late expected loss was captured in the difference in magnitude in the slopes of the loss function.

Statistical tests were conducted to see if the selected departure time model differed significantly from a uniform probability departure time model or from a departure time model consisting of only the constants in the specification. The test statistic is:

$$2(\log \text{ likelihood of selected model} - \log \text{ likelihood of reduced model}) \quad (7.1)$$

and is distributed  $\chi^2$  with degrees of freedom equal to the difference in the number of coefficients estimated by the models being compared. For both the uniform probability model and the model consisting of only the constants, the hypothesis that the model is the same as the selected departure time model is easily rejected at the .05 level.

A validation test was also conducted on sub-samples of the sample used for model estimation to determine whether the selected model was properly specified. The sample was separated into single occupant auto, transit, and carpool users, and chosen departure times were predicted for each modal group using the departure time models.\* These results were compared to actual departure times reported in the UTDFP data set.

The test results appear in Table 7.7. In general, predicted choices compare quite favorably with actual choices. The model behaves particularly well in predicting transit and carpool departure time choices, and exhibits

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\*The predictions were obtained by applying the model to each individual in the sample for the purposes of predicting individual probabilities of selecting particular departure times. The relevant individual probabilities were then summed to form group predictions of departure time.

Table 7.7 Selected Departure Time Model Validation Test

	<u>ACTUAL CHOICE</u>			
	Auto	Bus	Carpool	Total
40E	10	3	5	18
35E	3	2	4	9
30E	24	4	11	39
25E	4	2	5	11
20E	10	5	7	22
15E	31	13	19	63
10E	22	12	14	48
5E	15	18	10	43
On Time	93	30	26	149
5L	2	1	2	5
10L	2	2	2	6
15L	<u>7</u>	<u>3</u>	<u>2</u>	12
TOTAL	223	95	107	

	<u>PREDICTED CHOICE</u>			
	Auto	Bus	Carpool	Total
40E	8.3	2.7	5.6	16.6
35E	9.4	3.0	6.0	18.4
30E	10.4	3.2	6.3	19.9
25E	11.2	3.4	6.8	21.4
20E	11.9	3.6	7.2	22.7
15E	23.7	16.4	13.9	54.0
10E	23.6	16.3	13.8	53.7
5E	21.5	12.8	12.0	46.3
On Time	93.0	26.8	29.2	149.0
5L	2.1	1.5	1.3	4.9
10L	2.6	1.7	1.6	5.9
15L	<u>5.3</u>	<u>3.4</u>	<u>3.3</u>	12.0
TOTAL	223.0	94.5	107.0	

slight problems in predicting early arrival times for auto users.\* The results do, however, validate the reasonableness of the selected departure time model.

Another modeling concern was the sensitivity of the early and late expected loss coefficients to assumptions about the loss function. Recall that the loss function was estimated on a very small sample, and there was some concern about the confidence of the parameter estimates. To assess this problem, a sensitivity analyses was conducted by varying the magnitude of the slopes of the loss function, recomputing the early and late expected losses, and reestimating the model to produce new coefficient estimates. In each case, coefficient estimates were compared to the estimates in the selected model.

Four cases were considered:

- Case 1: recompute early expected loss assuming a 20% increase in the slope of the early loss function
- Case 2: recompute late expected loss assuming a 20% increase in the slope of the early loss function

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\*The perfect prediction of expected on-time and late arrival totals is not coincidental; rather, it results from the model specification.

Case 3: recompute early expected loss assuming a  
20% increase in the slope of the late  
loss function

Case 4: recompute late expected loss assuming a  
20% increase in the slope of the late  
loss function

For each case the new variable replaced the affected  
variable in the model specification, and the new coefficient  
was estimated. The results were:\*

<u>New Variable</u>	<u>New Coefficient</u>	<u>Replaced Coefficient</u>	<u>% Change in Coefficient</u>
Case 1	-2.423	-3.168	-23.5
Case 2	-25.713	-25.728	0.0
Case 3	-3.359	-3.168	+6.0
Case 4	-21.449	-25.728	-16.6

Based on these limited results, a few tentative  
conclusions can be drawn. First, it appears that changes in  
the slope of the early loss function have little effect on  
the coefficient for late expected loss; a similar relation  
holds for changes in the slope of the late loss function and  
its effect on early expected loss. Secondly, the percent  
increase in the slope of the loss function is roughly  
equivalent to the percent decrease in the coefficient value

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\*In all cases, neither the value of the log-likelihood nor  
the values of the other model coefficients changed by an  
appreciable amount.

of the directly affected variable, although this may only hold true for some cases. This suggests an elasticity of the estimated expected loss coefficient with respect to slope of the loss function of approximately one.

A further step in the departure time research was to estimate models with and without the reliability-related (arrival time) variables (EARLOSS and LATELOSS) and to compare the results. The estimation result for the model with omitted reliability-related variables appears in Table 7.8 and was compared to the selected model which appears in Table 7.6.

The major difference between the two models is in the values of the constants. There is very little change in the coefficient value of the other explanatory variables. What is particularly interesting is that the coefficient for mean travel time changes by only 5%. These results present a strong argument that the arrival time variables in the departure time model are not highly correlated with variables used in existing models, and that most of the implications of on-time arrival and related uncertainty are omitted effects absorbed into constants in existing models. The implications of this finding are that explanatory variables in existing models may not have overly biased variable coefficients due to the omission of arrival time

Table 7.8 Omitted Variable Model Results

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic Standard Error</u>	<u>Asymptotic T-Statistic</u>
TIME	-0.039	0.031	-1.271
FLEXON	1.072	0.226	4.736
FLEXLATE	3.160	0.756	4.181
ADUM	0.648	0.224	2.900
BDUM	-0.724	0.314	-2.304
BRIDGE	2.774	1.062	2.612
INCOME	2.055	1.032	1.991
AGE	1.090	0.308	3.543
OCCI	-0.467	0.277	-1.690
OCC2	-0.564	0.249	-2.261
ONTIME	3.741	0.757	4.938
EARLY 1	2.647	0.754	3.510
EARLY 2	3.444	0.748	4.605
LATE 1	-0.851	0.533	-1.597
LATE 2	-0.683	0.500	-1.365

log likelihood = -822.719

L(0) = -1056.082

# of observations = 425

# of cases = 5100



variables, but existing models will still provide inconsistent forecasts for any policy changes that alter the existing conditions of arrival time and arrival time uncertainty.\*

A final step in the departure time research was to compare the selected model to a model estimated using Cosslett's specification (see Equation 4.1). The model results using Cosslett's specification were:

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic T-statistic</u>
y(t)	-0.044	-1.454
R(t)	-0.064	-11.126
L(t)	-1.687	-10.272
log likelihood = -978.724		

This estimated model differs from Cosslett's original work in the following ways:

- (1) y(t) was defined as total travel time rather than in-vehicle travel time as defined by Cosslett;
- (2) the standard deviation of travel time for this model was derived using the expressions described in Chapter 5. Cosslett used the following definition:

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\* It is also interesting to note that a  $\chi^2$  test conducted on the hypothesis that the loss variables have coefficients equal to zero could not be rejected at the .05 level.

$$\sigma = .2(y(t) - y(\text{off peak})) \quad (7.2)$$

- (3) this model used a full sample of auto, transit, and carpool users. Cosslett did not consider transit users, and estimated separate departure time models for auto and carpool users;
- (4) this model was estimated on a sample of respondents with official work start times between 7:00 a.m. and 9:30 a.m., while Cosslett considered respondents with official work start times between 6:00 a.m. and 10:00 a.m.; and
- (5) probability of late arrival was computed on the basis that arrival after the official work start time is considered late arrival; Cosslett defined late arrival as arrival after the official work start time plus the number of minutes a respondent felt he/she could arrive late at work.

The estimation results show a surprising similarity in coefficient values for travel time in the Cosslett specification and the selected specification. The coefficient for  $R(t)$  in the Cosslett specification is significant, but because of the way the variable is constructed, it serves the purpose of alternative-specific

constants since every traveler for a particular alternative has the same  $R(t)$ .  $L(t)$ , the probability of lateness, also has a significant coefficient, but it is difficult to make any conclusive statements about this result, since because the model has such few explanatory variables, it is quite likely that several omitted effects exist which are affecting the magnitude and significance of the coefficients in the model. The log likelihood of the Cosslett model suggests that the model is much weaker than the selected departure time model. On both behavioral and statistical grounds, it appears that the selected model is a more attractive model than a departure time model based on Cosslett's specification.

### 7.3 Diagnostic Tests of IIA Violation

Having completed departure time model estimation, the next step in the research would be to estimate a mode choice model which includes departure time model outputs as inputs to the mode choice model. However, before proceeding, it is important to examine the estimated departure time model and determine whether estimating a logit model for the departure time problem using the selected specification has violated the underlying logit assumption of Independence of Irrelevant Alternatives (IIA).

A number of diagnostic tests have been proposed for determining violation of the IIA assumption in logit.\* Two of the more popular tests include: 1) the universal logit method, and 2) tests based on conditional choice.

The universal logit method is based on the notion that a universal logit model exists which is more general than the multinomial logit model in that each alternative  $i$  can be characterized by the attributes for alternative  $i$  and depend on attributes of the other alternatives as well. The test involves specifying a universal logit model which includes attributes of all alternatives in each alternative utility, estimating the model, and testing the significance of the interaction (cross-attribute) effects. The null hypothesis is that the interaction effects are zero. If the hypothesis can be rejected, then the IIA assumption has been violated.

Tests based on conditional choice are based on the premise that if IIA holds, then coefficients estimated from a reduced choice set should not statistically differ from the corresponding coefficients estimated on the full choice set. The test involves estimating several models, eliminating a different alternative from each model.

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\*A discussion of these tests appears in McFadden, Train, and Tye (1976).

Statistical tests are conducted on the hypothesis that the coefficients estimated on the sub-sample are the same as those estimated on the full choice set. If the hypothesis can be rejected, then the IIA assumption presumably does not hold.

Because the estimated departure time has twelve alternatives and since each alternative is defined by a number of independent variables, the number of variables (and coefficients) required to conduct a universal logit test precluded any consideration of that test for this research.

The conditional choice test appeared more promising although running the test over the entire choice set would require twelve separate tests. A modified approach was adopted whereby the departure time alternatives were separated into the following four macro-choices:

- 1) expected arrival extremely early - alternatives 40E, 35E, 30E, 25E, 20E;
- 2) expected arrival slightly early - alternatives 15E, 10E, 5E;
- 3) expected arrival on-time;
- 4) expected late arrival - 5L, 10L, 15L;

Four conditional tests were conducted, with each macro-choice eliminated from one model.

