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16. Abstract

The consideration of user responses is important in planning reconstruction activities and in developing control strategies. Extensive surveys of actual commuter behavior in the North Central Expressway corridor in Dallas, Texas, were conducted to characterize the day-to-day dynamics of commuter decisions and to calibrate the user decision models incorporated in a methodology to analyze the dynamics of traffic commuting systems. Three aspects of commuter behavior are investigated in depth: trip chaining, trip timing, and path selection. The resulting data provide unique information that is of value to a wide array of travel demand measures and traffic operations, including intelligent vehicle highway systems (IVHS).

17. Key Words

driver responses, reconstruction activities, control strategies, commuter decisions, trip chaining, trip timing, path selection, travel demand, Dallas commuters

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DAILY VARIABILITY OF COMMUTER DECISIONS: DALLAS SURVEY RESULTS

by

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Thomas Joseph

Research Report 1216-1

Driver Responses to Traffic Disturbances and Control Strategies
Research Project 3-18-89/1-1216

conducted for the

Texas Department of Transportation

in cooperation with the

U.S. Department of Transportation
Federal Highway Administration

by the

CENTER FOR TRANSPORTATION RESEARCH
Bureau of Engineering Research
THE UNIVERSITY OF TEXAS AT AUSTIN

December 1992

IMPLEMENTATION STATEMENT

The findings of this study can be used by two primary groups. Traffic system operations at the state and district level can use the procedures developed to design and analyze such control measures as ramp controls and IVHS traffic management schemes. Transportation planners concerned with travel demand management and systems planning will find a wealth of useful information on travel behavior of commuters in the Dallas North Central corridor area, with applicability to other metropolitan areas in Texas. The procedures have particular applicability to the planning of major reconstruction activities and other disruptive events.

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented within. The contents do not necessarily reflect the official views or policies of the Federal Highway Administration or the Texas Department of Transportation (TxDOT). This report does not constitute a standard, specification, or regulation.

NOT INTENDED FOR CONSTRUCTION,
BIDDING, OR PERMIT PURPOSES

Hani S. Mahmassani, P.E. (Texas No. 57545)
Study Supervisor

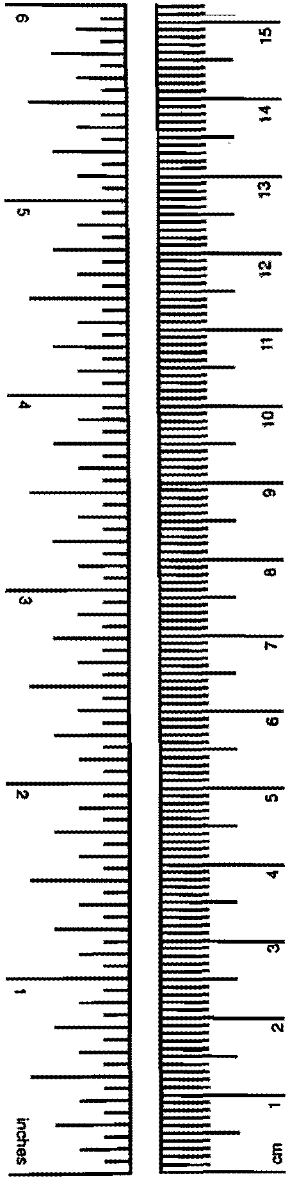
METRIC (SI*) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply by	To Find	Symbol
	LENGTH			
in	inches	2.54	centimeters	cm
ft	feet	0.3048	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
	AREA			
in^2	square inches	645.2	millimeters squared	mm^2
ft^2	square feet	0.0929	meters squared	m^2
yd^2	square yards	0.836	meters squared	m^2
mi^2	square miles	2.59	kilometers squared	km^2
ac	acres	0.395	hectares	ha
	MASS (weight)			
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams	Mg
	VOLUME			
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.0328	meters cubed	m^3
yd^3	cubic yards	0.0765	meters cubed	m^3

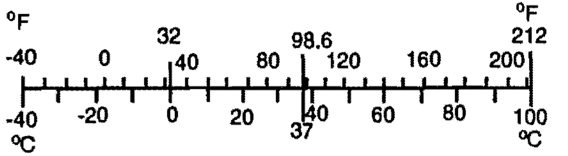
NOTE: Volumes greater than 1,000 L shall be shown in m^3.

Symbol	When You Know	Multiply by	To Find	Symbol
	TEMPERATURE (exact)			
°F	Fahrenheit temperature	5/9 (after subtracting 32)	Celsius temperature	°C



APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply by	To Find	Symbol
	LENGTH			
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
	AREA			
mm^2	millimeters squared	0.0016	square inches	in^2
m^2	meters squared	10.764	square feet	ft^2
m^2	meters squared	1.20	square yards	yd^2
km^2	kilometers squared	0.39	square miles	mi^2
ha	hectares (10,000 m^2)	2.53	acres	ac
	MASS (weight)			
g	grams	0.0353	ounces	oz
kg	kilograms	2.205	pounds	lb
Mg	megagrams (1,000 kg)	1.103	short tons	T
	VOLUME			
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	meters cubed	35.315	cubic feet	ft^3
m^3	meters cubed	1.308	cubic yards	yd^3
	TEMPERATURE (exact)			
°C	Celsius temperature	9/5 (then add 32)	Fahrenheit temperature	°F



These factors conform to the requirement of FHWA Order 5190.1A.

* SI is the symbol for the International System of Measurements

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CHAPTER 6. COMPARISONS OF WAVES ONE AND TWO

CHAPTER 7. DAY-TO-DAY SWITCHING MODELS

CHAPTER 8. CONCLUSION

SUMMARY

This report presents the findings of a set of surveys of commuters conducted in the Dallas North Central Corridor area between June 1990 and May 1991. These surveys constitute the observational component of study 1216, "Driver Responses to Traffic Disturbances and Control Strategies." This report is a companion to the final technical report for that study, titled "Dynamic Framework for the Analysis of User Responses to Traffic System Disruptions and Control Actions" (CTR Technical Report 1216-2F). The data were obtained in conjunction with the initial phases of the reconstruction of the North Central Expressway (I-75) in the area of interest.

A novel survey diary approach, initially developed and tested in Austin, was adapted and used to observe actual commuter behavior. The surveys have resulted in a unique data set of observations, containing information on previously undocumented aspects of commuter behavior. The particular aspects that have been investigated with this data include: 1) trip chaining, or the inclusion of stops to pursue activities for various purposes along the commute to or from work; 2) trip timing, for both morning and evening commutes, and its daily variability; and 3) route choice, for which link-level descriptions of the path actually used by commuters were obtained.

Several aspects of trip chaining were investigated, including the extent to which it is practiced by commuters, its frequency, the purposes of the various intervening stops, the duration of the stops, its spatial characteristics, as well as its variability from day-to-day. The results indicate that trip chaining is an essential feature of work-trip commuting. It is more extensive in connection with the evening commute than with the morning commute.

Trip chaining was also found to significantly influence the daily variability of departure time and route choice decisions of commuters. In general, commuters tend to switch departure time more frequently than route. Several methodological and definitional issues were examined and resolved in characterizing the daily switching behavior of commuters. Models relating the respective frequencies of trip chaining, departure time switching, and route switching to the characteristics of the commuter, his/her work environment, and the traffic system were developed and calibrated. These models yield useful insights for the design and marketing of various travel demand management strategies.

The data also served to calibrate the principal behavioral response models used in the user decisions component of the traffic corridor modeling framework developed in this study and described in the companion report. In particular, models based on the notion of an indifference band of schedule delay were developed to predict the changing of route and/or departure time from day-to-day in response to experienced congestion with the system.

Comparisons between Austin and Dallas indicated considerable similarity in commuting behavior and its determinants between the two cities. Differences in behavior between the two cities can be attributed principally to the (obvious) differences in size and associated network characteristics, rather than to socio-economic and demographic variables.

Comparisons between the two survey waves over time suggested an increase in congestion between the two periods (most likely a result of the reconstruction activities), as well as a slight increase in daily variability and switching behavior. Furthermore, many commuters included in both surveys modified individual patterns during the interval.

The results contained in this report provide an important reference on commuting patterns in urban corridors in Dallas and Austin, with likely applicability in other areas as well. These results will be useful for planning activities in connection with planned reconstruction work, travel demand management, and IVHS strategies.

CHAPTER 1. INTRODUCTION

PROBLEM DEFINITION

Traditional approaches to relieving urban congestion, such as increasing the capacity of the road network by constructing additional lanes, are in most cases precluded by the scarcity of the required land resources, the associated high capital costs, and by public concerns regarding negative environmental aspects. The Federal Highway Administration estimated in 1987 that it would cost around $6 billion a year just to maintain the 1983 performance levels of minimum safety and operations standards. This is over $2 billion more than is currently being spent (Ref 1). In addition to improving mobility, congestion relief strategies also represent efforts to comply with the requirements of the Clean Air Act Amendment in nonattainment areas, as well as to meet directives of the Intermodal Surface Transportation Efficiency Act (ISTEA).

Several emerging approaches, including peak period spreading actions, in-vehicle guidance systems, and telecommuting, are part of the array of approaches used to improve mobility in the face of increasing congestion. While the types of demand-side solutions are very diverse, their success depends on a deeper understanding of tripmaker behavior, since travel demand is a result of individual travel decisions in a given corridor over a given time period. In particular, work commuting trips during morning and evening peak periods are the primary target in most urban areas, since they account for over 20 percent of all person trips (Ref 2). Similarly, the performance of system operations strategies that involve the provision of information to tripmakers, such as Advanced Traveler Information Systems and Advanced Traffic Management Systems, depends on the users' responses to these strategies. The behavior of commuters is therefore a central element in the implementation and formulation of these congestion relief measures.

There are four principal travel choices or decisions that the commuter has to make at the beginning of every trip: whether or not intermediate destinations (stops) will be visited, what time to depart, which route to take, and what mode to ride (including carpooling). This report addresses the first three choice dimensions of work commuters who are all auto drivers. Mode choice is not discussed in this report, as changes in this dimension tend to take place over longer timeframes than the first three. Interactions among these dimensions are also considered, in the context of the pattern of activities in which commuters are engaged.

The commuter's behavior, which is dynamic in nature, requires observation over an extended period of time. It is clear that traditional survey approaches, in the form of single-day cross-sectional travel surveys, are inadequate as a basis for studying the above essential travel behavior processes. For this reason, a longitudinal survey approach was developed to obtain information for the study of commuter behavior dynamics. The design of the survey is addressed in the following chapter.

This report develops and tests a systematic procedure for capturing changes in trip decisions in response to traffic conditions, which can be used to develop effective traffic control strategies and management techniques. In a companion report (Ref 3), the framework for the development and analysis of traffic control strategies taking user responses into consideration is described. This report focuses on the observational component of the study and is aimed at documenting the procedures and analyses conducted in connection with the survey data. In addition to their specific purpose in connection with that framework, the results in this report constitute a unique base of information on commuter behavior and its daily variability.

MOTIVATION

The dynamics of commuter decisions in congested corridors have been the focus of a series of interactive laboratory-like experiments conducted by Mahmassani and co-workers (Refs 4, 5, 6). The interactive experiments involved real commuters supplying departure time and route choices in a simulated traffic system. Although such experiments provide a useful approach to the study of complex human decision systems, observations of actual behavior in the real world are required to confirm the substantive conclusions resulting from such experiments. For this reason, observation of commuters in their actual daily commute is the necessary next step beyond laboratory experiments.

The Dallas, Texas, area has had major highway repair or reconstruction activities underway since 1990. Reconstruction of the North Central Expressway (HWY 75), by all accounts one of the densest urban corridors in Dallas, began in June, 1990. *The Dallas Morning News* described the serious congestion of North Central Expressway on May 19, 1990, as follows:

> Portions of the highway carry as many as 153,000 cars a day, which exceeds its design capacity of 110,000 cars. It is the nation's fifth most dangerous freeway and has a 13-hour rush hour. About 30 percent of North Central's traffic will shift to other routes during the reconstruction south of Mockingbird.

The inconvenience caused by reconstruction and major repair activities can be expected to alter users' tripmaking, especially as these activities persist over a long period of time. For example, a user may be required to adjust his/her usual route or departure time in order to mitigate disruptive side effects. Thus, some valuable insights into behavior in response to and during major disruptions could be obtained during the reconstruction period.

Motivated by the need to observe commuters in their actual daily commute and by the advantage of capturing the behavior of commuters responding to changes in service quality, we selected the North Central corridor in Dallas for this study.