The test statistic is the likelihood ratio statistic:

$$\chi^2 = 2 (\log \text{likelihood sub-model} - \log \text{likelihood sub-model with restricted coefficients from full model}) \quad (7.3)$$

This statistic is asymptotically distributed chi square ( $\chi^2$ ) with degrees of freedom (df) equal to the number of parameter restrictions (i.e., number of coefficients in the sub-model). The test statistic is compared to a critical value (i.e., .05) of  $\chi^2$  with the appropriate degrees of freedom. The hypothesis that the coefficients estimated on the sub-sample are the same as those estimated on the full choice set cannot be rejected if the test statistic is lower than the critical value.

Results of the diagnostic tests appear in Table 7.9. The results show that, for all tests, the hypothesis cannot be rejected at the .05 level.

Table 7.9 Diagnostic Tests of IIA Violation in the Selected Departure Time Model

Statistic	Expected Arrivals		Expected Arrivals		Expected Arrivals		Expected Arrivals Late Omitted
	Extremely Early Omitted		Slightly Early Omitted		On-Time Omitted		
log likelihood at convergence for subsample choosing alternatives within subset	-444.033		-394.743		-574.197		-722.929
log likelihood with restricted coeffi- cients from full sample, full choice model	-446.198		-395.623		-575.216		-723.180
test statistic value	4.330		1.760		2.038		0.502
df	13		14		13		13
critical (0.05 level) value of $\chi^2$ with appropriate df	22.362		23.685		22.362		22.362

## 7.4 Summary

A logit model of departure time choice was estimated for twelve alternatives representing discrete approximations of successive five minute departure time intervals. A number of variables were considered for inclusion in the model, several model specifications were estimated, and the "best" model was selected based on criteria consisting of intuitive reasoning, estimated coefficients having the expected sign, statistical significance of the coefficients (in terms of t-statistics), the overall statistical fit of the model (in terms of log-likelihood) and validation tests conducted on sub-samples of the sample used for model estimation.

The selected departure time model included the following explanatory variables:

- total travel time
- arrival time expected loss (early and late)
- actual chosen mode
- use of the Bay Bridge to reach the work location
- income
- age
- occupational characteristics
- work arrival time flexibility



Each alternative utility was defined by some function of these explanatory variables. The selected model also compared quite favorably with a model estimated using the specification used by Cosslett in his research.

A number of conclusions were drawn based on model results and related analyses. It was found that reliability-related arrival time variables have significant coefficients and appear to lend additional explanatory power to the departure time model. Since the arrival time variables consist of loss derived from arriving to work at a particular time and the uncertainty of arrival about that time, the estimation results imply that a primary departure time consideration is the implications of when the traveler will arrive at work and the uncertainty associated with it, and the perceived penalties for arriving about that particular time. It is also important to note that the effect of loss derived from arrival time considerations consists primarily of loss derived from arriving at a particular time, and much less so from the uncertainty of arrival about that time. This result is somewhat surprising, but may perhaps be due to the quality of the data used in estimation (leading to lack of variation in the reliability data) or methodological problems rather than an indication that reliability is truly of marginal importance.

Another important finding was that reliability-related arrival time variables in the departure time model are not highly correlated with explanatory variables used in existing models, and that most of the implications of on-time arrival and related uncertainty are omitted effects absorbed into constants in existing models. This implies that the independent variables in existing models may not have very biased coefficients due to the omission of reliability-related arrival time variables, but existing models will still yield biased forecasts for any policy changes that alter the existing conditions of arrival time and arrival time uncertainty.

Diagnostic tests based on conditional choice were conducted on the selected departure time model to determine whether it violated the underlying logit assumption of IIA. Four macro-alternatives were defined (extremely early expected arrival, slightly early expected arrival, on-time expected arrival, and late expected arrival); four tests were conducted, each based on omitting one of the macro-alternatives from the model. The results indicated that use of the logit form to estimate the selected departure time model cannot be rejected.

## 8. MODE CHOICE MODEL ESTIMATION

This chapter describes the mode choice model estimation process. The chapter format is similar to Chapter 7, with discussion focusing on model specification, estimation results and implications, and diagnostic tests of IIA violation.

### 8.1 Model Specification and Estimation Results

The approach used to select the best mode choice model was similar to that used for departure time model estimation. The initial phase consisted of selecting variables which a priori made intuitive sense as explanatory variables of mode choice. These variables were initially defined generically in the model, and alternative-specific specifications were examined in the second phase of model estimation. With the addition of each new variable into the model specification, the estimation results were examined for statistical significance, proper signs, and for the possibility of different independent variables explaining similar effects in the model.

Single occupant auto, transit, and carpool were the three alternatives defined for the mode choice model. For cases where no autos were owned by the household, the single

occupant auto alternative was not considered as a feasible alternative.\* The variables considered for inclusion in the model consisted of  $\hat{D}^*$  (the departure time model estimate for  $D^*$ ), home location, travel cost, employment density of the work location, arrival time flexibility, age, sex, peak transit headway, number of transit transfers, automobile ownership, the number of drivers and workers in the household, occupation, and location of where the respondent lives and works. As explained in Chapter 3, some of the attributes which appeared in the departure time model were also considered for inclusion in the mode choice model. Variable definitions, the justification for considering these variables, and expected results are presented in the following discussion.

$\hat{D}_m^*$  ( $\hat{D}_m^*$  denotes the estimate of  $D_m^*$ ) is the term computed from the estimated departure time model which represents the utility of the optimal departure time for each mode. This enters into the mode choice model because of the belief that when a commuter makes a mode choice decision, he/she takes account of the optimal departure time circumstances for each mode. Recall that  $\hat{D}_m^*$  is the log of the sum of the exponentiated utilities for the departure time alternatives. Thus,  $\hat{D}_m^*$  includes explanatory effects

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\*There were 40 observations in the sample for which there were no autos owned by the household.

of arrival time flexibility, occupational characteristics, income, age, Bay Bridge travel, travel time and expected loss as they relate to departure time choice. A positive coefficient sign was expected, since a higher optimal departure time utility for a given mode should lead to a higher likelihood that the mode will be chosen.

The UTDFP data set included responses to two home location questions which might help explain mode choice decisions. The first question asked respondents if they chose their house on the basis that it was close to transit. Presumably if proximity to transit was a criteria for choosing a home location, there is a good possibility that the commuter would be predisposed to be a transit user. For this reason, two Boolean variables were defined (1 if choosing a house close to transit was somewhat important, and 0 otherwise; 1 if choosing a house close to transit was very important, and 0 otherwise) for the transit alternative only. Positive coefficient signs were expected for each variable.

The second home location characteristic was whether respondents lived in or near the CBD. It was felt that respondents who lived in the CBD would be more likely to commute by transit. Two Boolean variables were defined (1 if living near the CBD, and 0 otherwise; 1 if living in the

CBD, 0 otherwise). Because these variables were considered only for the transit alternative, a positive sign was expected.

Travel cost entered into all of the alternatives. The variable was defined as the travel cost divided by the post-tax hourly wage rate in order to represent the income effect on travel cost considerations (i.e., a \$5 daily parking charge has different mode choice implications if the worker earns an annual salary of \$10,000 compared to a worker earning \$50,000 per year). Since increasing travel costs for any mode discourages its use, a negative coefficient sign was expected.

Employment density at the work location was used as a proxy to represent the potential for carpooling. If a person works in an area which has a large employment density, there is a greater probability of finding ridesharing matches (i.e., more workers in an employment location implies more people who live in your residential zone). The employment density variable appeared only in the carpool alternative, and a positive sign was expected.

An arrival time flexibility variable was included because it was felt that the uncertainties of transit and carpool travel might discourage people from considering

those modes unless their schedule was flexible enough to handle potentially regular service disruptions. A Boolean variable was defined (1 if can be late to work; 0 otherwise), and initially the variable was entered into the utilities for both transit and carpool (with the same coefficient), with a positive coefficient value expected.

Age was also considered as a variable in the mode choice model specification. It was felt that older, more established workers might be more inclined to drive rather than take transit or carpool. The age variable was only included in the single occupant auto alternative, with a positive estimated coefficient expected.

A sex variable (1 = male, 0 = female) was entered into the model on the basis that males might be more likely to commute in single occupant autos than females. This variable was entered only into the single occupant auto alternative, and a positive sign was expected.

Peak transit headway was considered in the mode choice model; the justification for including this variable is based on an earlier discussion appearing in Section 3.2. Recall that at the mode choice level, it was hypothesized that travelers might be impacted by uncertainties independent of arrival time considerations, as well as

exposure to infrequent but excessively long delays. It is well known that transit travel time variance can be related to the variance of the headway distribution, and that headway variance can be related to mean headway. Therefore, it was felt that peak transit headway might be a good proxy for uncertainties independent of arrival time considerations. It was also felt that the frequency of excessively long delays might also be related to the peak transit headway. Thus, peak transit headway was included in the transit alternative, to represent those previously omitted transit reliability problems which are not present in automobile-related modes. It was also recognized that the peak transit headway variable might also serve as a proxy for other omitted transit effects (i.e., discontinuities of transit service) related to transit headway. Because larger headways imply greater uncertainty, frequency of extreme delay, and discontinuity of service, a negative coefficient sign was expected.

The number of transit transfers was also included in the transit utility to capture inconveniences associated with transit travel. A negative coefficient sign was expected, since additional transfers should discourage transit use.



Various combinations of automobile ownership and the number of licensed drivers and workers in the household were considered in order to represent auto availability for the work trip. The number of autos owned by the household divided by the number of household licensed drivers was defined as a variable with the intent of capturing the availability of an automobile for work travel considering the needs of all household commuters and other household drivers who might need a car during the day for non-work purposes. A second variable, the number of household autos divided by the number of workers, was also defined and focused more directly on the competition for an automobile solely for work purposes. Each variable was entered into the utilities for the single occupant auto and carpool alternatives, with the same coefficient. Positive coefficient signs were expected for both variables, since higher relative levels of automobile ownership would encourage some form of automobile commuting.

A Boolean variable for occupation (1 if professional/technical or management/administration; 0 otherwise) was included in the single occupant auto alternative based on the belief that salaried employees would have a higher incidence of automobile use than the sample as a whole. A positive coefficient sign was expected.

The respondent's residence and employment locations were again related to Bay Bridge travel, with the feeling that transit users would have better access over the Bay Bridge than other Bay Bridge commuters. At the mode choice level, the Bay Bridge variable was defined as a Boolean variable equal to 1 if crossing the Bay Bridge to work and 0 otherwise. This variable was included in the utility for transit only, and a positive sign was expected.

Finally, modal constants were specified in the model to represent omitted effects. The ensuing paragraphs provide discussions of combined first and second phase attempts to model each of the described variables. As in the case of departure time model estimation, a number of specifications were defined and tested to arrive at the conclusions presented.

$\hat{D}^*$ , cost/wage, sex, peak transit headway and Bay Bridge coefficient estimates had the proper sign and were statistically significant based on models estimated during the first phase. The variables were also not redefined or altered in any way based on second phase tests of alternative specific variable coefficients.

Of the two variables defined to measure if respondents chose their house on the basis that it was close to transit,

only the Boolean variable equal to one if this criteria was very important and 0 otherwise entered significantly into the mode choice model during model estimation in the first phase. This variable was not respecified based on second phase specification analysis.

Of the two CBD residential location variables, only the Boolean variable defined as 1 if living in the CBD and 0 otherwise entered significantly into the model. During the second phase, a separate CBD residential location variable was defined for carpool, and yielded positive and significant estimated coefficients. The magnitude of transit CBD residential location coefficient was larger than the carpool coefficient by a factor of 2.5. Because of the large difference in magnitude of the coefficients but the statistical significance of each, both variables were retained in the model.

The Phase 1 coefficient estimate for employment density at the work location also had the proper sign and was statistically significant. During Phase 2, a separate employment density variable was defined for the transit alternative. The coefficient estimates for both the carpool and transit employment density variables were statistically significant and of similar magnitude. A combined variable was defined and placed in the model. The significant effect

of employment density on transit choice is likely due to measurement error caused by the use of network-computed zonal transit access and egress times. Areas of high employment are likely to have better than average transit access, and this variable is perhaps reflecting this previously omitted effect.

The arrival flexibility variable was initially entered into the utilities for both transit and carpool, but the resulting coefficient estimate was small in value and statistically insignificant. The variable was subsequently dropped from the carpool alternative and retained in the transit alternative, which resulted in a statistically significant coefficient with the proper sign. The arrival flexibility variable was not altered based on second phase analysis.

Coefficient estimates of the age variable were low in value and statistically insignificant during first phase estimation, and the variable was subsequently dropped from further consideration.

There was some concern that the transfers variable would measure similar effects as the transit headway variable. This was borne out by model results. Although the estimated coefficient for number of transit transfers

had the expected sign, the statistical significance of the coefficient changed noticeably as other variables (particularly  $\hat{D}^*$  and transit headway) were considered in the model. For this reason, the transfers variable was ultimately excluded from the model, while  $\hat{D}^*$  and transit headway were retained.

Initially, it was assumed that since most workers have driver's licenses, autos/licensed drivers and autos/workers would essentially measure the same effect, implying that only one of the two variables should eventually remain in the model specification. However, estimation results for specifications including both variables showed them to be significant despite their correlation, and a decision was made to keep both variables in the specification. For one set of specifications, however, separate coefficients were estimated for each variable for each mode, to determine whether there was a dramatic difference in the impact of auto availability on the demand for single occupant auto and carpool. The coefficient estimates for separate auto and carpool variables all had the proper sign and were significant. The coefficient estimate for autos/drivers in the single occupant auto alternative was three times greater than the coefficient for autos/drivers in the carpool alternative; estimated coefficients for the auto/workers

variables differed only slightly. Based on this result, all four variables were included in the final model.

Coefficient estimates for the occupation variable always had the wrong expected signs and were never statistically significant. It appears that perhaps the occupation variable was defined to represent a similar effect as other variables in the model, particularly the auto ownership variables and perhaps the sex variable to a lesser extent. The occupation variable was subsequently eliminated from consideration.

Tables 8.1, 8.2, and 8.3 present the selected mode choice model specification and estimation results. The results are discussed in more detail in the following section.

## 8.2 Implications of Model Results

Mode choice model estimation results appear in Table 8.3. All the estimated coefficients have the expected signs, and the estimated coefficients are all statistically significant. Statistical tests were conducted to see if the selected mode choice model differed significantly from a uniform probability mode choice model or from a mode choice

Table 8.1 Mode Choice Model Specification: Variable Definition

MODE CHOICE ALTERNATIVES: Auto, Transit, Carpool

INDEPENDENT VARIABLES:

ACON = 1 if auto drive alone  
0 otherwise

BCON = 1 if transit  
0 otherwise

COST/WAGE = total cost/post-tax wage rate

$\hat{D}^*$  = log of the denominator of the estimated departure  
time model

SEX = 1 if male  
0 if female

FLEXARR = 1 if can be late to work  
0 otherwise

DENSITY = employment density of work location

CLOTRANS = 1 if choosing a house close to transport was  
very important  
0 otherwise

AUTDRA = autos/licensed drivers (drive alone)

AUTDRC = autos/licensed drivers (carpool)

AUTWKA = autos/workers (drive alone)

AUTWKC = autos/workers (carpool)

BAY = 1 if crossing Bay Bridge to work  
0 otherwise

HOMELOC2 = 1 if home location in CBD (transit)  
0 otherwise

HOMELOC3 = 1 if home location in CBD (carpool)  
0 otherwise

HEADWAY = peak transit headway

Table 8.2 Mode Choice Model Specification: Alternative Definition

<u>VARIABLE</u>	<u>AUTO</u>	<u>TRANSIT</u>	<u>CARPOOL</u>
ACON	x		
BCON		x	
COST/WAGE	x	x	x
$\hat{D}^*$	x	x	x
SEX	x		
FLEXARR		x	
DENSITY		x	x
CLOTRANS		x	
AUTDRA	x		
AUTDRC			x
AUTWKA	x		
AUTWKC			x
BAY		x	
HOMELOC2		x	
HOMELOC3			x
HEADWAY		x	

Note: an 'x' denotes that the attribute listed in the left-hand column of the table is entered into the utility for the alternative listed at the top of the table.



Table 8.3 Mode Choice Model Estimation Results

<u>Variable</u>	<u>Coefficient Estimate</u>	<u>Asymptotic Standard Error</u>	<u>Asymptotic T-Statistic</u>
ACON	-0.804	0.659	-1.220
BCON	2.875	0.656	4.378
COST/WAGE	-0.044	0.020	-2.230
$\hat{D}^*$	0.572	0.292	1.962
SEX	0.513	0.261	1.967
FLEXARR	0.480	0.332	1.448
DENSITY	0.003	0.001	3.071
CLOTRANS	0.874	0.432	2.021
AUTDRA	3.248	0.812	4.000
AUTDRC	1.267	0.680	1.863
AUTWKA	1.432	0.530	2.704
AUTWKC	1.375	0.523	2.629
BAY	1.014	0.532	1.905
HOMELOC2	0.981	0.407	2.411
HOMELOC3	0.386	0.263	1.468
HEADWAY	-0.104	0.037	-2.851

---log likelihood = -299.429

L(constants) = -400.8

L(0) = -450.61

# of observations = 425

# of cases = 1235

model consisting of only the constants in the specification. For both the uniform probability model and the model consisting of only the constants, the hypothesis that the reduced model is the same as the selected mode choice model is easily rejected at the .05 level.

The "value of time" is often derived from model results and used as a test of whether the model estimates are plausible. Value of time is computed by examining the coefficients for the mean travel time and travel cost variables in the model specification. However, for the model structure adopted for this research, the mean travel time variable appears in the departure time model while the travel cost variable is divided by the wage rate and appears in the mode choice model. Some simplifying assumptions are required to compute value of time.

The observable utility for mode choice can be written as:

$$V_m = \dots - .044 \text{ TCPTWR}_m + \dots .597 \hat{D}_m^* \quad (8.1)$$

Since  $\hat{D}_m^* = \ln \sum e^{\frac{V_d}{V_m} | m}$ , if we assume that all departure time utilities have the same attributes, then:

$$\begin{aligned} \hat{D}_m^* &= \ln 12 e^{\frac{\bar{V}_d}{V_m} | m} = \ln 12 + \frac{\bar{V}_d}{V_m} | m \\ &= \ln 12 + (-.041 \text{ TIME}_m + \dots) \quad (8.2) \end{aligned}$$

Thus:

$$V_m = \dots - .044 \text{ TCPTWR}_m + .597 (\ln 12 - .041 \text{ TIME}_m \dots) \quad (8.3)$$

Now that all variables of interest are in the same expression, the value of time can be derived as:

$$\frac{dV_m/dt}{dV_m/dc} = \frac{.597(-.041)}{-.044} y \quad (8.4)$$

where  $y$  is the post-tax wage rate expressed in terms of cents per minute. To convert  $y$  to dollars per hour, we multiply by .6, which results in:

$$\text{Value of Time} = \frac{.597 (-.041)(.6)y}{-.044} = .334y \quad (8.5)$$

where  $y$  is the wage rate in terms of dollars per hour. This result compares quite favorably to the accepted ball park commuter value of time of 35-40% of the hourly wage rate, and helps support the validity of the estimated models.

Three rather interesting research results emerge from examining the mode choice model. First, the mode choice model provides insight into the interdependence of commuters' departure time and mode choice decisions. For a nested logit model of departure time and mode choice, the coefficient for the inclusive term ( $D^*$ ) provides information on the random component in the mode choice specification,  $\epsilon_m$

(Ben-Akiva and Lerman, 1979). If the coefficient for  $D^*$  is equal to one,  $\text{Var}(\epsilon_m) = 0$ , and the only random component present in the model is  $\epsilon_{dm}$ , the joint random component of the conditional departure time decision. If this were the case, a joint departure time-mode choice structure would be appropriate.

The estimated coefficient is equal to .572, with a standard error of .292. Using a t-test, the result shows that one can be 85% confident that the estimated coefficient differs from one. However, the true standard error of the coefficient for  $D^*$  is likely to be higher than .292, since  $\hat{D}^*$  itself is an estimate subject to error. Nevertheless, it would still seem likely that  $\text{Var}(\epsilon_m) \neq 0$ . This result suggests that mode and departure time decisions should be structured as a nested choice rather than as a joint choice.

The second result is inferred from the significance of the peak transit headway variable. Recall that this variable is a proxy for transit unreliability independent of arrival time considerations and the frequency of excessive delays (as well as a proxy for other omitted transit effects). The significance of the headway coefficient suggests that these modal reliability attributes may have a separate and significant effect on the mode choice decision.