OBJECTIVES

The primary objectives of this report are to:

(1) describe a systematic methodology to capture the dynamic behavior of commuters, and, more generally, urban tripmakers;
(2) share the methodological and substantive insights from two surveys: a minor one in Austin and a more extensive one in Dallas;
(3) investigate the daily variability of commuter behavior;
(4) examine changes in commuting behavior during reconstruction of the North Central Expressway.

OUTLINE OF REPORT

This report is divided into eight chapters. The next chapter describes the survey design and the survey instruments, and presents summary statistics from the first-stage and second-stage surveys. Chapters 3, 4, and 5 discuss and compare some of the substantive results obtained from the Austin and Dallas surveys. Chapter 3 details trip chaining behavior, that is, frequency of stops, purpose of stops, variability of trip chaining, routine stops, and stop location. Chapter 4 focuses on the exploratory analysis of trip timing and path selection decisions. Chapter 5 applies regression models to establish relationships between commuters' daily switching behavior and their attributes and commuting environments. Chapter 6 compares the commuter behavior in wave one and wave two of the second-stage survey to investigate the effect of North Central Expressway reconstruction. Chapter 7 develops dynamic switching models that can capture the serial correlation and state dependence due to the consecutive time series data. Chapter 8 provides a summary of the critical findings of this study.

CHAPTER 2. SURVEY DESIGN AND GENERAL RESULTS

INTRODUCTION

This chapter presents the methodology used for the collection of the commuter behavior data. It also describes the general results of the surveys. The second section discusses the criteria used for selecting the study area in Dallas. The third section details the design of the first- and second-stage surveys. The material in sections 2 and 3 is also described elsewhere (Refs 3, 7). The fourth and final section highlights the general characteristics of the first- and second-stage respondents.

STUDY AREA

The particular survey addressed in this report was intended primarily for a commuting corridor possessing the following characteristics:

(1) the majority of the work trips should terminate in a zone within the study area; and
(2) the area should contain distinct major facilities that anchor the principal commuting routes (e.g., freeways or major arterials) that are parallel to each other and terminate in the above zone.

In the study area in Dallas, located north of the CBD, west of the North Central Expressway (HWY 75), and east of the Dallas Tollway (Figure 2.1), the majority of the work-related trips terminate in the CBD. Several parallel facilities pass through or terminate in the CBD (the Dallas Tollway, Preston Road, Hillcrest Road, Coit Road, Greenville Avenue, Skillman Road, Abrahms Road, and the North Central Expressway [HWY 75]).

As mentioned in the previous chapter, major reconstruction was scheduled along the North Central Expressway (HWY 75) around the time of the survey. It was hoped that the survey would therefore also provide data on the adjustment behavior of commuters during a long-term disruption.

SURVEY DESIGN

The survey methodology was comprised of two stages. In the first stage, a short (one-page, two-sided) questionnaire was mailed to 13,000 households in the study area. Each household received two survey forms, one for each commuter in two-worker households. The questions were designed to achieve the following survey objectives:

(1) acquire data on items that are relatively constant over extended periods (e.g., commuter characteristics);
(2) obtain information on commuter attitudes and other potentially important factors that contribute to the decision-making process; and
(3) provide a mechanism to screen for prospective candidates for the second stage.

Questions in the first-stage survey can be split into three categories (Figure 2.2). The first category addressed the first objective of the survey and included questions on the workplace address, mode used to travel to work, type of work and commuting time to work. Responses to these questions were used to characterize the commuter tripmaking situation. These characteristics were also expected to remain constant during the survey period. This information was used in screening and sampling candidates with the desired characteristics for the second stage.

A second category of questions addressed commuter attitudes and important issues in decision making, including the commuter's:

(a) decision state, i.e., whether the commuter exhibits a routinized, limited problem-solving or extensive problem-solving type of behavior with respect to trip-related decision making (e.g., the question asking the commuter if he/she normally adjusts the departure time or route specifically with traffic conditions in mind);

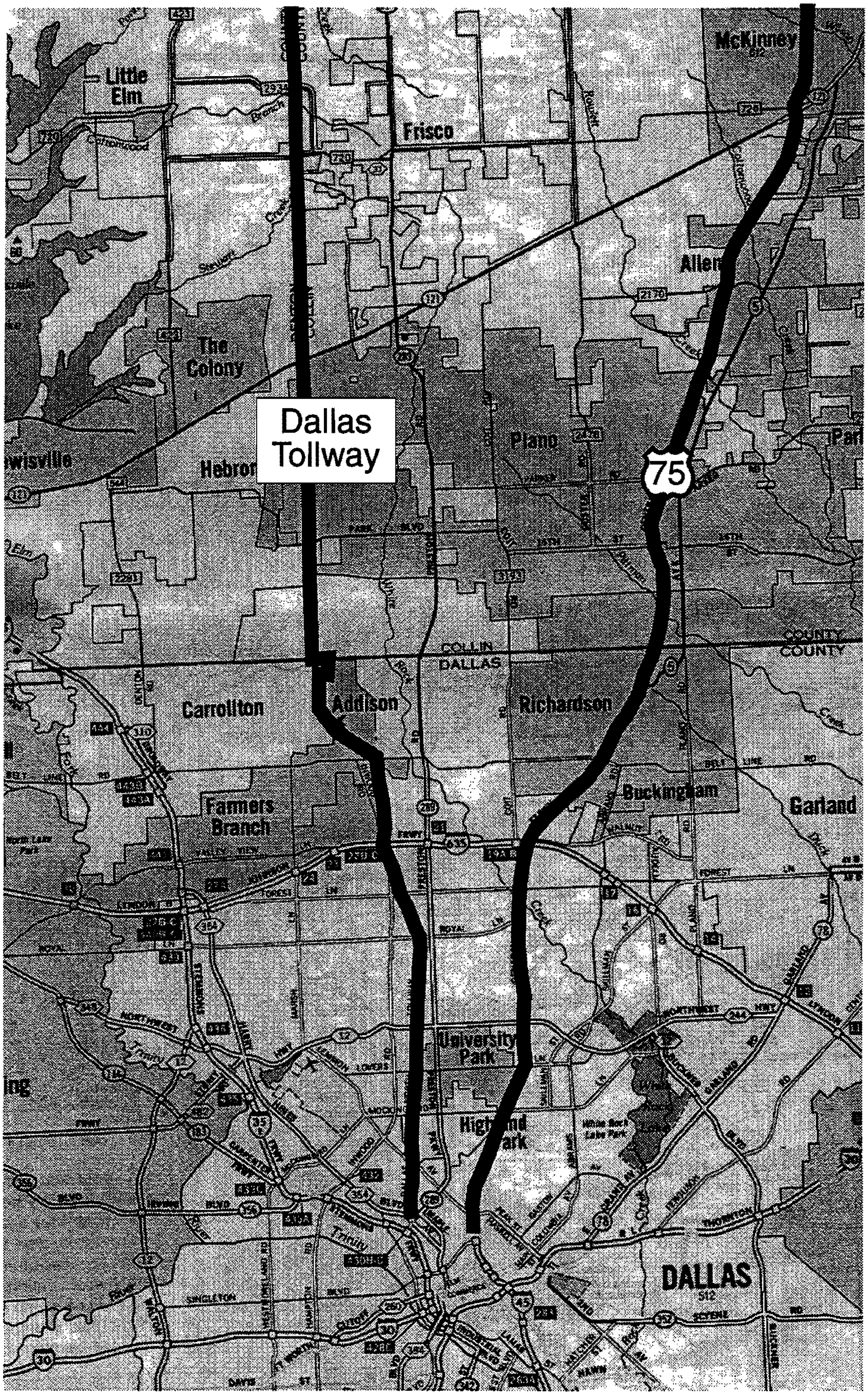


Figure 2.1 Survey area

TRANSPORTATION SURVEY

Thank you for participating in our survey. Before you begin, are there other people in the household who also commute to work? If so, please have them complete the additional enclosed survey. Please answer all questions to the best of your knowledge. All answers, of course will be kept strictly confidential. Thank you.

1. What is your work address? ______________________ Number and street (work) ________ City

2. How long have you worked at (or within a mile of) your current location? ___ Years.

3. How long have you lived at (or within a mile of) your current location? ___ Years.

4. Currently, how do you commute to work?
___ Car (alone) ___ Car Pool
___ Transit ___ Park & Ride
___ Other (specify) ______________

5. How would you best describe your work hours?
___ Regular Work Hours: (___ am to ___ pm)
___ Scheduled Shift Work
___ Flexible hours: (___ hours a week)
___ Other ______________________

6. How many minutes before your work officially starts do you prefer to arrive at your workplace? ___ Minutes.

7. How important is it for you to not be late to work?
___ I am expected to arrive on time.
___ I am allowed to arrive up to ___ minutes late.
___ It does not matter if I am late.

8. On a typical day, how long is your commuting time:
from home to work? ______ Minutes.
from work to home? ______ Minutes.

9. Do you normally adjust the <u>time</u> at which you leave specifically with traffic conditions in mind on your trip:
from home to work? ___ Yes ___ No
from work to home? ___ Yes ___ No

10. Do you normally modify the <u>route</u> you drive specifically with traffic conditions in mind on your trip:
from home to work? ___ Yes ___ No
from work to home? ___ Yes ___ No

11. In the past two weeks, how many times have you arrived after your intended time of arrival at work?
___ More than 5 times.
___ Between 1 and 5 times.
___ None.

12. How important are the following characteristics in your selection of a travel route?

	Extremely important	Somewhat important	Neutral
Construction activity	___	___	___
Familiarity of route	___	___	___
Driving time	___	___	___
Reliability of travel time	___	___	___
Environment (aesthetics)	___	___	___
Safety	___	___	___
Frequent traffic lights	___	___	___
Congested conditions	___	___	___

(Please turn over)

13. Do you normally obtain information on traffic conditions:
before leaving home for work? ___ Yes ___ No
before leaving work for home? ___ Yes ___ No

14. During your usual drive to and from your workplace, do you listen to traffic reports on the radio? ___ Yes ___ No

15. Do you have a cellular car phone? ___ Yes ___ No

16. How frequently do you use these roads (not necessarily to commute to work) ?

	Never	Seldom	Frequently
North Central Expressway (HWY 75)	___	___	___
Tollway	___	___	___
Preston road	___	___	___
Coit road	___	___	___

17. If you normally use the North Central Expressway (HWY 75) in your commute to work, where do you enter and exit:
from home to work? Enter _____ Exit _____
from work to home? Enter _____ Exit _____

18. If you are aware of the following sources of information related to the reconstruction of the North Central Expressway (HWY 75), have you had an occasion to use them?

	Yes	No	Unaware
Video tapes produced by the Highway Department.	___	___	___
Periodic brochures printed by the Highway Department.	___	___	___
Information Phone numbers (eg. 'WIDEN 75').	___	___	___

19. Are you satisfied with the availability and frequency of public transit service to your neighborhood?
___ Yes
___ No
___ Do not know

20. If you do not use public transit to commute to work, do you consider the existing service a convenient alternative to your current mode of travel?
___ Yes
___ No
___ Do not know

The next six questions will only be used in determining our test sample demographics.

21. What is your job title? ______________________ (e.g.: Store Manager, Professor, Secretary, Coach)

22. Do you rent or own your home? ___ Rent ___ Own

23. How many children (below age 16) presently live in your household? ___

24. If you drive a car to work, what is the year and make of the car? ______________________ Year and Make (e.g.: 1987 Ford Taurus)

25. What is your age?
___ under 18 ___ 18-29 ___ 30-44
___ 45-60 ___ over 60

26. What is your gender? ___ Male ___ Female

27. Would you be willing to assist in providing (through the mail) more detailed information on your commuting habits?
___ Yes ___ No ___ Possibly

PLEASE RETURN THIS SURVEY IN THE ENCLOSED ENVELOPE, regardless of whether or not you choose to participate in any further studies. Thank you for your promptness and cooperation. Your assistance will help us better understand the problems of traffic congestion. If you have any questions, please feel free to enclose them. Thank you again for your time and effort.

Figure 2.2 First-stage survey questionnaire

(b) decision mediators, i.e., the factors that affect the decision (e.g., the commuter's attitude towards the various factors affecting route choice, like the number of signals or safety);

(c) information acquisition process, i.e., whether the commuter actively or passively acquires information for trip-related decision making (e.g., whether the commuter owns a cellular phone or normally obtains information on traffic conditions before or during the trip); and

(d) evoked set of alternatives, i.e., the possible alternatives that the commuter considers during trip-related decision making (e.g., the question on the frequency of use of the various routes reflects the prospective alternatives available to the commuter).