Both of the previous mode choice findings are subject to some question, however, when the selected model is compared to a model estimated on the same specification, but with the peak transit headway variable omitted. The comparative estimation results are:

	Selected Model <u>Specification</u>	Headway Variable <u>Omitted</u>
$\hat{D}^*$ (coefficient)	0.572	1.096
$\hat{D}^*$ (t-statistic)	1.96	4.30
log-likelihood	-299.429	-304.098

In addition to the significant change in the estimated coefficient for  $\hat{D}^*$ , the estimated coefficients for BAY, AUTDRA, and AUTDRC also changed noticeably.

Since the magnitude and significance of the coefficient estimate for  $\hat{D}^*$  changes so dramatically when the transit headway variable is omitted, one could make the argument that peak transit headway is representing a similar effect as the level of service attributes represented in the inclusive term from the departure time model. If this were the case, then one might conclude that the peak transit headway is not a proxy variable for previously omitted effects, and that the coefficient for  $\hat{D}^*$  implies that modeling departure time and mode choice as a joint decision might be appropriate.

However, the log likelihood for the selected model specification is considerably lower than for the reduced model (the models differ significantly at the .05 level), which suggests that the selected model does represent a better overall statistical fit. Furthermore, the derived value of time based on the reduced model would be questionably high (61% of wage rate). On this basis, it is appropriate to retain the selected model and interpretation of the results, but one should be mindful of the sensitivity of the model specification to the model results and related implications.

The third result is derived from examination of the estimated coefficient for variable FLEXARR in the mode choice model. Recall that this variable represents the individual's perceived work arrival time flexibility. The statistical significance of this variable in the mode choice model suggests that arrival time considerations impact mode choice decisions as well as departure time decisions.

### 8.3 Diagnostic Tests of IIA Violation

Three conditional choice tests were conducted on the mode choice model, with one alternative mode eliminated from each test. Recall that the null hypothesis is that the

coefficients estimated on the sub-sample are the same as those estimated on the full choice set. If the hypothesis can be rejected, then the IIA assumption has been violated. The test statistic is the likelihood ratio statistic described in Equation 7.1, distributed  $\chi^2$  with degrees of freedom equal to the number of coefficients in the sub-model. The test statistic is compared to the critical value of  $\chi^2$  and the hypothesis is rejected if the test statistic is greater than the critical value.

Results of the mode choice model diagnostic tests are summarized in Table 8.4. The results show that, for all tests, the hypothesis cannot be rejected at the .05 level.

#### 8.4 Summary

A multinomial logit model of mode choice was estimated for single occupant auto, transit, and carpool alternatives. As in the case of the departure time model, selection of the "best" mode choice model specification was based on intuitive reasoning, the coefficients having the expected sign, statistical significance of the coefficients (in terms of t-statistics), and the overall statistical fit of the model (in terms of log-likelihood).

Table 8.4 Diagnostic Tests of IIA Violation in Mode Choice Model

<u>Statistic</u>	<u>All Modes Except Auto</u>	<u>All Modes Except Transit</u>	<u>All Modes Except Carpool</u>
log likelihood at convergence for subsample choosing an alternative within subset	-86.068	-179.943	-78.576
log likelihood with restricted coefficients from full sample, full choice model	-87.826	-181.336	-80.614
test statistic value	3.516	2.786	4.076
df	10	8	12
critical (0.05 level) value of $\chi^2$ with appropriate df	18.307	15.507	21.026



The selected mode choice model included the following explanatory variables:

- total cost/post-tax wage rate
- log of the sum of the exponentiated utilities from the departure time model
- sex
- work arrival time flexibility
- employment density of the work location
- home location characteristics
- autos/workers
- autos/drivers
- use of the Bay Bridge to reach the work location
- peak transit headway

Each alternative utility was defined by some combination of these explanatory variables. Statistical tests of whether the model differed from a uniform probability model or from a model of just constants, coupled with a study of the derived value of time, helped validate the reasonableness of the estimated model. Results of diagnostic tests of IIA violation also indicated that use of the logit form to estimate the selected mode choice model cannot be rejected.

Three rather interesting research results emerged from an examination of the estimated mode choice model. First, the magnitude and statistical confidence of the coefficient for the inclusive departure time utility term implies that departure time and mode choice decisions appear to be interrelated in a way that suggests structuring departure time-mode choice decisions as a nested choice rather than as a joint choice. Secondly, the significance of the estimated

peak transit headway coefficient suggests that transit unreliability independent of arrival time considerations and the frequency of excessive transit delays (along with other omitted transit effects related to mean headway) may have a significant impact on the mode choice decision. Finally, it appears that arrival time considerations impact mode choice decisions as well as departure time decisions.

## 9. APPLICATION OF MODEL FOR POLICY ANALYSIS

This chapter presents a hypothetical example of how a planner might consider using the developed models for policy analysis. The example includes a description of the problem scenario, a discussion of how the problem is structured within the model framework, and the resulting model forecasts.

### 9.1 Scenario

Suppose a metropolitan transit authority were facing a certain cutback in state subsidies for the coming fiscal year. In order to balance the budget for the coming year, the transit authority must either generate additional revenues while providing existing service, or cut back on existing services to reduce the net cost of operations. Suppose the present travel pattern in the area is as described under base case conditions in Tables 9.1 and 9.2. Suppose also that the authority were considering the following two strategies:

- 1) double transit fares systemwide.
- 2) increase headways systemwide by 100%.

Ridership and departure time forecasts could be made for these strategies using the estimated departure time and mode choice models. This process is described in the following sections.

## 9.2 Structuring the Problem

This section discusses how the problem is structured to facilitate forecasting using the departure time and mode choice models. At the departure time level, only transit user departure time utilities are affected; only the transit utility is affected at the mode choice level.

Case 1 is the simplest of the two strategies to represent. Because transit cost only appears at the mode choice level, the predicted departure times conditioned on mode will not change as a result of this proposed service change. At the mode choice level, only the utility for transit will be affected, with the change represented as an increase in the travel cost/post-tax wage rate variable. New mode probabilities are then computed for each individual and individual probabilities are aggregated over the sample to form predicted ridership.

In Case 2 both departure time and mode choice are affected. At the departure time level, new headways are defined for each transit user for each departure time, which result in increases in wait time and wait time standard deviation for each departure time. This leads to increases in the mean and standard deviation of total travel time, which also impacts early and late expected loss. New utilities are then computed, which are used in departure time prediction.

At the mode choice level, new transit departure time utilities are computed for the entire sample (not just transit users) to form a new  $\hat{D}^*$  for transit. A change is also made to the peak transit headway variable in the transit utility. The new transit utility is coupled with existing auto and carpool utilities to predict individual mode choices and forecast sample ridership.

### 9.3 Analysis Results

Table 9.1 presents the departure time model predictions. Case 1 does not introduce any changes to departure time utilities, and thus departure times would not be expected to change from base case conditions. For Case 2, transit departure times shift noticeably away from

Table 9.1 Departure Time Model Prediction

Base Case (Percent of Sample)

<u>Alternative</u>	<u>Auto</u>	<u>Transit</u>	<u>Carpool</u>	<u>Row Total</u>
40E	1.9	0.6	1.3	3.9
35E	2.2	0.7	1.4	4.3
30E	2.4	0.8	1.5	4.7
25E	2.6	0.8	1.6	5.0
20E	2.8	0.8	1.7	5.3
15E	5.6	3.9	3.3	12.7
10E	5.6	3.8	3.2	12.6
5E	5.1	3.0	2.8	10.9
On Time	21.9	6.3	6.9	35.1
5L	0.5	0.4	0.3	1.2
10L	0.6	0.4	0.4	1.4
15L	1.2	0.8	0.8	2.8
Column Total	52.5	22.3	25.2	100.0

Case 2 (Percent of Sample)

40E	1.9	1.0	1.3	4.3
35E	2.2	1.1	1.4	4.7
30E	2.4	1.2	1.5	5.2
25E	2.6	1.3	1.6	5.6
20E	2.8	1.4	1.7	5.9
15E	5.6	3.1	3.3	11.9
10E	5.6	3.0	3.2	11.8
5E	5.1	2.0	2.8	9.9
On Time	21.9	6.3	6.9	35.0
5L	0.5	0.5	0.3	1.3
10L	0.6	0.5	0.4	1.5
15L	1.2	0.9	0.8	3.0
Column Total	52.5	22.3	25.2	100.0

expected arrival times slightly earlier than the official work start time, and there is a noticeable increase in expected very early arrival at work and expected late work arrival for transit users. This makes intuitive sense since increases in mean travel time and travel time uncertainties would result in travelers who have to arrive on-time planning to arrive even earlier to accommodate increased wait times and uncertainties, and with travelers who do not have to arrive on-time maintaining their present departure time but likely having later arrival times due to longer travel times. Since each individual's official work start time is known, these results can also be used to predict changes in peak load requirements of the transit system due to changes in service.

Mode choice model predictions appear in Table 9.2. As expected, transit ridership decreases for both cases. Doubling the fare has a predicted effect of decreasing transit ridership by 11.4%; cutting service frequency in half is forecasted to reduce transit ridership by 35.8%. In each case, there are predicted increases in single occupant auto and carpool use.

Table 9.2 Mode Choice Model Prediction

Percent of Sample			
<u>Mode Alternative</u>	<u>Base Case</u>	<u>Case 1</u>	<u>Case 2</u>
Auto	52.9	54.0	56.5
Transit	22.1	19.6	14.2
Carpool	25.0	26.4	29.3
	<hr/>	<hr/>	<hr/>
TOTAL	100.0	100.0	100.0



#### 9.4 Summary

The applied example described in this chapter was intended to demonstrate how the mode choice and departure time models could be used for policy analysis. The example was purely hypothetical. The reader should be mindful that the use of any travel demand forecasting model is only one of many inputs into the policy decision-making process. Furthermore, the state-of-the-art of travel demand modeling is such that model results should typically be interpreted as indications of potential impacts rather than as conclusive forecasts.

## 10. CONCLUDING REMARKS

### 10.1 Summary and Implications of Doctoral Research

This dissertation has focused on understanding the impact of service reliability on work travel behavior. Since work trip frequency and destination are fixed, the research problem was narrowed to a study of the impact of service reliability on commuter decisions of mode choice and trip departure time. The problem was further restricted by studying only home-to-work travel, in part due to the lack of available data on the afternoon (evening peak) return trip. Working with the hypothesis that service reliability is an important attribute in explaining departure time and mode choice, measures of service reliability were proposed which capture the impact of this attribute on work travel decisions. The theory was subsequently tested empirically through the estimation of departure time and mode choice models.