A question with significant implications on commuter behavior asked for the time at which the commuter would prefer to arrive at the workplace, or preferred arrival time (PAT). It was realized that this question would be subject to different interpretations. For example, commuters may have had an initial PAT that was unattainable in their current situation because of congestion or parking problems. They may have reconciled to another attainable and satisfactory PAT. This value of PAT may be reported as a response to the question. Two versions of the question were finally designed. About half the households were asked to provide their PAT with no conditions set (case 1, Figure 2.2), while the other half were asked to provide it under the assumption of no congestion and no parking difficulties (case 2). An analysis of the distribution of the PAT obtained from both versions would provide interesting insights into the adjustment of the PAT. A related question asked about how important it was for the commuter to avoid being late for work. The response to this question would reflect the combined effects of the actual policy at the workplace, the perception of the policy by the commuter, and the personal characteristics (attitude) of the commuter towards arriving late for work.

A third category of questions addressed the socio-economic characteristics of the commuters that may be related to commuter behavior. These included questions on job title, owning or renting a home, number of children, etc. Although these questions were primarily used to establish the sample demographics, it was also expected that some of these variables would serve as proxies to explain certain aspects of commuter behavior.

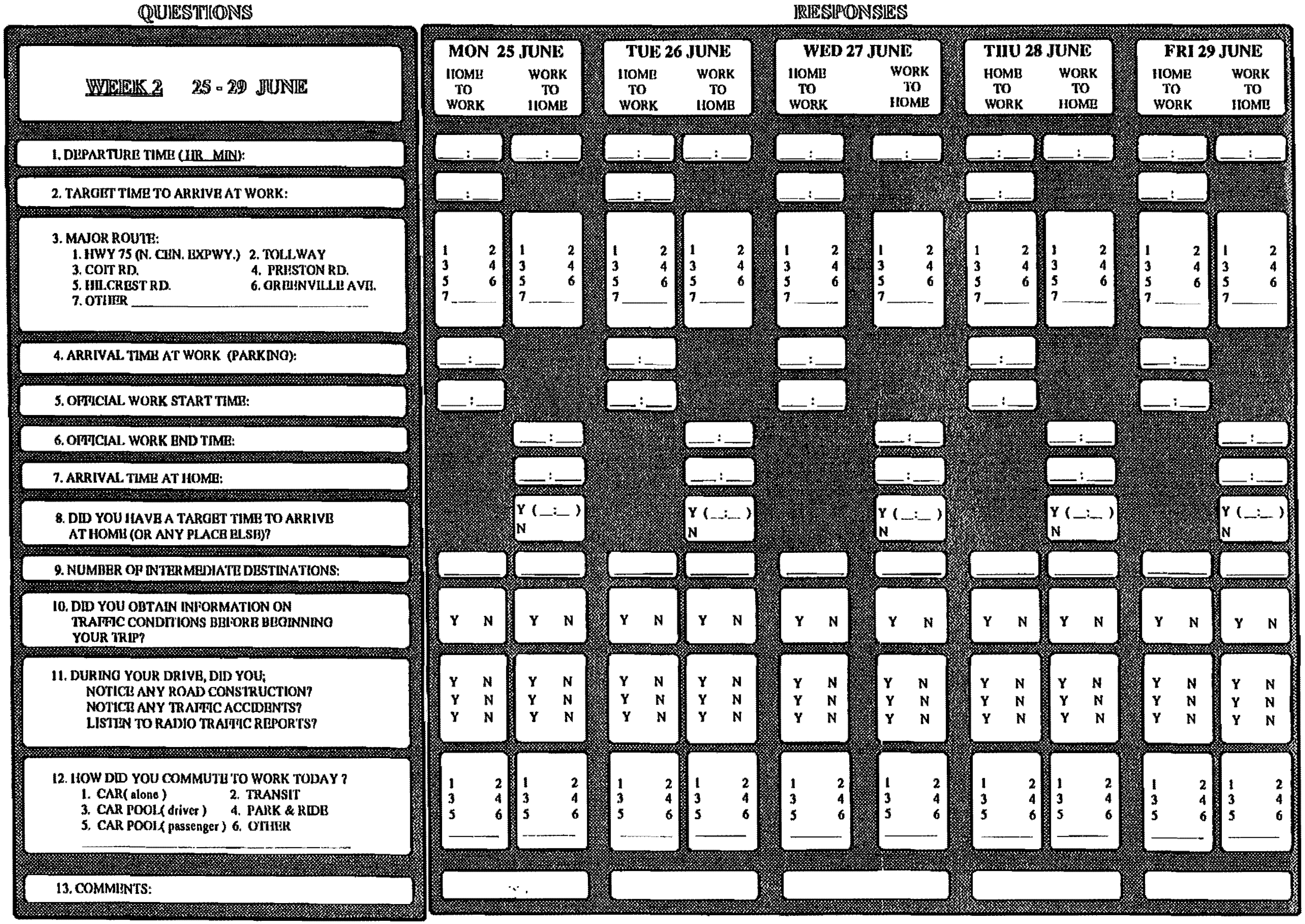
A final question asked the participant if he/she were willing to provide more detailed information on their commuting status. The available responses to this question were "yes", "no," and "possibly." The "possibly" option was included to retain potentially agreeable commuters who were not yet willing to commit without obtaining additional information.

For the second stage, two types of diaries (a long and short version) were designed to record the day-to-day behavior of a smaller sample of commuters over a two-week period. The length of the trip diary stage (10 working days) was determined to be sufficient for examining short-term dynamic behavior, but not so lengthy as to harm the respondents' goodwill. The booklet was designed to be easy for the commuter to handle while in the car. Each day had separate pre-dated pages for the morning and evening commutes. Also included in the booklets were detailed instructions and a sample of a completed day's entries. Figures 2.3 and 2.4 illustrate sample pages from the short and long diaries, respectively.

The second-stage survey differed from the first stage survey in that the amount of interpretation and recollection required of the respondent was reduced, while the level of detail was significantly increased. For this reason, the data from this stage were expected to be more accurate than those from the first stage. For each trip to work, the commuter was asked to record the departure time, arrival time, official work start time, and details of route selected.

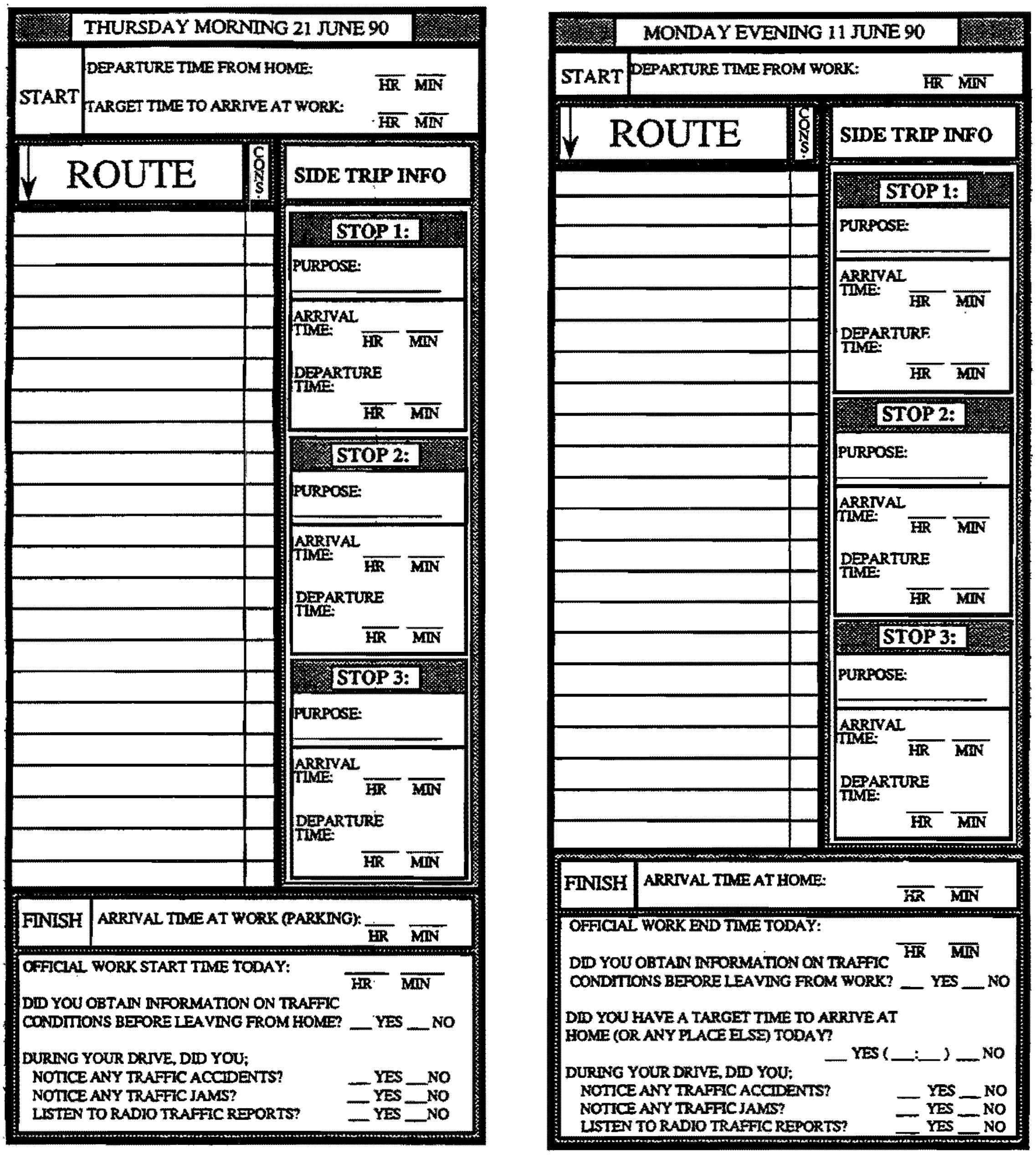
The level of detail required in route description was significantly different in the long and short versions of the diary. In the long version, a link-by-link description of the route, including minor deviations, was required; by contrast, only the name of the major facility used along the commuting route was requested in the short version. Similarly, commuters were asked for the details of every intermediate stop in the long version (the arrival and departure times, and the purpose of the stop); only the number of stops was required in the short version. The focus of this report is on the long-version diary, which is considerably more extensive and complete in terms of the commuting information supplied by the respondents.

Prior to their departure to work, commuters were also asked to note their "target" arrival time at work. The difference between the target arrival time and the departure time provides the commuter's estimate of his/her travel time for the trip. The intent was therefore to obtain information on the commuter travel time prediction process and the significance of arrival time constraints (e.g., tolerance of lateness). However, it was also realized that this question was subject to the risk of being interpreted differently by different commuters. For example, commuters may consider the target time as the time when they



QUESTIONS	RESPONSES									
WEEK 2 25 - 29 JUNE	MON 25 JUNE		TUE 26 JUNE		WED 27 JUNE		THU 28 JUNE		FRI 29 JUNE	
	HOME TO WORK	WORK TO HOME	HOME TO WORK	WORK TO HOME	HOME TO WORK	WORK TO HOME	HOME TO WORK	WORK TO HOME	HOME TO WORK	WORK TO HOME
1. DEPARTURE TIME (HR MIN):	___:___	___:___	___:___	___:___	___:___	___:___	___:___	___:___	___:___	___:___
2. TARGET TIME TO ARRIVE AT WORK:	___:___		___:___		___:___		___:___		___:___	
3. MAJOR ROUTE: 1. HWY 75 (N. CEN. EXPWY.) 2. TOLLWAY 3. COIT RD. 4. PRESTON RD. 5. HILCREST RD. 6. GREENVILLE AVE. 7. OTHER ____________	1 2 3 4 5 6 7 ____	1 2 3 4 5 6 7 ____	1 2 3 4 5 6 7 ____	1 2 3 4 5 6 7 ____	1 2 3 4 5 6 7 ____	1 2 3 4 5 6 7 ____	1 2 3 4 5 6 7 ____	1 2 3 4 5 6 7 ____	1 2 3 4 5 6 7 ____	1 2 3 4 5 6 7 ____
4. ARRIVAL TIME AT WORK (PARKING):	___:___		___:___		___:___		___:___		___:___	
5. OFFICIAL WORK START TIME:	___:___		___:___		___:___		___:___		___:___	
6. OFFICIAL WORK END TIME:		___:___		___:___		___:___		___:___		___:___
7. ARRIVAL TIME AT HOME:		___:___		___:___		___:___		___:___		___:___
8. DID YOU HAVE A TARGET TIME TO ARRIVE AT HOME (OR ANY PLACE ELSE)?		Y (__:__) N		Y (__:__) N		Y (__:__) N		Y (__:__) N		Y (__:__) N
9. NUMBER OF INTERMEDIATE DESTINATIONS:	______	______	______	______	______	______	______	______	______	______
10. DID YOU OBTAIN INFORMATION ON TRAFFIC CONDITIONS BEFORE BEGINNING YOUR TRIP?	Y N	Y N	Y N	Y N	Y N	Y N	Y N	Y N	Y N	Y N
11. DURING YOUR DRIVE, DID YOU; NOTICE ANY ROAD CONSTRUCTION? NOTICE ANY TRAFFIC ACCIDENTS? LISTEN TO RADIO TRAFFIC REPORTS?	Y N Y N Y N	Y N Y N Y N	Y N Y N Y N	Y N Y N Y N	Y N Y N Y N	Y N Y N Y N	Y N Y N Y N	Y N Y N Y N	Y N Y N Y N	Y N Y N Y N
12. HOW DID YOU COMMUTE TO WORK TODAY ? 1. CAR(alone) 2. TRANSIT 3. CAR POOL(driver) 4. PARK & RIDE 5. CAR POOL(passenger) 6. OTHER ____________	1 2 3 4 5 6 ____	1 2 3 4 5 6 ____	1 2 3 4 5 6 ____	1 2 3 4 5 6 ____	1 2 3 4 5 6 ____	1 2 3 4 5 6 ____	1 2 3 4 5 6 ____	1 2 3 4 5 6 ____	1 2 3 4 5 6 ____	1 2 3 4 5 6 ____
13. COMMENTS:										

Figure 2.3 Sample page from diary (short version)



THURSDAY MORNING 21 JUNE 90

START
DEPARTURE TIME FROM HOME: ___ ___ HR MIN
TARGET TIME TO ARRIVE AT WORK: ___ ___ HR MIN

ROUTE

CONS.

SIDE TRIP INFO

STOP 1:
PURPOSE:
ARRIVAL TIME: ___ ___ HR MIN
DEPARTURE TIME: ___ ___ HR MIN

STOP 2:
PURPOSE:
ARRIVAL TIME: ___ ___ HR MIN
DEPARTURE TIME: ___ ___ HR MIN

STOP 3:
PURPOSE:
ARRIVAL TIME: ___ ___ HR MIN
DEPARTURE TIME: ___ ___ HR MIN

FINISH
ARRIVAL TIME AT WORK (PARKING): ___ ___ HR MIN

OFFICIAL WORK START TIME TODAY: ___ ___ HR MIN
DID YOU OBTAIN INFORMATION ON TRAFFIC CONDITIONS BEFORE LEAVING FROM HOME? __ YES __ NO
DURING YOUR DRIVE, DID YOU;
NOTICE ANY TRAFFIC ACCIDENTS? __ YES __ NO
NOTICE ANY TRAFFIC JAMS? __ YES __ NO
LISTEN TO RADIO TRAFFIC REPORTS? __ YES __ NO

MONDAY EVENING 11 JUNE 90

START
DEPARTURE TIME FROM WORK: ___ ___ HR MIN

ROUTE

CONS.

SIDE TRIP INFO

STOP 1:
PURPOSE:
ARRIVAL TIME: ___ ___ HR MIN
DEPARTURE TIME: ___ ___ HR MIN

STOP 2:
PURPOSE:
ARRIVAL TIME: ___ ___ HR MIN
DEPARTURE TIME: ___ ___ HR MIN

STOP 3:
PURPOSE:
ARRIVAL TIME: ___ ___ HR MIN
DEPARTURE TIME: ___ ___ HR MIN

FINISH
ARRIVAL TIME AT HOME: ___ ___ HR MIN

OFFICIAL WORK END TIME TODAY: ___ ___ HR MIN
DID YOU OBTAIN INFORMATION ON TRAFFIC CONDITIONS BEFORE LEAVING FROM WORK? __ YES __ NO
DID YOU HAVE A TARGET TIME TO ARRIVE AT HOME (OR ANY PLACE ELSE) TODAY? __ YES (__:__) __ NO
DURING YOUR DRIVE, DID YOU;
NOTICE ANY TRAFFIC ACCIDENTS? __ YES __ NO
NOTICE ANY TRAFFIC JAMS? __ YES __ NO
LISTEN TO RADIO TRAFFIC REPORTS? __ YES __ NO

Figure 2.4 Sample page from diary (long version) were required to arrive at their workplace, rather than a consequence of some sort of travel time prediction process.

If reconstruction activity was observed during a particular trip, the commuter was asked to note the street on which this occurred. Two questions were directed towards the acquisition of information on traffic conditions prior to and during the trip. From the responses to these, valuable information on the extent of pre-trip planning, states of commuter decision making (e.g., routinized, extensive problem solving, etc.) and the potential for information-based strategies (e.g., ATIS/ATMS) can be extracted. Commuters were also asked to indicate if they had observed any accidents or traffic jams during their trip.

Questions pertaining to the trip from work were similar to those for the trip to work. At the end of the survey, commuters were asked to respond to six final questions on the last page of the diary. The first three questions were related to parking and included the type of parking, cost of parking, and time required to travel from the parking lot to the workplace. These were intended to provide information on the influence of parking-related factors on trip-maker behavior and decision process. The final three questions were related to information acquisition and measured the propensity to acquire and use information (if provided), and the potential of various information sources. As mentioned earlier, because this stage requires extensive record keeping on the part of the participants, the maximum duration for the participation of a given commuter was limited to two weeks. In order to obtain information on commuter patterns in the area over a longer period during the initiation of the freeway reconstruction activity, the first wave included two partially overlapping survey periods. The first period extended from the 11th to the 22nd of June, 1990. The second period extended from the 18th to the 29th of June, 1990.

A second wave was conducted about a year later in an attempt to capture possible long-term effects of the reconstruction activity on commuter patterns. Participants in the second wave included a combination of new participants and participants who had taken part in the previous wave. The new participants were requested to fill out two-week diaries from the 29th of April to the 10th of May, 1991, while the repeat participants were asked only for one-week diaries, from the 29th of April to the 3rd of May, 1991. To improve the return rate on these diaries, telephone calls were made to a considerable number of prospective participants at strategic times to encourage them to participate in this stage. The sampling strategies for the first- and second-stage surveys are described elsewhere (Refs 3, 7).

FIRST-STAGE SURVEY RESULTS: GENERAL CHARACTERISTICS

Summary statistics for the first-stage survey results are presented in Table 2.1 The vast majority of respondents (94 percent) used their own cars to commute, and only 2.3 percent were transit riders (including Park and Ride), probably reflecting the absence of competitive public transportation service. The majority of respondents (71 percent) had regular work hours. Of those commuters having regular work hours, the majority had work start times between 7:45 and 8:15 AM, and work end times between 4:45 and 5:15 PM. The relatively low percentage of workers with flexible work hours suggests the potential for peak spreading as a traffic relief strategy.

The preferred arrival time (PAT) represents a safety margin to protect against lateness at work and allows some time for preparation at the onset of the working day. It was found to be an important determinant of the dynamics of commuter behavior in previous experiments (Ref 8). As noted in the previous section, two versions of this question were used, with the wording in the second case specifically indicating that the PAT was intended in the absence of congestion and/or parking problems. The average was 16 minutes for the reported PAT with no conditions stated (case 1) and 15 minutes for the PAT in the absence of congestion and/or parking difficulties (case 2). The stated PATs under the two definitions follow the distributions shown in Figure 2.5, which reveals that around 50 percent prefer to arrive at their workplace within ten minutes before the official work start times in both cases. A chi-squared test indicates that the two distributions are significantly different at any reasonable confidence level. This result is probably due to the higher percentage of commuters with a PAT of zero in case 1.

Table 2.1 Summary statistics for first-stage survey results

Mode of Travel for Commuter (2518*)	
Car (alone)	93.6%
Car Pool	2.4%
Transit	1.0%
Park and Ride	1.3%
Other	1.7%
Type of Work Hour (2518)	
Regular Work Hours	70.5%
Scheduled Shift Work	2.9%
Flexible Work Hours	20.0%
Other	6.6%
Preferred Arrival Time at Work Place	
Case 1: No Conditions Specified (1178)	16 minutes
Case 2: In the Absence of Congestion or Parking Problem (1192)	15 minutes
Tolerance of Late Arrival at Work Place	
Unlimited	38.2%
Given Time	7.3%
None	54.5%
Average Daily Travel Time	
From Home to Work (2485)	25 minutes
From Work to Home (2346)	27 minutes
Commuter Adjusting Departure Time	
From Home to Work (2489)	52.9%
From Work to Home (2461)	31.4%
Commuter Modifying Route	
From Home to Work (2487)	47.1%
From Work to Home (2467)	46.1%
Arrival after Intended Time (2482)	
More than 5 Times	8.3%
Between 1 and 5 Times	42.3%
None	49.4%
Commuter Listening to Radio Traffic Report (2494)	70.6%
Commuter Having Cellular Car-Phone (2503)	10.5%
Age (2504)	
Under 18	0.6%
18-29	14.9%
30-44	46.5%
45-60	31.3%
Over 60	6.7%
Gender (2505)	
Male	63.3%
Female	36.7%
Commuter Willing to Help Further (2514)	
Yes	49.6%
No	18.6%
Possibly	31.8%

* Total sample size is 2,521. Value in parentheses is the number of responses for each question.

Over one-third of the respondents indicated that they had unlimited lateness tolerance, whereas more than 50 percent indicated there was no lateness tolerance at their workplace. The remainder (7.3 percent) reported various lateness tolerance intervals, with 10, 15, and 30 minutes being the most common. The average reported travel time to work was 25 minutes and the return commute averaged 27 minutes. The distributions are shown in Figure 2.6. A chi-squared test reveals that the two distributions are significantly different.

More commuters adjust their departure time for the morning commute than for the evening commute, but there is only a 1-percent difference in reported route switching between the home-to-work and return commutes. It is noteworthy that a considerably larger percentage switches route than switches departure time in the evening commute, while a somewhat larger percentage of commuters report adjusting departure time rather than route in the home-to-work commute. The results suggest that different considerations govern commuter switching behavior in the morning and evening commutes. Similar general insights were obtained in an earlier survey conducted in Austin (Ref 9). Almost half of the respondents indicated no arrivals after their intended time of arrival at work. Only 8 percent reported "more than five times." Seventy percent of the commuters reported listening to traffic reports on the radio during their usual commutes. However, only 10 percent indicated having cellular car phones.

In the first-stage survey, commuters were asked about departure time and route switching in general terms only, in connection with "usual" behavior. No specific time frames were specified, and no attempt was made to obtain recalled information about recent switches. As such, the responses may be more reflective of the users' perceptions of their own attitudes towards switching rather than actual behavior. To obtain more specific information on the latter, the second-stage diary survey was conducted, providing detailed and reliable information on actual departure times, routes, and intermediate stops in connection with the AM and PM commutes. The next section highlights some of the results of the second stage.

SECOND-STAGE SURVEY RESULTS

The first wave of the second-stage survey contained detailed morning and evening trip information for a period of two weeks (ten work days). The diary included actual trip departure and arrival times, link-by-link route descriptions, and information on the location, purpose, and timing of stops in multi-purpose chains. Commuters were asked to provide official work start times. A total of 198 respondents from both periods completed the diary. Possible differences between the two overlapping periods are not examined here, and the results hereafter are given for the entire sample of respondents from both periods. The subsequent analysis is limited to those trips which begin and end with the usual home and work locations (for each commuter), resulting in 1,724 and 1,639 usable morning and evening trips for wave one, respectively.