The research effort began with a review of studies conducted to assess travelers' attitudes about service reliability. Study findings indicated that service reliability, particularly how it relates to arrival at the intended time, is one of the most important attributes to work travelers, regardless of the mode being considered.

However, since little is known about the relationship between attitudes and behavior, the survey results primarily served as an indication of the need to establish a consistent set of reliability measures and analyze the impact of service reliability on work travel behavior.

The approach used to address this problem was to examine ways to improve existing models through the definition of objective reliability measures which could be related to behavioral responses by travelers. Consideration of travel time attributes in current models has been typically restricted to modeling mean travel time, and travel time uncertainty and arrival time implications have been largely ignored. If reliability is an important influence of travel behavior, then existing models are not policy sensitive to service reliability issues; furthermore, if reliability variables are correlated with independent variables in the existing models, current models may be providing inconsistent forecasts for policies directed solely at service changes other than reliability changes, since the coefficients for existing variables are likely to be artificially higher or lower than their true values, depending on their correlation with omitted reliability attributes.

This prompted the development of a theory of how service reliability impacts work travel decisions. It was proposed that the effect of service reliability on the departure time decision stems from the implications of service reliability (and resulting uncertainty in travel time) on the predictability of traveler arrival time at work. Specifically, it was proposed that reliability of service can be represented in the distribution of individual arrival times at work, and that travelers perceive varying degrees of loss associated with different arrival times at work. The loss function could be integrated over the associated individual arrival time distribution to form a traveler's expected loss, which represents traveler perceived losses due to different arrival times at work as well as sensitivities due to uncertainty of arrival time at work.

It was also proposed that travelers might be sensitive to service reliability independent of its implications on arrival time. This situation might typically arise at the mode choice level where, for example, inherent variations in transit service or exposure to infrequent but excessive long service delays might cause traveler dissatisfaction irrespective of whether a traveler is under pressure to arrive at work at a particular time.

The development of a methodology to test this theory included a review of other travel behavior models which have considered service reliability, as well as more general literature relating to the relationship between service reliability and both transit operations and travel behavior. Earlier attempts to model objective service reliability measures in mode choice models had run into difficulty due to problems encountered in collecting accurate level of service data. The use of scaled reliability measures (i.e., 1 = service is very reliable, 2 = somewhat reliable, etc.) in mode choice models proved statistically significant and improved the predictive power of the models. However, the use of these variables threatens the validity of transferring the model for forecasting in other areas, and also makes it difficult to evaluate reliability improvement policies and measure tradeoffs of reliability investment versus other transit improvement strategies.

Departure time research has examined more closely the tradeoff between travel times and work arrival times. Empirical work has been restricted primarily to auto travelers, but important advances have been made in differentiating between traveler sensitivities to early and late arrival times, and recognizing the impact of work flexibility and occupation on departure time decisions.

Despite these accomplishments, several obstacles remained. Although the importance of arrival time at work as an explanatory indicator of departure time choice had been demonstrated, the effect of travel time uncertainty had not been properly considered. In addition, the interdependency of mode choice and departure time decisions was virtually ignored. Finally because past research had been restricted to studying auto-related travel, an indepth analysis of the effect of service reliability on transit use was lacking from the state-of-the-art.

Based on this review of previous research, and through the design and implementation of additional analyses, the final analysis methodology was defined. A nested modeling structure would be used, with departure time choice conditional on mode choice. Departure time would be represented as a continuous choice (approximated using discrete intervals), using a logit model formulation. Multinomial logit would be used to estimate mode choice.

The range of departure time choice was set from an expected arrival time of 42.5 minutes earlier than the official work start time to an expected arrival 17.5 minutes later than the official work start time, to conform to available departure time data. Mode choice alternatives were single occupant auto, transit, and carpool.

The Urban Travel Demand Forecasting Project (UTDFP) data set collected in the San Francisco Bay Area was selected for use in the estimation of departure time and mode choice models. The UTDFP sample was reduced by eliminating observations which did not pertain to the scope of the research (i.e., observations where the respondent's official work hours begin outside the morning peak) as well as observations for which there was incomplete data. For the remaining sample of 425 observations, travel time moments and expected losses for each mode at each departure time were computed in order to complete the information required for model estimation.

A logit model of departure time choice was estimated using twelve discrete alternatives representing successive five minute departure time intervals corresponding to the previously defined range of departure time choice. The "best" model was selected based on criteria consisting of intuitive reasoning, estimated coefficients having the expected sign, magnitude and statistical significance of the coefficients (in terms of t-statistics), the overall statistical fit of the model (in terms of log-likelihood), and validation forecasts made on sub-samples of UTDFP respondents. The selected departure time model included attributes of total travel time, arrival time expected loss, chosen mode, use of the Bay Bridge to reach the work

location, income, age, occupational characteristics, and work arrival time flexibility. The utility of each alternative was defined by some function of these explanatory variables.

A number of conclusions were drawn based on the departure time model results and related analyses. It was found that reliability-related arrival time variables have significant coefficients and appear to lend additional explanatory power to the departure time model. Since the arrival time variables consist of loss derived from arriving to work at a particular time and the uncertainty of arrival about that time, the estimation results imply that a primary departure time consideration is the implications of when the traveler will arrive at work and the uncertainty associated with it, and the perceived penalties for arriving about that particular time. It is also apparent that this effect consists primarily of traveler sensitivity to arriving at a particular time, and much less so from the uncertainty of arrival about that time. This result is somewhat surprising, but may perhaps be due to the quality of the UTDFP data and reliance on previous studies which used inadequate data, either of which might lead to the lack of variation in the reliability data, or other methodological problems rather than an indication that reliability is truly of marginal importance.



Another important finding was that reliability-related arrival time variables in the departure time model are not highly correlated with explanatory variables used in existing models, and that most of the implications of on-time arrival and related uncertainty are omitted effects absorbed into constants in existing models. This implies that the independent variables in existing models may not have biased coefficients due to the omission of reliability-related arrival time variables, but existing models will still provide inconsistent forecasts for any policy changes that alter the existing correlation between arrival time conditions and the independent variables in existing models.

Diagnostic tests based on conditional choice were conducted on the selected departure time model to determine whether it violated the underlying logit assumption of independence of irrelevant alternatives (IIA). Four macro-alternatives were defined (extremely early expected arrival, slightly early expected arrival, on-time expected arrival, and late expected arrival); four tests were conducted, each based on omitting all of the micro-alternatives (i.e., the five minute intervals) from one of the macro-alternatives from the original model. The results indicated that use of the logit form to estimate the selected departure time model cannot be rejected.

A multinomial logit model of mode choice was estimated for single occupant auto, transit, and carpool alternatives. The selected mode choice model included variables for total cost divided by post-tax wage rate, an inclusive term from the departure time model representing the expected utility for the optimal departure time for each mode, sex, work arrival time flexibility, employment density of the work location, home location characteristics, autos/workers, autos/drivers, use of the Bay Bridge to reach the work destination, and peak transit headway. Each alternative utility was defined by some combination of these explanatory variables. Results of diagnostic tests of IIA violation indicated that use of the logit form to estimate the mode choice model can not be rejected.

Three rather interesting research results emerged from an examination of the estimated mode choice model. First, the mode choice model provides insight into the interdependence of commuters' departure time and mode choice decisions. The magnitude and statistical confidence of the coefficient for the estimated inclusive departure time utility term implies that departure time and mode choices appear to be interrelated in a way that suggests structuring departure time-mode decisions as a nested choice rather than as a joint choice. However, the additional uncertainty introduced because the inclusive term itself is an estimate

subject to error, could impact the conclusiveness of this finding.

A second mode choice model finding is suggested by the magnitude and significance of the peak transit headway variable. This variable serves as a proxy for the attribute of transit unreliability independent of arrival time considerations and exposure to infrequent but excessively long service delays as well as other omitted transit effects (i.e., discontinuities of transit service) related to transit headway. The significance of the estimated headway coefficient suggests that these additional reliability considerations may have a significant effect on mode choice decisions. However, the explanatory effect of this variable may be due to other transit omitted effects as well.

The third result is derived from the significance of the arrival time flexibility variable in the mode choice model. This suggests that arrival time considerations impact mode choice decisions as well as departure time decisions.

This effort has made a number of contributions to the state-of-the-art in transportation research. This research has explored the impact of reliability on commuters' mode choice and departure time decisions. The demonstrated

importance of arrival at work and uncertainties associated with it at the departure time level and the significance of the transit reliability proxy at the mode choice level should result in the application of travel demand models which are more behaviorally appealing. Furthermore, this should lead to improved forecasts in general, since the explanatory effect of a previously omitted variable will be included in the model.

The estimated models should also enable planners to consider how reliability improvement strategies impact travel decisions. Until now, since reliability-sensitive variables were not included in travel demand models, there was no way to analyze potential impacts of reliability-related policies. Of particular interest for planners is the capability of developing insight into tradeoffs between policies directed at improved reliability versus investments in improved travel speed, reduced fares, or other service changes.

Another important contribution has been the definition and use of objective measures of service reliability. Past research had demonstrated that the inclusion of scaled reliability variables were statistically significant, but questions were raised concerning the transferability of scaled measures and how they could be used to evaluate

reliability improvement policies. The measures developed in this research are not only behaviorally appealing, but should also alleviate the problems encountered by the use of scaled measures.

In addition, the research examined the interrelationship of commuter mode choice and departure time decisions. Through the development of a sequential departure time and mode choice decision structure and the subsequent estimation of departure time and mode choice models, the interdependencies of these decisions can be represented in the planning process. This allows planners the capability of predicting both mode shift and peaking responses to service changes.

This research has also led to the development of a more fully specified departure time model. The estimated departure time model represents improvements over previous work in that it more explicitly considers arrival time uncertainty, relates departure time choice to mode choice, considers departure time decisions for transit travelers, and includes additional socio-economic factors which can potentially affect departure time choice.

The estimation of a departure time model that includes transit users represents a particularly important

contribution for policy analysis. Because this model can be used to analyze the effects of various policies on transit departure times, the results can be used to study transit system peak load requirements and how transit peaking problems can be eased by implementing policies that redistribute transit use more uniformly during the peak period.

Methodological contributions have also been made as a result of this research. The notion of traveler arrival time loss functions and the use of direct utility assessment to measure these functions have also been integrated into transportation analysis methodology. The loss function is an appealing concept because it can be used to relate travel considerations to activity considerations, a construct which makes intuitive sense since activity interests usually create the demand for travel. The use of activity-related loss functions in transportation analysis can be widespread when one considers that each individual has a different loss function for different trip purposes. Direct utility assessment has been used sparingly in travel demand research, but appears to be a promising approach to understanding how travelers tradeoff a number of travel considerations in determining their preferences and decisions. This methodological approach is effective

because it blends elements of decision theory and choice theory into analyzing travel demand.