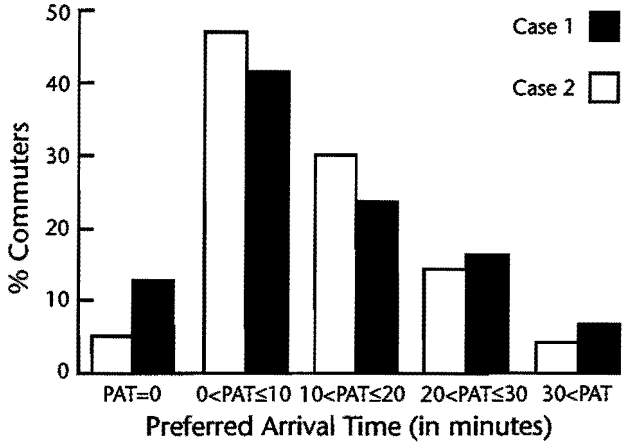


Figure 2.5 *Relative frequency distributions of preferred arrival time*

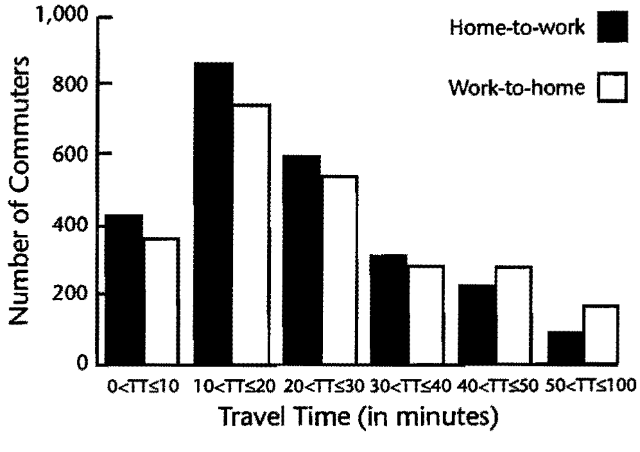


Figure 2.6 *Frequency distributions of reported travel times for the home-to-work and work-to-home commutes*

Table 2.2 summarizes the general characteristics of wave one diary respondents. The average travel times to and from work for the commuters on days with no intervening stops are 24.6 and 26.5 minutes, respectively. The majority of commuters are males, regular hour workers, and own their place of residence. The majority of participants are between the ages of thirty and sixty. About 52 percent of the commuters reported tolerance to lateness in excess of five minutes at the workplace. The average preferred arrival time before work start for this sample is 15 minutes. Overall, comparisons of the distributions of the variables in Tables 2.1 and Table 2.2 indicate that the diary participants are representative of the first-stage respondents. In particular, the travel time to and from work, preferred arrival time, gender, and age characteristics are very similar.

The general characteristics of wave two diary respondents are presented in Table 2.3. A total of 126 respondents, consisting of 52 new and 74 repeat participants, completed the diary. The average travel times on days without intervening stops are 23.5 minutes to work and 24.5 minutes to home, respectively. More than 60% of the commuters are males and around 75% of the commuters own their place of residence. Eighty percent of the commuters were from 30 to 60 years old. The average preferred arrival time before work start is 16.24 minutes. As in wave one, 52 percent of the commuters reported tolerance to lateness in excess of five minutes at the workplace.

Table 2.2 Characteristics of the 198 first-wave diary respondents

Average actual travel time to work (no intervening stops)		24.60 min
Average actual travel time to home (no intervening stops)		26.50 min
Commuters with		
	Regular work hours	82.29%
	Flexible work hours	14.58%
	Shift/other work hours	3.12%
Male/Female		66.77/33.30%
Percentage with lateness tolerance (>5 min) at work		51.60%
Average preferred arrival time before work start		15.29 min
Age		
	18-29	15.62%
	30-44	47.92%
	45-60	31.25%
	over 60	5.21%
Commuters who rent		21.30%

Table 2.3 Characteristics of the 126 second-wave diary respondents

Average actual travel time to work (no intervening stops)		23.50 min
Average actual travel time to home (no intervening stops)		24.50 min
Commuters with		
	Regular work hours	64.39%
	Flexible work hours	22.73%
	Shift/other work hours	12.88%
Male/Female		61.8/38.2(%)
Percentage with lateness tolerance (>5 min) at work		51.90%
Average preferred arrival time before work start		16.24 min
Age		
	18-29	12.21%
	30-44	47.33%
	45-60	34.35%
	over 60	6.11%
Commuters who rent		24.81%

CHAPTER 3. EXPLORATORY ANALYSIS OF TRIP-CHAINING BEHAVIOR

INTRODUCTION

This chapter presents the analysis of the trip-chaining behavior revealed in the first wave diaries. In this context, trip chaining refers to the temporal and spatial linkage of individual stops during commutes. The available diary information for each stop includes its purpose, location, arrival time, and departure time. Stop locations were coded to the nearest node (or centroid) of the Dallas network. The frequency, purpose, variability, routine vs non-routine nature and location of stops made during morning and evening commutes are explored in this chapter. To understand the differences and similarities of commuters' trip-chaining behavior between cities, comparisons between Dallas and Austin are highlighted throughout the chapter.

FREQUENCY OF OBSERVED STOPS

Tables 3.1 and 3.2 show the number of AM and PM stops, respectively, made by Dallas and Austin participants. As shown, only 75.1% of all morning and 63.9% of all evening commutes contain no stops in Dallas, a situation that compares to Austin's. This phenomenon indicates that trip chaining is an essential characteristic of commuting in both areas. As expected, commuters stop more often during evening commutes. This is likely the result of fewer time constraints on commuters after work, as well as of the availability of more stopping opportunities (more stores open, etc.). Furthermore, commuters are willing to make more than one stop during the evening commute: in Dallas, the average number of stops per trip (given that stops are made) is 1.18 for the morning and 1.36 for the evening trips.

Chi-square tests are performed to check whether these two distributions are similar between Austin and Dallas. The results of these tests for independence indicate that one cannot reject the null hypothesis that the frequency distribution of observed stops in Dallas is similar to the distribution in Austin during the morning and evening commutes at the 5% level of confidence (chi-square value of 3.37, 3 df, p = 0.338 for morning commuters and chi-square value of 7.236, 3 df, p = 0.065 for evening commuters). If the number of stops is divided into three categories instead of four (i.e., 0, 1, ≥ 2), and if the chi-square test is then performed, the null hypothesis cannot be rejected at the 15% level of confidence (chi-square value of 2.264, 1 df, p = 0.322 for morning commuters and chi-square value of 3.72, 2 df, p = 0.156 for evening commuters). The tests seem to indicate that there are no significant differences for number of stops between Dallas and Austin. However, a chi-square test led to the rejection of the hypothesis that the distributions of the number of AM stops and PM stops in Dallas are similar (chi-square value of 74.27, 3 df, p = 0.000).

Table 3.1 Number of AM stops (%) made in Dallas and Austin

Number of stops	0	1	2	≥3	Total
Dallas	1294 (75.06)	360 (20.88)	63 (3.65)	7 (0.41)	1724 (100)
Austin	1002 (74.83)	268 (20.01)	58 (4.33)	11 (0.82)	1339 (100)

Table 3.2 Number of PM stops (%) made in Dallas and Austin

Number of stops	0	1	2	≥3	Total
Dallas	1050 (64.10)	419 (25.58)	127 (7.75)	42 (2.56)	1638 (100)
Austin	796 (60.67)	371 (28.28)	95 (7.24)	50 (3.81)	1312 (100)

For each commuter, one can calculate the total number of stops made. In Dallas, only 21.2% never stopped on the way home during their recorded trips, while 33.8% of commuters did not make any stops on the way to work. On the other hand, 11.6% of the evening commuters and 5% of the morning commuters made more than 10 total stops. Over 20% of the commuters had 6-9 total stops during the recorded trips in the evening. However, only 8.8% of commuters had that many stops in the morning, further illustrating that commuters make more stops on the return home commute.

For each commuter, a stops ratio was calculated by dividing the number of trips with stops by the total number of trips reported by that commuter (morning and evening trips separately). For example, a stops ratio of 1.0 indicates that the commuter stopped on each of his/her morning or evening commutes. The relative frequency distribution of the stops ratio across Dallas commuters is shown in Figure 3.1. The differences in the distributions of the stops ratio between morning and evening commutes reflect the different trip chaining patterns of AM and PM commutes. In particular, the distribution of the PM stops ratio appears to be more evenly spread across commuters than that of the AM stops ratio. While 32.2% (38.8% for Austin) of commuters did not make any stops on the way to work, only 18.6% (14% for Austin) never stopped on the way home (stops ratio = 0.0). At the other extreme, only 6.8% (6% for Austin) of the commuters made stops on every morning trip and 5.8% (5% for Austin) of them made stops on every evening trip (stops ratio = 1.0). The distributions indicate a wide spread of values for the stops ratio, reflecting both different commuter trip-linking habits and daily variability in the commuting pattern of each participant (both inter- and intra-personal variability).

Figure 3.2 contains the cumulative distribution of the average number of stops per trip for the Dallas commuters during morning and evening commutes. These curves further confirm the differences between morning and evening commutes; 13% of commuters average more than one stop per evening trip, while only 5.6% of commuters average more than one stop per morning trip. The average number of stops per trip is 0.51 for PM (0.55 for Austin) and 0.31 for AM (0.30 for Austin). The strong similarity between the Austin and Dallas samples is quite remarkable.

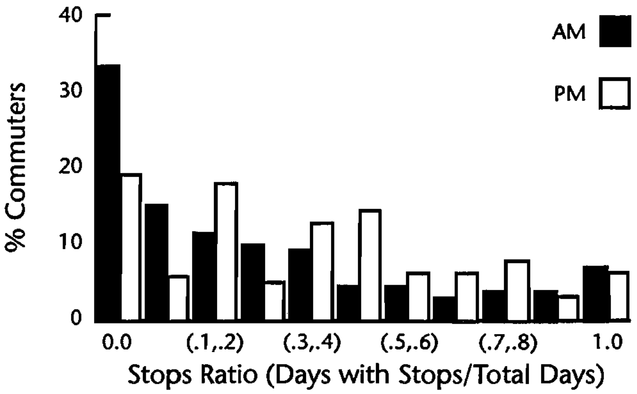


Figure 3.1 Distribution of stops ratio for AM and PM trips

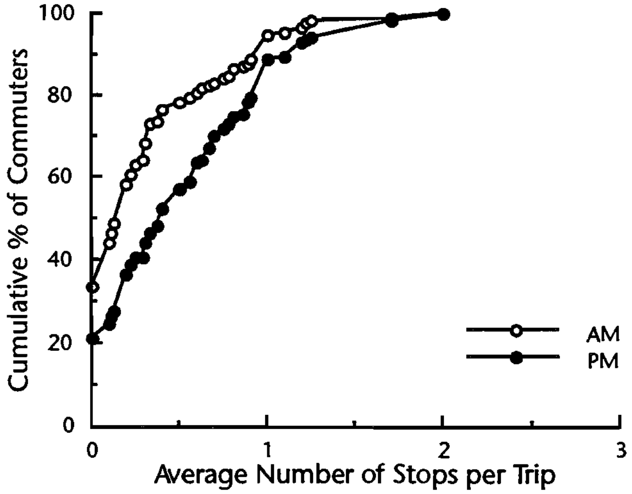


Figure 3.2 Cumulative distribution of the average number of stops per trip, morning and evening commutes, Dallas

PURPOSE OF STOPS

The type of activities pursued at stops during commutes is of direct interest in any trip linkage analysis. Twenty-two original stop purposes were coded and subsequently combined into five major categories for analysis (in order to compare with Austin). The frequency distributions of activity types of stops made by Dallas and Austin commuters are shown in Table 3.3. While the serve passenger and personal business activities account for 64.2% (62% for Austin) of all AM stops, they only account for 44.5% (41% for Austin) of all PM stops. The main difference between AM and PM for both cities is that shopping accounts for almost one-fifth of all stops made during the commute from work to home. The relative AM (home to work) frequencies of food/social and "other" stops are quite similar to those for PM (work to home) frequencies. Furthermore, personal business is the predominant activity pursued during the commuting day, accounting for 33.6% (27% for Austin) of all AM and PM stops.

A chi-square test for independence indicates that one cannot reject the null hypothesis that the frequency distribution of stop purpose in Dallas is similar to the distribution in Austin during the morning at the 10% level of confidence (chi-square value of 6.764, 4 df, p = 0.149). However, the null hypothesis should be rejected for evening commuters (chi-square value of 23.896, 4 df, p = 0.000). The results indicate that there are no significant differences in purposes of stops between Dallas and Austin during the morning commutes. The differences observed for the evening commute between the two cities may reflect the likely availability of greater opportunities for personal business activity in Dallas, which is considerably larger than Austin. Again, a chi-square test led to rejection of the hypothesis that the distributions of the purpose of AM stops and of PM stops in Dallas are similar (chi-square value of 94.322, 4 df, p = 0.000).

VARIABILITY OF COMMUTER TRIP CHAINING

The previous sections have explored the frequency and purpose of individual stops reported during commutes. The incidence of these stops in the observed trip-chaining patterns is explored in what follows. The definitions used in this section follow those outlined by Mahmassani et al (Ref 10).