In closing this discussion, it is important to note that the results and implications of this research should not be interpreted as conclusive, but rather as indications of directions transportation researchers should pursue more vigorously in future travel demand research. Some of these directions are addressed in the following section.

## 10.2 Directions for Further Research

There are many directions in which the research conducted herein could be improved or extended. Several of these issues are addressed in the following discussion.

One obvious deficiency in this research effort was the size of sample used for loss function estimation. Ideally loss function estimation should be carried out on a sufficiently large sample to allow for estimation for different markets, segmented perhaps by occupational characteristics. (An alternate approach might be to estimate the slopes of the loss function directly in the model estimation process through the use of revealed preferences of choice based on UTDFP data.) Improving loss

function estimation is an important research priority. Consideration should be given to developing a streamlined survey that would allow for collection of a large sample without incurring large amounts of time and resources. Finally, measures of loss should be defined in units which are compatible with other level of service measures so that service tradeoffs can be directly examined. One approach to developing these measures might be to use functional measurement techniques to assess traveler preferences for alternative attribute combinations, where reliability attributes are one of several travel attributes included in the attribute set.

Another major problem encountered in developing the analysis methodology was the lack of objective reliability data from which to define reliability variables. Much of the reliability data for this research was inferred from results reported in the literature. In many cases, the reported results were based on data taken on several observations for one day rather than the same set of observations across several days. Transit data was particularly deficient in this regard. The collection of a sound "reliability" data set and the development of causal relationships between reliability measures and direct observations would be extremely useful and should be treated as a high research priority. Recent transit data collected



as part of an UMTA Service and Methods Demonstration project in Minneapolis might provide some useful insights into these problems, although additional data should be collected for all modes in order to better understand reliability and its impacts on travelers and operators.

There is also a definite need to define simpler measures of reliability. The intent of this research was to demonstrate the need to consider service reliability in analyzing work travel decisions. Thus, an emphasis was put on defining measures which could capture this impact. However, the measures used for this research are not necessarily compatible with the kind of data and measures which might typically be available to operators. Future research endeavors should consider the development and testing of relevant but easily obtained measures.

Future departure time modeling efforts should also consider other explanatory variables not tested in this research. In particular, travel cost, return trip reliability, and official work hours might be appropriate model inputs. The UTDFP data did not have travel cost variations across departure times, so travel cost was not considered in the departure time model. However, a data set which has cost variation could be used to include cost in the departure time model. This would allow planners to

study the impacts of congestion pricing policies. A more detailed study of indicators of late arrival time choice and the development of a methodology for determining the discontinuities of available transit departure times would also enhance future departure time model development.

A possible research extension would be to consider the impact of reliability on non-work trips. Reliability might be a particularly important attribute for medical, shopping, recreational, and school trips. Also, for some of these trip purposes, reliability might impact trip frequency and destination choice in addition to departure time and mode choice.

Finally, once better models are developed which include reliability effects, a considerable amount of research should be directed at assessing the tradeoffs of forecasting with and without reliability variables, validation of models including reliability variables using data other than that used for estimation purposes, and the development of iterative procedures to forecast equilibrium departure time and mode choices (since they impact one another). In several respects, this research effort has only touched the surface of a problem area that requires much more detailed study before any conclusive results and implications can be put into practice.

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## APPENDICES

### APPENDIX A. Impact of Transit Wait Time Assumption on Computed Expected Loss

It has been suggested that a transit user's wait time distribution more closely resembles a bi-modal distribution than a normal distribution. The purpose of this analysis is to determine the expected loss using both distributions, and to compare the results to ascertain what, if any, error is introduced by assuming normality when the actual distribution is bi-modal.

#### A.1 Methodology

Assume a departure time to work of 7:15 a.m., an official work start time of 8:00 a.m., a mean in-vehicle travel time of 30 minutes, and an in-vehicle travel time variance of zero (i.e., fixed in-vehicle travel time). This implies a mean arrival time to work of 7:45 a.m. plus the mean transit wait time. With this information, the wait time distribution can be transformed to an arrival time distribution, where the wait time point  $x = 15$  minutes (see Figure A.1) corresponds to the official work start time.

The loss function,  $l(x)^*$  and the distribution of arrival time (based on wait time),  $f(x)$ , are defined over the region and the expected loss is expressed as:

$$E(\text{loss}) = \int_0^{\infty} f(x)l(x)dx \quad (\text{A.1})$$

The expected loss is calculated with  $f(x)$  represented as a bi-modal distribution and then as a normal distribution (defined to have the same mean and variance as the bi-modal distribution), and the results compared (see Figure A.1).

Four cases were considered:

#### Case 1

mean wait time = 12 min.  
 wait time variance = 43.5 min.<sup>2</sup>  
 $l(x) = .375 - .025x$  for  $0 \leq x \leq 15$   
 $= .125x - 1.875$  for  $15 \leq x$

#### Case 2

mean wait time = 12 min.  
 wait time variance = 17.4 min.<sup>2</sup>  
 $l(x) = .375 - .025x$  for  $0 \leq x \leq 15$   
 $= .125x - 1.875$  for  $15 \leq x$

#### Case 3

mean wait time = 6 min.  
 wait time variance = 10.87 min.<sup>2</sup>  
 $l(x) = .375 - .025x$  for  $0 \leq x \leq 15$   
 $l(x) = .125x - 1.875$  for  $0 \leq x \leq 15$

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\*Lateness loss is weighted five times higher than earliness to reflect higher penalties perceived for late arrival. It is also assumed that loss is minimized by arriving at the official work start time. This differs somewhat from empirical results which show lateness loss to be weighted three times higher than earliness, with loss minimized by arriving slightly over six minutes early.

Table A.1 Computed Expected Loss for Wait Time Distributions by Case

	Normal $\int_0^{\infty} f(x) dx$	Normal E(loss)	Bi-Modal $\int_0^{\infty} f(x) dx$	Bi-Modal E(loss)	Fractional Error**
Case 1	.9721	.28*	1.008	.312	-.103
Case 2	.9972	.160	0.992	.170	-.059
Case 3	.9655	.219*	1.008	.227	-.035
Case 4	1.0104	.227	1.00	.225	.009

\* In cases 1 and 3, restricting the normal range to greater than 0 resulted in the integration of a truncated normal. The results for normal expected loss are the computed integral normalized to account for the use of a truncated distribution.

\*\* Fractional Error =  $(E(\text{loss})_{\text{normal}} - E(\text{loss})_{\text{bi-modal}}) / E(\text{loss})_{\text{bi-modal}}$

#### Case 4

mean wait time = 6 min.  
wait time variance = 4.66 min.<sup>2</sup>  
 $l(x) = .375 - .025x$  for  $0 \leq x \leq 15$   
 $= .125x - 1.875$  for  $15 \leq x$

It was felt that, collectively, the cases represent a wide range of possible wait time situations experienced by travelers, ranging from unreliable, low frequency service in Case 1 to reliable, high frequency service in Case 4. Cases 1 vs. 3 and 2 vs. 4 represent variations in mean wait time with the same variance. Cases 1 vs. 2 and 3 vs. 4 represent variations in wait time variance about the same mean. In each case, the normal and bi-modal distributions have the same wait time mean and variance.

Expected loss was calculated using a FORTRAN program. Calculations were based on Simpson's rule for continuous functions (Texas Instruments, 1977):

$$\int_{x_0}^{x_n} f(x) dx = h/3 (f_0 + 4f_1 + 2f_2 + 4f_3 + 2f_4 + \dots + 2f_{n-2} + 4f_{n-1} + f_n) \quad (A.2)$$

where  $h = \frac{x_n - x_0}{n}$  and  $n$  = number of sub-intervals

In all cases,  $n$  was set equal to 16.

## A.2 Results and Implications

Table A.1 presents summary results of the analysis. The quantity of interest is the fractional error in computed expected loss introduced by using the normal in place of the bi-modal distribution. In general, the fractional error is a function of the difference between the normal and bi-modal distributions, weighted by the shape and magnitude of the loss function,  $l(x)$ . In most cases, the use of a normal distribution underestimated the expected loss computed using a bi-modal distribution.

As the mean and variance increase, the discrepancy in computed expected loss increases. However, for what could be considered a worst case situation (Case 1, mean = 12 min., variance = 43.5 min.<sup>2</sup>), the fractional error is only on the order of 10%. The fractional error is almost zero for the low mean, low variance case.

The results, when placed in perspective, demonstrate that under the conditions described herein, if the wait time distribution is actually bi-modal, a normal approximation will yield expected loss computations which even in extreme cases are within 10% of the actual expected loss. Furthermore, it is important to recognize that empirical evidence does not exist showing that the wait time