Transportation planners have traditionally treated the commuting trip as a repetitive and unchangeable phenomenon. One way to assess such regularity is to quantify the number of distinct trip chains in each commuter's diary (for morning and evening commutes separately). A distinct trip chain here refers to a unique sequence of stop locations (or no stop), regardless of the actual route followed to link these stops. For example, a commuter who has five no-stop trips, four trips with a stop at a specific node, and one trip with a stop at another node has three distinct trip chains. Another measure of trip-linking variability is the relative frequency with which each commuter follows his/her mode

Table 3.3 *Activity types of stops made by Dallas and Austin commuters during morning and evening commutes*

Activity Type	AM Frequency	%	PM Frequency	%
Serve passenger	132*	27.4	100	12.9
	(128)**	(30.6)	(121)	(16.8)
Personal business	177	36.8	246	31.6
	(131)	(31.3)	(174)	(24.2)
Food/Social/Recreational	77	16.0	127	16.3
	(85)	(20.3)	(143)	(19.9)
Shopping	16	3.3	146	18.8
	(18)	(4.3)	(171)	(23.8)
Other	79	16.4	159	20.4
	(57)	(13.5)	(110)	(15.3)
TOTALS	481	100.0	778	100.0
	(419)	(100.0)	(719)	(100)

*Dallas ** (Austin)

(most frequent) trip-chain. Thus, for commuter i, we defined:

Distinct Trip
Chain Ratio$_i$ = Number of distinct trip-chains$_i$/total trips$_i$
Mode Chain Ratio$_i$ = Number of trips with mode chain$_i$/total trips$_i$

It should be noted that these ratios are computed only for those commuters with two or more trip-chaining patterns. Figures 3.3 and 3.4 depict the cumulative distributions of these two variables, respectively, for both morning and evening trips in Dallas. For the morning commute, 38% (42% in Austin) of the tripmakers had a single distinct trip chain (and a mode chain ratio of 1.0). The remaining 62% (58% in Austin) had at least two chaining patterns. For the evening commute, only 22% (16% for Austin) of the participants had a single distinct trip chain, while 78% (84% for Austin) had at least two chaining patterns. Of those with two or more patterns, the average distinct trip chain ratio is 0.361 (0.358 for Austin) for AM and 0.485 (0.507 Austin) for PM commutes. Only 18.4% (7.3% for Austin) of all commuters had a trip chain ratio greater than 0.5 for AM trips, while 40.4% (36.6% for Austin) of all commuters did so for PM commutes.

The average mode chain ratio is 0.825 (0.833 for Austin) for AM and 0.688 (0.659 for Austin) for PM commutes. In other words, commuters followed their mode trip chaining pattern (whether or not this involved stops) on around 80% of all morning trips and 60% of all evening trips (on the average). About 29.6% (30% for Austin) of the commuters had a mode chain ratio of 0.75 or less for AM trips, while 55.1% (58.5% for Austin) of commuters had a similar ratio for PM trips.

Clearly, the trip chaining habits of commuters in both cities for the trip from home to work are less variable than those for the trip from work to home, as displayed by both the distinct trip chain ratio and the mode chain ratio. The difference in behavior undoubtedly causes differences in route selection and time scheduling decisions of commuters between morning and evening trips.

ROUTINE STOPS

The purpose of this section is to examine those stops made repeatedly by commuters. Some workers routinely make a stop during their commute; for example, a commuter may regularly pick up or drop off his/her friend or household member at a certain place on the way to or from work. The commuting behavior of routine stoppers may vary significantly from that exhibited by those making non-routine stops. The set of all stops was separated into "routine" and "non-routine" stops. A stop was classified as routine if it is made (for a given commuter):

(1) at the same location; and
(2) with a frequency of at least three per five commuting trips (the location had to be visited at least three times to be considered) (Ref 10).

This definition is based on the location and not on the purpose of the stops, though most stops at a given location will have the same purpose.

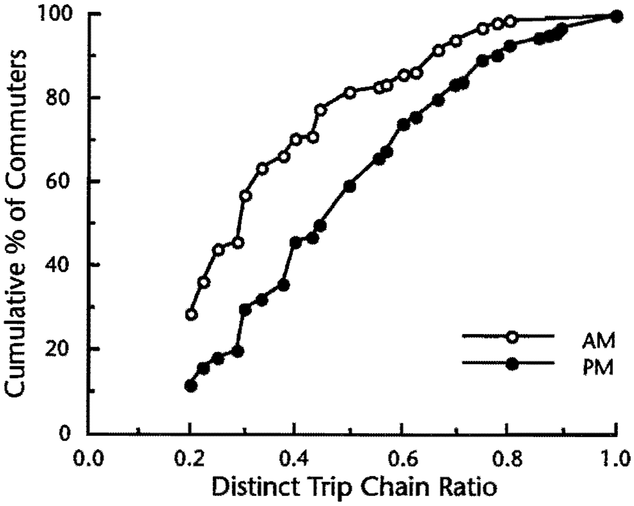


Figure 3.3 ***Cumulative distribution of the distinct trip chain ratio, morning and evening commutes, Dallas***

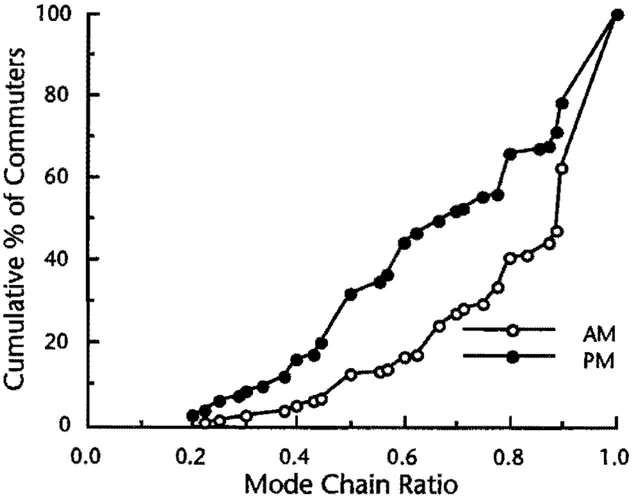


Figure 3.4 ***Cumulative distribution of the mode chain ratio, morning and evening commutes, Dallas***

Tables 3.4 and 3.5 give a breakdown of the activities pursued at routine and non-routine stops for morning and evening commutes, respectively. By this definition, 20.8% of the AM stops and 10.2% of the PM stops are routine stops in Dallas, indicating that AM stops are more likely to be routine than PM stops, same as in Austin. As expected, these activities differ between the two types of stops. The serve passenger activity tends to be routinely pursued on both AM and PM commutes, as in Austin. Personal business, food/social /recreational, shopping, and 'other' stops are predominantly non-routine. Chi-square tests for independence lead to a clear rejection of the null hypothesis that the stop-activity frequency distributions are similar for the two stop

Table 3.4 Activities completed at routine and non-routine stops on the trip to work

	AM Commutes			
Activity Type	**Routine stops frequency**	**%**	**Non-routine stops frequency**	**%**
Serve passenger	67* (75)**	67.0 (53.2)	65 (53)	17.1 (19.1)
Personal business	19 (17)	19.0 (12.1)	158 (114)	41.5 (41.0)
Food/Social/Recreational	6 (36)	6.0 (25.5)	70 (49)	18.4 (17.6)
Shopping	0 (0)	0.0 (0.0)	17 (18)	4.4 (6.5)
Other	8 (13)	8.0 (9.2)	71 (44)	18.6 (15.8)
TOTALS	100 (141)	100.0 (100.0)	381 (278)	100.0 (100.0)

*Dallas ** (Austin)

Table 3.5 Activities completed at routine and non-routine stops on the trip to home

	PM Commutes			
Activity Type	**Routine stops frequency**	**%**	**Non-routine stops frequency**	**%**
Serve passenger	38* (72)**	48.1 (62.6)	62 (49)	8.9 (8.1)
Personal business	8 (7)	10.1 (6.1)	238 (167)	34 .0 (27.7)
Food/Social/Recreational	6 (15)	7.6 (13.0)	121 (128)	17.3 (21.2)
Shopping	0 (13)	0.0 (11.3)	146 (157)	20.9 (26.0)
Other	27 (8)	34.2 (7.0)	132 (102)	18.9 (16.9)
TOTALS	79 (115)	100.0 (100.0)	699 (603)	100.0 (100.0)

*Dallas **(Austin)

types, for both AM (chi-square value of 124.9, df = 3, $p < 0.001$) and PM (chi-square value of 99.9, df = 3, $p < 0.001$).

Tables 3.4 and 3.5 also show that there is a lower percentage of routine stops in Dallas than in Austin both in the morning (20.8% < 33.7%) and evening (10.2% < 16.0%). On the other hand, Dallas has a higher percentage of non-routine stops than Austin for morning and evening commutes. This may be due to the presence of a larger number of stopping opportunities along the (longer) commute in Dallas. Alternatively, it may be that commuters in Dallas prefer to satisfy a particular stop purpose as part of the commute, whereas commuters in Austin might make a separate trip for such a purpose. In the absence of information on the entire tripmaking pattern over the whole day, this will remain a matter for speculation.

In Dallas, fourteen commuters (7.1% of all commuters, 10.7% of those with AM stops) had one morning routine stop. Five of these fourteen commuters made the routine stop on every recorded AM commute (in fact, 85.5% of all morning trips completed by routine-stop commuters contained routine stops). Eleven commuters (5.6% of all commuters, 7.1% of those with PM stops) had one evening routine stop. Three of these eleven made the routine stop on every recorded PM commute (80.6% of all evening trips completed by routine-stop commuters contained routine stops).

The propensity of morning routine stoppers to make evening routine stops is also relevant to the analysis of a commuter's activity pattern. Four individuals in the Dallas study group made routine stops during both commuting trips. All of these four (three males, one female) made a serve passenger stop at the same location during both the trip to work and the return trip home.

DURATION OF STOPS

Since a commuter is not actually 'in the transportation system' while carrying out an activity at a particular stop, it is useful to quantify the time spent at stops during commutes. The duration of a stop is simply the time spent at that stop (obtained by subtracting the stop arrival time from the stop departure time in the diaries). However, stoptime refers to the time spent at one or more stops on a given trip. Diary participants were instructed to round all times to the nearest minute; therefore, all durations are integer values.

Because the duration of a stop depends on the desired activity, the durations are analyzed for the five major stop activity types separately. Even within these activity types, much variability is expected because of the diverse individual stop purposes contained in these groups, the large interpersonal differences between individuals in this study group, and the fact that many facets of a stop are beyond the control of these individuals (e.g., number of people in line at a store). Because the behavior of routine stoppers may vary from that of non-routine stoppers, the durations are also categorized by stop type. Table 3.6 and Table 3.7 contain the duration information for morning and evening commutes, respectively.

In Dallas, the overall average duration of morning stops (14.5 minutes) is considerably shorter than that of evening stops (36.1 minutes), as are the averages for the same activity types; this is also the case in Austin. The differences between AM and PM trips for "all stops" are statistically significant (using a two-sample t-test) at the 10% level for each activity type, separately, as is the case for Austin. The differences could partly be attributed to less stringent time constraints on commuters for the trip from work to home. Furthermore, different activity purposes are pursued during evening commutes, including many stops for social, recreational, and shopping. Thus, the grouping of stop purposes affects the comparison between durations. However, informal comparison of the average duration of individual stop purposes for AM and PM trips revealed a similar trend for nearly all purposes. It is interesting that no commuters indicated AM routine stops for shopping in either city.

For Dallas and Austin, routine stops are typically shorter than non-routine stops during morning commutes; however, personal business is the only type of activity for which routine stops are significantly shorter than non-routine stops (by activity type) during evening commutes. This may be another reflection of less stringent time constraints on commuters for this trip. The serve passenger activity typically has the shortest duration of AM and PM stops, followed by shopping, personal business, food/social, and other for AM stops and shopping, personal business, other, and food/social for PM stops. The average duration of "all stops" and for each type of stop activity in Dallas are all greater than in Austin, except for shopping and other. It should be noted that the large values of the standard deviations indicate high variability of stop duration as well as the presence of data outliers.