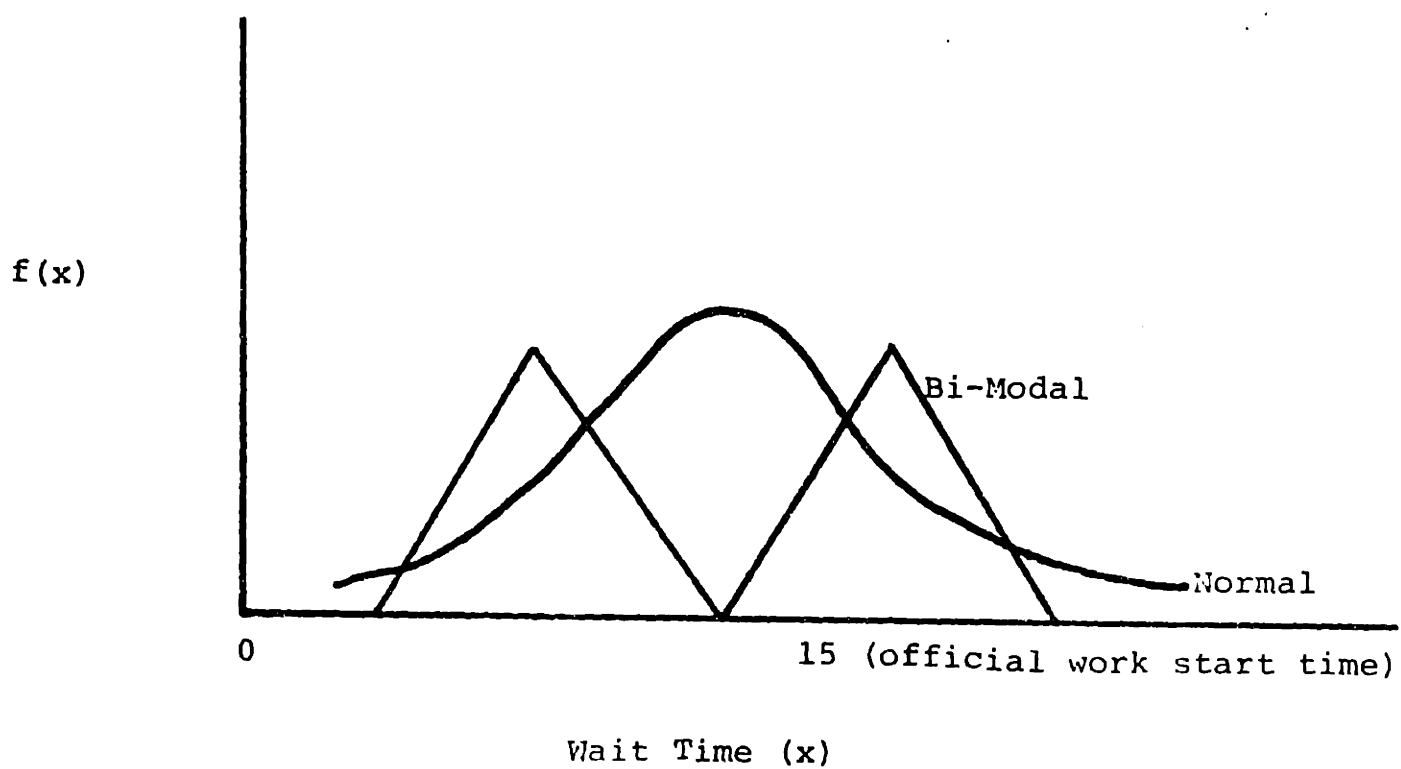
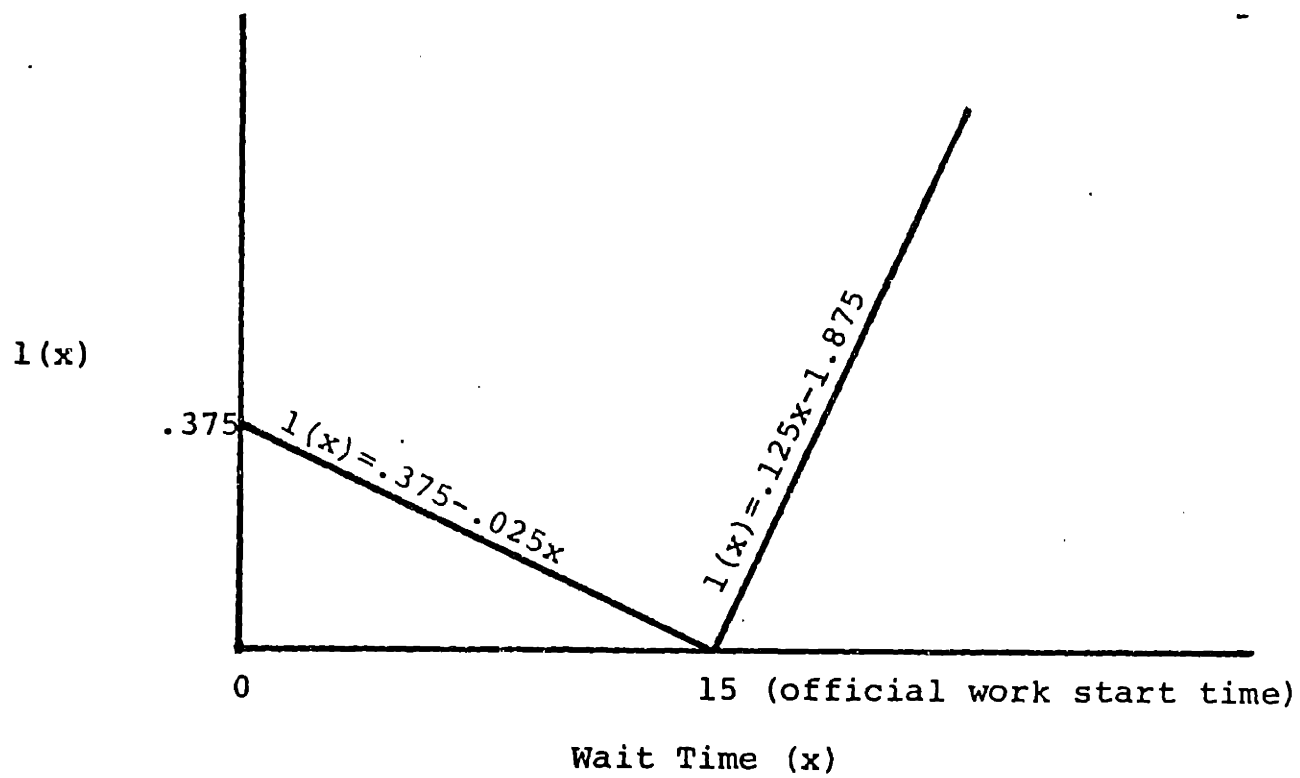


Figure A.1 Defining the Arrival Time Region

distribution is bi-modal. Given our lack of knowledge of the actual form of the wait time distribution, this analysis indicates that a normal approximation is a reasonable assumption, since even if wait time is not normally distributed, the use of a normal distribution will still yield reasonably accurate results.



## APPENDIX B. Impact of Auto In-Vehicle Time Assumption on Computed Expected Loss

This analysis was conducted to determine the magnitude of the error introduced in computed expected loss by using a normal approximation for a lognormal distribution of auto in-vehicle travel time.

### B.1 Methodology

Four scenarios were considered in this analysis. In the first scenario, a traveler departs home at 8:35 a.m., has a mean arrival time at work of 8:50 a.m., and an official work start time of 9:00 a.m. In the second scenario, the traveler's depart time is 8:43 a.m., his/her mean arrival time is 8:58 a.m., and his/her official work start time is 9:00 a.m. In scenario 3, the depart time is 8:10 a.m., mean arrival time is 8:50 a.m., and official work start time is 9:00 a.m. In the fourth scenario, a traveler departs at 8:18 a.m., has a mean arrival time of 8:58 a.m., and an official work start time of 9:00 a.m. For all four scenarios, the standard deviation of in-vehicle travel time is computed using equation 5.8.

Since the auto in-vehicle information infers the arrival time information, the scenarios described in the preceding paragraph correspond to the following four cases:

#### Case 1

mean arrival time = 530 minutes (after midnight)  
arrival time standard deviation = 1.274 minutes

#### Case 2

mean arrival time = 538 minutes  
arrival time standard deviation = 1.274 minutes

#### Case 3

mean arrival time = 530 minutes  
arrival time s.d. = 2.414

#### Case 4

mean arrival time = 538 minutes  
arrival time s.d. = 2.414 minutes

It was felt that, collectively, the cases represented a wide range of possible auto in-vehicle time situations experienced by travelers, ranging from high variability, long commutes to low variability, short commutes. Cases 1 vs. 2 and 3 vs. 4 represent variations in mean arrival time with the same standard deviation. Case 1 vs. 3 and 2 vs. 4 represent variations in the standard deviation of arrival time about the same mean arrival time.

The expected loss is calculated with  $f(x)$  represented as a normal distribution and then as a lognormal distribution, and the results compared. In each case, the normal and lognormal distributions have the same mean and standard deviation.

All cases were tested using the following assumed loss function:

$$\begin{aligned}l(x) &= 540-x \text{ for } x \leq 540 \text{ min.} \\l(x) &= 4(x-540) \text{ for } x \geq 540 \text{ min.}\end{aligned}$$

For this loss function, lateness loss is weighted four times higher than earliness loss to reflect higher penalties perceived for late arrival, and loss is minimized by arriving at official work start time.\*

Expected loss was calculated using a FORTRAN program based on Simpson's rule for continuous functions (see Appendix A).

## B.2 Results and Implications

Table B.1 presents summary results of the analysis. The quantity of interest is the fractional error in computed expected loss introduced by using the normal in place of the lognormal distribution. In general, the fractional error is a function of the difference between the normal and lognormal distributions, weighted by the shape and magnitude of the loss function,  $l(x)$ . In most cases, the use of a

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\*This differs somewhat from empirical results which show lateness loss to be weighted three times higher than earliness, with loss minimized by arriving slightly over six minutes early.

Table B.1 Computed Expected Loss for Auto In-Vehicle Distributions by Case

	<u>Normal</u>		<u>Lognormal</u>		<u>Fractional Error*</u>
	$\int_0^{\infty} f(x) dx$	E(loss)	$\int_0^{\infty} f(x) dx$	E(loss)	
Case 1	.9957	9.9568	1.0341	9.9443	.0001
Case 2	.9957	2.1572	1.0374	2.1658	-.004
Case 3	.9972	9.9722	1.0001	10.0348	-.006
Case 4	.9972	3.3655	1.0001	3.3827	-.005

\* Fractional Error =  $(E(\text{loss})_{\text{normal}} - E(\text{loss})_{\text{lognormal}}) / E(\text{loss})_{\text{lognormal}}$

normal distribution slightly underestimated the expected loss computed using a lognormal distribution.

For later mean arrival times and for higher in-vehicle time standard deviations, the discrepancy in computed expected loss increased. However, even for the most extreme case, the fractional error was always less than 1%! These results clearly indicate the use of a normal approximation for a lognormal auto in-vehicle time distribution in computing expected loss is quite acceptable.

## APPENDIX C. Impact of Transit In-Vehicle Time Assumption on Computed Expected Loss

This analysis was conducted to determine the magnitude of the error introduced in computed expected loss by using a normal approximation for a beta distribution of transit in-vehicle travel time.

### C.1 Methodology

An arrival time region was defined to lie between 0 and 1 to accommodate general restrictions of the beta distribution. The point  $x=.5$  represents the official work start time (see Figure C.1). The loss function,  $l(x)$ , and the distribution of arrival times (based on in-vehicle travel time),  $f(x)$ , are defined over the region and the expected loss is computed as follows\* :

$$E[\text{loss}] = \int_0^1 f(x)l(x) dx \quad (C.1)$$

The expected loss is calculated with  $f(x)$  represented as a beta distribution (restricted to  $0 \leq x \leq 1$ ) and then as a normal distribution (unrestricted) and the results are compared. Two cases were considered:

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\*The bounds in this equation are for the beta distribution. The normal expected loss computations were given different bounds, set to represent an unrestricted range.