STOP LOCATION

The last two attributes of stops to be discussed in this chapter are the relative location of the stops and trip stoptime along the routes followed by the commuters. The relative location of a stop

Table 3.6 ***Average and standard deviation of duration of routine, non-routine, and all stops for the trip to work, by activity type (in minutes), Dallas***

AM Commutes			
Activity Type	**Routine stops average (std. dev.)**	**Non-routine stops average (std. dev.)**	**All stops average (std. dev.)**
Serve passenger	5.3 (4.3) n=67	3.5 (4.6) n=65	4.4 (4.5) n= 132
Personal business	5.2 (1.7) n=19	8.4 (15.2) n=158	8.1 (14.4) n=177
Food/Social/Recreational	2.7 (1.6) n=6	16.3 (27.5) n=70	15.2 (26.6) n=76
Shopping	-	8.1 (7.1) n=16	8.1 (7.1) n=16
Other	50.9 (5.9) n=8	46.5 (61.7) n=69	46.9 (58.4) n=77
ALL TYPES	8.8 (13.1) n=100	16.0 (33.9) n=378	14.5 (30.9) n=478

Table 3.7 ***Average and standard deviation of duration of routine, non-routine, and all stops for the trip to home, by activity type (in minutes), Dallas***

PM Commutes			
Activity Type	**Routine stops average (std. dev.)**	**Non-routine stops average (std. dev.)**	**All stops average (std. dev.)**
Serve passenger	8.2 (7.5) n=37	8.0 (14.3) n=62	8.0 (12.1) n=99
Personal business	1.6 (0.7) n=8	19.5 (38.3) n=238	18.9 (37.8) n=246
Food/Social/Recreational	80.8 (25.2) n=6	79.4 (93.9) n=118	79.4 (91.7) n=124
Shopping	-	18.0 (15.0) n=144	18.0 (15.0) n=144
Other	64.5 (47.1) n=27	63.4 (59.5) n=128	63.6 (57.4) n=155
ALL TYPES	32.6 (41.7) n=78	36.5 (58.4) n=690	36.1 (56.9) n=768

was determined on the basis of the trip timing information provided by the participant. This information was used (instead of actual distances) for two main reasons:

(1) the arrival time at a stop provided by the commuter was often the best indication of stop location, since the street addresses of stops were not requested and the actual locations of stops were often difficult to code; and
(2) the travel time is highly correlated with distance.

A variable between zero and one was defined to denote the relative location of the stop between home and work. For the morning commute, the variable STAH (stop time away from home) was defined as the travel time to the stop divided by the total travel time of the commute. For the evening commute, the variable STAW (stop time away from work) was defined as the travel time to the stop divided by the total travel time of the commute. Stop durations were not included in these calculations.

Figure 3.5 depicts the relative frequency distribution of STAH for all stops made on morning trips in Dallas, by activity type. The legend contains four ranges of possible STAH values. The closer the value of STAH is to zero, the closer to home the stop is made. The closer the value of STAH is to one, the closer to work the stop is made. A STAH value of 0.5 indicates that the stop location is about halfway (in terms of travel time) between home and work. Serve passenger stops tend to occur closer to home than to work, which is different from Austin. The locations of these stops include schools, day care centers, and offices. These stops tend to be routine (as shown in previous section), and therefore tend to be frequently represented in the overall sample. Personal business morning stops also tend to be made closer to home, which is the same as Austin. About 68.8% (61% Austin) of these stops had a STAH value of less than 0.5. Most morning food/social stops also tend to occur closer to home, while these stops are clustered in the middle of the commuting trip in Austin. The location of shopping stops is clustered toward the middle of morning commutes (in Austin, these stops do not exhibit any noticeable trend). 'Other' activity stops (including medical, church, and miscellaneous) tend to be made closer to home than work, which again is different from Austin. In fact, over 60% (55% Austin) of these stops have a STAH value less than 0.5.

Figure 3.6 shows the relative frequency distribution of STAW for all stops made on evening commutes in Dallas, by activity type (the closer the value of STAW is to zero, the closer the stop is to work). The serve passenger PM stops tend to be closer to home, consistent with the morning results. Personal business evening stops tend to be made closer to home than to work for both cities, also in agreement with the morning trend. The locations of food/social/recreational and shopping stops also tend to be closer to home, while they are clustered toward the middle of the evening commutes in Austin. Only 9% (13% Austin) of the shopping stops had a STAW value of less than 0.25. The "other" activity stops tend to be made closer to home than to work, which is similar to the morning trend. About 65.4% of these stops had a STAW value between 0.50 and 1.0 in Dallas.

It is interesting to note that only the location of personal business stops, which tend to be made closer to home than to work, is similar in relative terms to Austin. This is most likely due to the greater spatial extent of the Dallas area, and to the generally longer associated commute (the average travel time in Austin is much less than in Dallas). The longer the travel time, the less the familiarity with facilities in the middle of long trips. Therefore, stops tend to be made closer to home than to work, probably because the commuter is more familiar with facilities in the area near home. Since Austin is much smaller than Dallas, it is easier for commuters to flexibly control their travel time. Thus, the difference in spatial characteristics may cause different stop location distributions.

TRIP STOPTIME

Since more than 4% of all morning and about 11% of all evening commutes contained two or more stops in both cities, the relative impacts of second and third stops on the spatial attributes of a trip chain may be difficult to distinguish from the impact of the first stop. For this reason, the stoptime is defined as the total time spent at all stops on a given commute.

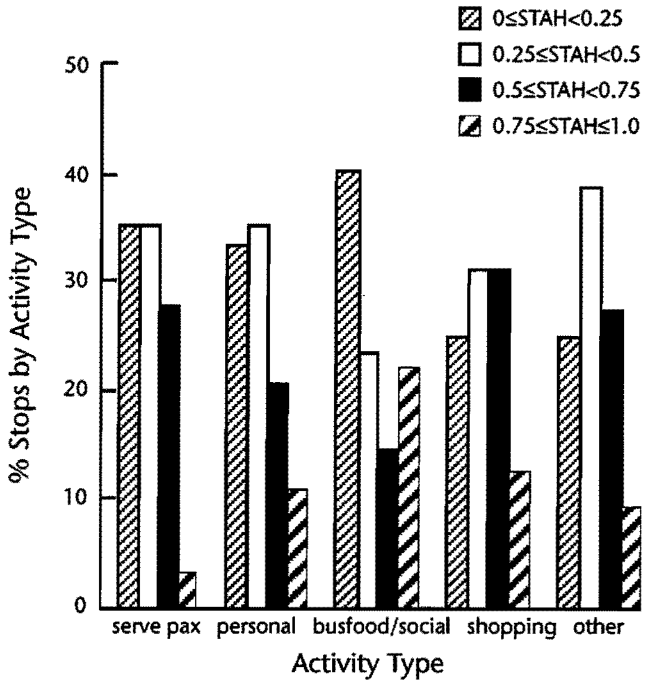


Figure 3.5 ***Relative frequency distributions of STAH for stops made during AM commutes, by activity type, Dallas***

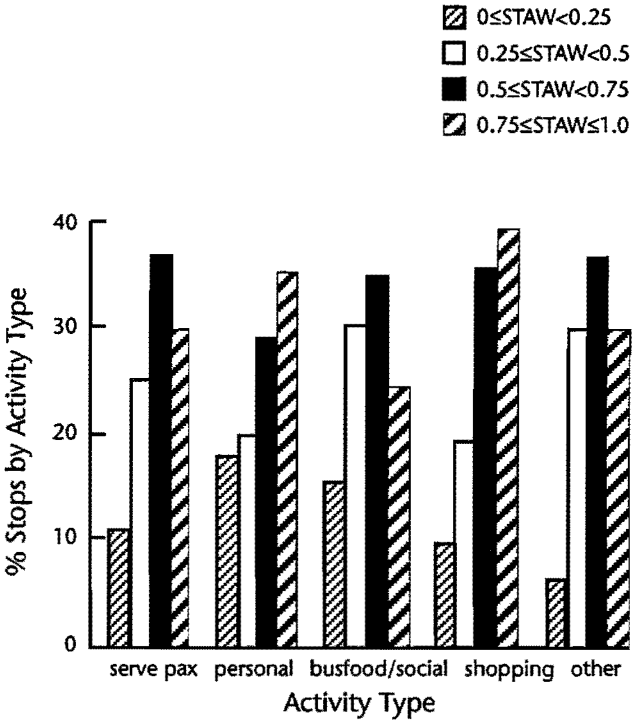


Figure 3.6 ***Relative frequency distributions of STAW for stops made during PM commutes, by activity type, Dallas***

Table 3.8 Average stoptime (minutes) for trips with stops, by trip type, for AM and PM commutes. Number of non-missing observations for each category is given

RS=Routine stops

Trip Type	AM Mean	AM Sample	PM Mean	PM Sample
All Trips	16.8*(13.4)**	428 (330)	48.6 (45.1)	581 (500)
Trips w/oRS	18.7 (17.1)	328 (200)	50.1 (48.7)	504 (393)
Trips w/RS	10.4 (7.80)	100 (130)	39.1 (31.8)	77 (107)

* Dallas ** (Austin)

Table 3.8 gives the mean values of the stoptimes for AM and PM trips with stops for both cities. As expected, the mean stoptime for PM trips is much higher than that for AM commutes. For both AM and PM commutes, the mean of the stoptime distribution for trips with routine stops is lower than the distribution without routine stops. In fact, in Dallas, the mean stoptime for non-routine stop trips (18.7 min) is 1.8 times greater than the mean for routine stop trips (10.4 min) in the morning (1.2 times greater in the evening). Compared with Austin, Dallas has higher average stoptimes for all trip types, both in the morning and evening. A two sample t-test was performed to test the significance of the difference in the mean daily stoptimes between routine stop commuters and non-routine stop commuters. This difference is statistically significant at the 10% level both for the morning and evening.

Figures 3.7 and 3.8 show the relative frequency distributions of the stoptimes for AM and PM trips with stops in Dallas, respectively. These figures illustrate the differences in the stoptime distributions for trips with and without routine stops. Because the majority of routine stops are made to serve passengers, the mean of the stoptime distribution for trips with routine stops was expected to be lower than the mean for trips with only non-routine stops. It is also shown that most of the morning commutes have shorter stoptimes for all three trip types. However, most of the evening trips have longer stoptimes for all trip types. Furthermore, chi-square tests indicate that the stoptime distributions are significantly different for non-routine trips and for routine trips in both morning and evening (AM: chi-square value of 12.63, df = 5 , p = 0.027; PM: chi-square value of 26.3, df = 5, $p < 0.001$). The above differences also exist in Austin.

CONCLUSION

The results presented in this chapter have highlighted the importance of trip chaining during the urban commute, and in urban tripmaking in general. No less than 25% of all AM commuting trips and 35% of PM trips involve at least one stop. Only about 21% of the responding commuters had no stops on any day in the PM commute, while only about 34% had no stops in the AM. The results clearly indicate that PM commutes involve more extensive trip chaining than AM commutes, reflecting less stringent constraints on the user.

The results pertaining to the frequency, extent, purpose and variability of trip chains are remarkably similar to those obtained in Austin in a previous study, suggesting transferability of behavioral characteristics across urban areas in Texas. However, results pertaining to the relative location of the stops (in terms of proximity to home or to the workplace) are different between the two cities, reflecting the underlying differences in size and spatial characteristics.

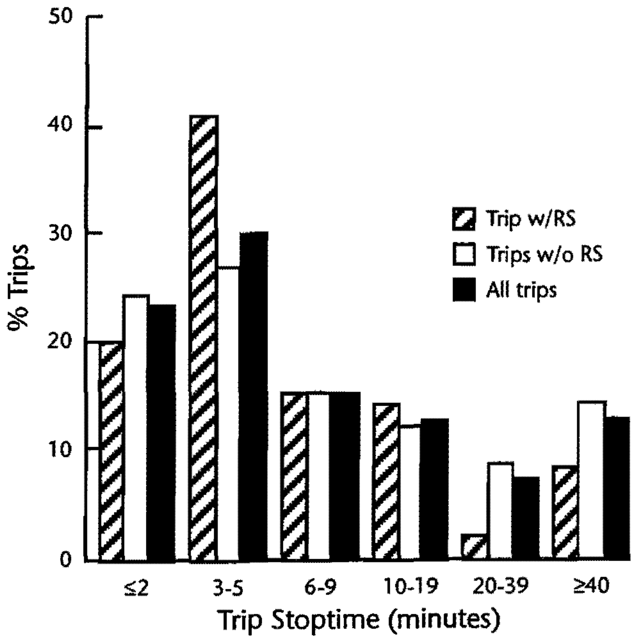


Figure 3.7 ***Relative frequency distribution of the stoptime for trips with stops on AM commutes, by trip type, Dallas***

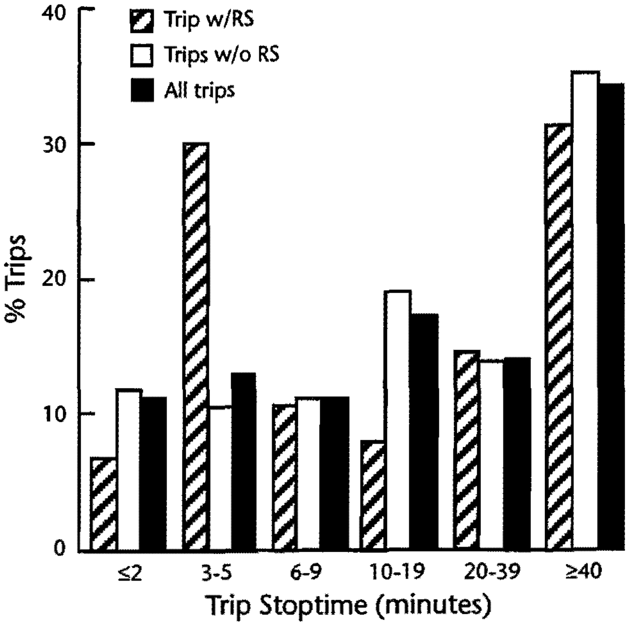


Figure 3.8 ***Relative frequency distribution of the stoptime for trips with stops on PM commutes, by trip type, Dallas***

CHAPTER 4. EXPLORATORY ANALYSIS OF THE VARIABILITY OF TRIP SCHEDULING AND ROUTE CHOICE

INTRODUCTION

This chapter presents the analysis of trip scheduling and route decisions of commuters. The second section documents the variation of commuter departure time decisions over the survey period. The third section describes the repetition and variability of commuters' route choices. The final section presents the analysis of the interaction between route and departure time decisions. It also describes the comparison of commuter behavior from the Austin survey with commuter behavior revealed by the Dallas survey.