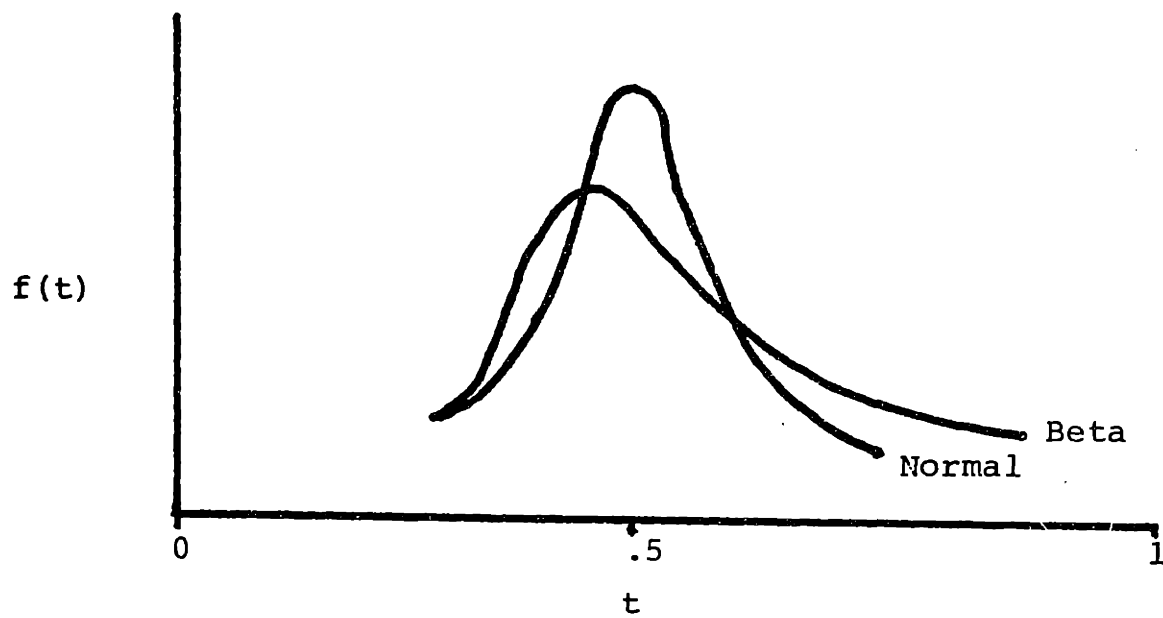
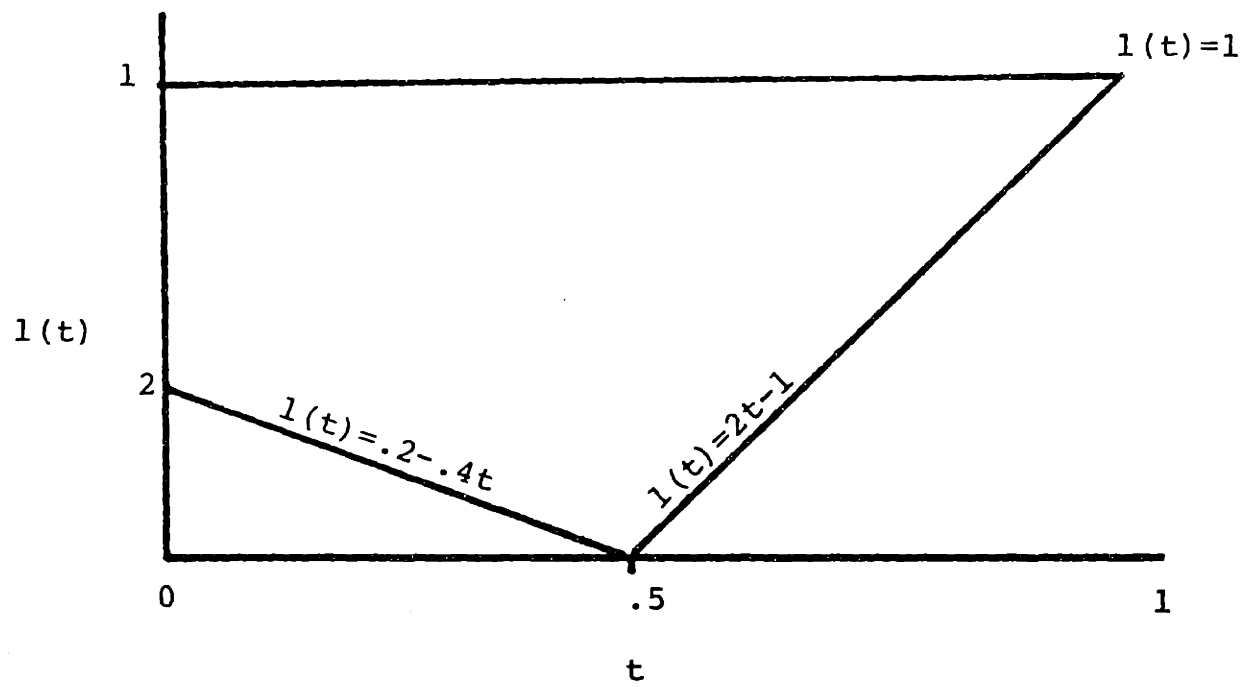


Figure C.1 Defining the Arrival Time Region

- 1)  $l(x) = .4(.5-x) \quad -\infty \leq x \leq .5$   
 $\quad = 2x-1 \quad .5 \leq x \leq \infty$   
mean = .5 variance = .125
- 2)  $l(x) = .4(.5-x) \quad -\infty \leq x \leq .5$   
 $\quad = 2x-1 \quad .5 \leq x \leq \infty$   
mean = .67 variance = .005

Case 1 assumes a hypothetical arrival time mean and variance. Case 2 uses the computed travel time mean and variance based on Polus' (1975) research. In each case, the normal and beta distributions have the same mean and variance. The loss function assumes lateness loss is weighted five times higher than earliness, with loss minimized by arriving at the official work start time.\*

## C.2 Results and Implications

Expected loss was calculated using a FORTRAN program based on Simpson's rule for continuous functions (see Appendix A). The quantity of interest is the fractional error in computed expected loss introduced by using the normal in place of the beta distribution. In general, the fractional error is a function of the difference between the normal and beta distributions, weighted by the loss function,  $l(x)$ .

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\*This differs somewhat from empirical results which show lateness loss to be weighted three times higher than earliness, with loss minimized by arriving slightly over six minutes early.



Table C.1 Characteristics of Normal and Beta Distributions

<u>Function</u>	<u>Density</u>	<u>Range of Parameters</u>	<u>Mean</u>	<u>Variance</u>
Normal with parameters $m$ and $\sigma$	$\frac{1}{\sqrt{2\pi}\sigma} \exp \left[ -\frac{(x-m)^2}{2\sigma^2} \right]$ for $-\infty < x < \infty$	$m$ real $\sigma > 0$	$m$	$\sigma^2$
Beta with parameters $p, q$	$\begin{cases} \frac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} x^{p-1} (1-x)^{q-1} & \text{for } 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$	$p > 0$ $q > 0$	$\frac{p}{p+q}$	$\frac{qp}{(p+q)^2 (p+q+1)}$

The results (see Table C.2) show that for the wider arrival time distribution, the discrepancy between the normal and beta distributions becomes more apparent. However, even under this condition, the unrestricted normal distribution expected loss is within 6% of that computed under the restricted beta distribution.

What is particularly important is that for the real world case (Polus data), the travel time distribution is tighter and the condition is quite similar to what is anticipated in this research. Under this condition, the expected loss computed under normality is within 5% of that computed using a beta distribution. Thus, it can be concluded that using an unrestricted normal distribution for transit in-vehicle travel time in place of a restricted beta distribution to compute expected loss is quite acceptable.

Table C.2 Computed Expected Loss for Transit In-Vehicle Time Distribution by Case

	<u>Normal</u>		<u>Beta</u>	<u>Fractional Error**</u>
	$\int_0^{\infty} f(x) dx$	$E(loss) * \int_0^{\infty} f(x) dx$	$E(loss) *$	
Case 1	.9905	.3288	.97	.3498
				-.06
Case 2	.9883	.3443	1.02	.3275
				.05

\* All reported expected losses are the computed expected loss normalized by  $\int_0^{\infty} f(x) dx$ .

\*\* Fractional Error =  $(E(loss)_{normal} - E(loss)_{beta}) / E(loss)_{beta}$

# APPENDIX D. Data Values for Estimation Sample

	<u>Sample Mean</u>	<u>Standard Deviation</u>
Autos/workers	1.07	0.71
Autos/drivers	0.81	0.32
employment density (zonal employees per acre)	128.9	178.6
auto travel cost/post-tax wage rate	12.2 min.	11.1
transit travel cost/post-tax wage rate	7.5 min.	5.6
carpool travel cost/post-tax wage rate	4.9 min.	4.5
mean auto travel time for departure period 1	24.1 min.	11.3
standard deviation of auto travel time for dep. period 1	1.46 min.	0.52
mean transit time for dep. period 1	59.8 min.	38.1
standard deviation of transit travel time for dep. period 1	4.1 min.	1.5
mean carpool time for dep. period 1	27.1	11.3
s.d. of carpool time for dep. period 1	2.2	0.4
mean auto time for dep. period 9	25.4	12.1
s.d. of auto time for dep. period 9	1.52	0.55
mean transit time for dep. period 9	59.8	37.2
s.d. of transit time for dep. period 9	3.8	1.2
mean carpool time for dep. period 9	28.4	12.1
s.d. of carpool time for dep. period 9	2.3	0.4
mean auto time for dep. period 12	24.8	11.3
s.d. of auto time for dep. period 12	1.49	0.52
mean transit time for dep. period 12	59.2	36.8
s.d. of transit time for dep. period 12	3.8	1.2
mean carpool time for dep. period 12	27.8	11.3
s.d. of carpool time for dep. period 12	2.2	0.4
early expected loss for chosen mode for dep. period 1	0.19	0.03
early expected loss for chosen mode for dep. period 9	0.06	0.00
early expected loss for chosen mode for dep. period 12	0.00	0.00
late expected loss for chosen mode for dep. period 1	0.00	0.00
late expected loss for chosen mode for dep. period 9	0.08	0.00
late expected loss for chosen mode for dep. period 12	0.37	0.00

	<u>Sample Mean</u>	<u>Standard Deviation</u>
peak transit headway	14.6 min	9.5
$\hat{D}^*$ auto	-4.6	0.8
$\hat{D}^*$ transit	-6.5	1.8
$\hat{D}^*$ carpool	-5.0	0.8