DEPARTURE TIME DECISIONS

The departure time decision is one of the critical elements of the behavior of auto commuters. Understanding the variation in daily scheduling of commuting trips is important for several transportation systems improvement measures. In contrast to the controlled experiments of Mahmassani and colleague (Refs 5, 6), where the commuting system was dynamically evolving and not at equilibrium, the aggregate rate of switching in the diaries remains about the same over the 10-day period, although daily oscillations around the average rate are detectable. For example, the average ranges of variation of the daily switch rates for the day-to-day definition are about 11% and 8% for AM and PM commutes, as shown by Figures 4.1 and 4.2. These figures contain the aggregate switch rates for the first 10 days of the survey only (June 11 to June 22). Trips completed between June 25 and June 29 (from the second subwave of the diaries) are not included because the sample size is too small to compute meaningful aggregate switching rates.

In previous work, Mahmassani et al defined four ways of capturing departure time switching behavior as follows:

(1) median switching: switching from a commuter's median departure time;
(2) median switching, either WSC (work start controlled) or WEC (work end controlled): switching from a commuter's median departure time with work start time or end time controlled;
(3) day-to-day switching: switching from a commuter's previous day's departure time; and
(4) day-to-day switching (WSC or WEC): day-to-day switching with work start or end time controlled (Ref 10).

All definitions are subject to a minimum threshold value. The median was selected so as to capture deviations from a daily routine. The day-to-day definitions capture more switches because the current commute is considered a switch from the previous day whenever the absolute value of the difference between their departure times is greater than or equal to some minimum threshold (3, 5, and 10 minutes in this study). Departure time switching caused by a different work start or end time is avoided by considering only commuter trips with the same (mode) work time or end time (definition 2), or trips within 5 minutes of the previous work start or end time (definition 4).

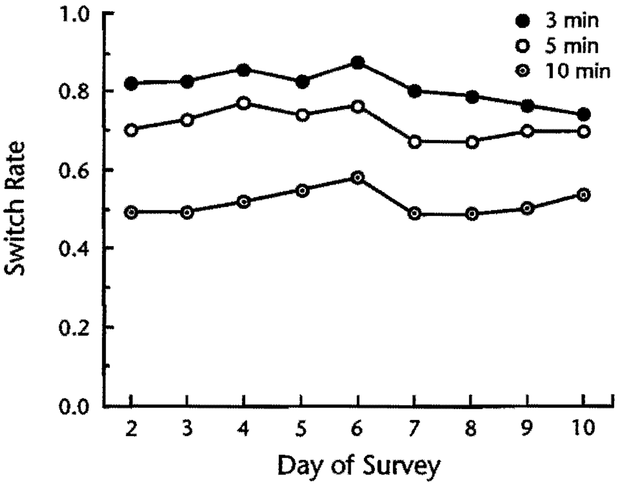


Figure 4.1 ***Daily AM departure time switch rate exhibited by commuters: day-to-day definition (uncontrolled work start). Day 1 is June 11***

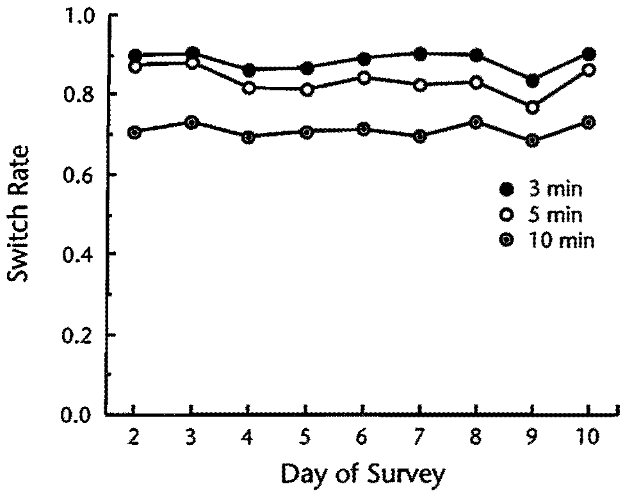


Figure 4.2 ***Daily PM departure time switch rate exhibited by commuters: day-to-day definition (uncontrolled work end). Day 1 is June 11***

Results of the departure time switching analysis are presented in Table 4.1. It is clear that commuters engage in a substantial amount of switching, for both morning and evening commutes in both cities. Departure time switching for the evening commute is more frequent than that for morning trips, under all definitions and thresholds. The day-to-day switching (definition 3) results in the highest percentage of switches among the other definitions, as expected. Even under the most restrictive case, definition 2 with a 10-minute threshold, at least 19% of AM trips and 40% of PM trips are switches in both cities. The 5- and 10-minute thresholds are appealing for the purpose of this study because they correspond better with clock time than the 3-minute threshold, which may be considered as "noise" rather than as corresponding to actual intended changes in departure time.

Chi-squared tests of the similarity between Dallas and Austin in terms of the presence of a 3, 5, or 10 minutes switch (total trips are divided into two categories, switch and no switch, for each threshold) were performed. Table 4.2 summarizes the test results for departure time switching. The null hypothesis that the overall switching pattern between Dallas and Austin is similar can be rejected at the 1% level of confidence for all definitions during the morning commute, and the first two definitions during the evening commute. However, the null hypothesis cannot be rejected for the day-to-day switch (definition 3 and 4) at the 3 or 5 minutes switch level for the evening commute. The overall switching pattern between these two cities is different for day-to-day 10-minute switches in the PM.

A commuter needing to make a non-routine stop(s) on the way to or from work will generally incur the stop duration(s) and the stop-induced extra travel time. Accordingly, this commuter may decide to shift departure time, arrival time, or both. An independence test is performed to determine whether trips with stops are more likely to be switches. To perform the test, the chi-squared statistic was computed for the hypothesis that the presence of a stop on a given commute is independent of whether that trip is a departure time switch or not. For the day-to-day definition, the presence of a stop on the current or the previous trip results in the 'stop-influence' on the current trip. For AM trips, the results, which are similar to the Austin results, led to the rejection of the independence hypothesis with over 95% confidence for all departure time switching definitions, confirming that trips with stops or stop-influence have a higher likelihood of inducing a switch. Table 4.3 summarizes the conditional fraction of trips with stops, given that the trip is a switch, for the various switch indicators, for AM commutes in Dallas and Austin. As shown, the proportion of trips with stops increases as the threshold increases. For all categories, this proportion is larger than the corresponding unconditional proportion. For PM trips, however, the independence hypothesis cannot be rejected even at the 30% significance level, for all definitions other than the 5-minute day-to-day definition. These results indicate that PM departure time switching is not significantly influenced by trip chaining considerations, possibly due to less stringent time constraints for the trip from work to home. Although the pattern in Dallas does not significantly differ from that in Austin, the values for Dallas in Table 4.3 are all less than those for Austin.

Table 4.1 Results of departure time switching analysis (WSC = work start controlled; WEC = work end controlled)

Percent of AM Trips that are Departure Time Switches

		Switch Threshold (minutes)			
Definition		**3**	**5**	**10**	**Considered Trips**
1. Median	D	69.7	58.6	38.8	1,720
	A	61.7	46.6	27.4	1,329
2. Median (WSC)	D	61.7	50.2	31.0	1,275
	A	54.7	39.6	19.5	1,077
3. Day-to-Day	D	78.7	69.5	49.1	1,520
	A	73.2	62.1	42.1	1,167
4. Day-to-Day (WSC)	D	75.7	65.4	42.5	1,235
	A	69.8	57.0	34.4	965

Percent of AM Trips that are Departure Time Switches

		Switch Threshold (minutes)			
Definition		**3**	**5**	**10**	**Considered Trips**
1. Median	D	75.8	68.4	55.2	1,633
	A	70.3	63.0	50.0	1,298
2. Median (WEC)	D	70.1	62.3	48.5	1,112
	A	63.8	55.7	40.8	961
3. Day-to-Day	D	86.6	81.7	70.0	1,434
	A	85.7	79.8	65.8	1,136
4. Day-to-Day (WEC)	D	82.7	76.4	62.3	1,047
	A	81.9	74.6	58.8	878

D: Dallas A: Austin

Table 4.2 Testing results of departure time switching analysis for Dallas and Austin

AM

	Switch Threshold (minutes)			
Definition	**3**	**5**	**10**	**Number of Trips**
1. Median	R	R	R	1,720
2. Median (WSC)	R	R	R	1,275
3. Day to-Day	R	R	R	1,520
4. Day-to-Day (WSC)	R	R	R	1,235

PM

	Switch Threshold (minutes)			
Definition	**3**	**5**	**10**	**Number of Trips**
1. Median	R	R	R	1,633
2. Median (WEC)	R	R	R	1,112
3. Day-to-Day	NR	NR	R	1,434
4. Day-to-Day (WEC)	NR	NR	R*	1,047

R: rejected at 1% level of significance
R*: rejected at 15% level of significance
NR: cannot be rejected at 20% level of significance

The values in Table 4.1 do not highlight differences across individuals, especially since different commuters reported different numbers of trips during the survey period. Switching ratios were obtained by dividing the number of switches by the number of possible switches, for each individual, for each departure time switching definition (a ratio of 1.0 indicates a switch on every possible day). Figures 4.3 and 4.4 depict the differences between departure time switching definitions by showing the cumulative relative frequency distributions (across commuters) of the alternate departure time switching ratios (for controlled work start/end times). For example, the percentage of workers never switching departure time for AM commutes is 30% according to the 10-minute median definition (40% for Austin), 22% by the 10-minute day-to-day definition (30% for Austin), 13% by the 5-minute median definition (14% for Austin), or 8% by the 5-minute day-to-day definition (7% for Austin). These discrepancies underscore the importance of definitional issues with regard to departure time switching. According to the conservative 10-minute median definition, only 12% of commuters never switched departure times in the evening (19% for Austin), and 49% had a switch ratio of 0.5 or higher (37% for Austin). Only 9 percent of the workers never switched departure times by the 10-minute day-to-day definition, 5 percent by the 5-minute median definition, or 3 percent by the 5-minute day-to-day definition The emerging picture of PM commuting habits clearly suggests high variability of the daily departure time from work.

Table 4.3 ***Impact of trip chaining on departure time switching behavior of AM commutes (uncontrolled work start). Proportion of AM trips with stops or stop-influence (for day-to-day) given that the trip is a switch (unconditional proportion is given in parenthesis)***

Threshold		Median	Day-to-Day
3 minute	D	0.254 (0.249)	0.376 (0.358)
	A	0.269 (0.252)	0.389 (0.364)
5 minute	D	0.276 (0.249)	0.391 (0.358)
	A	0.283 (0.252)	0.408 (0.364)
10 minute	D	0.306 (0.249)	0.423 (0.358)
	A	0.314 (0.252)	0.436 (0.364)

ROUTE DECISIONS

Route choice is also an important element of commuter behavior in this analysis. For transportation planning purposes, an understanding of actual route choices is critical to the effectiveness of traffic assignment models. Prior laboratory-like experiments by Mahmassani and colleagues considered only two routes as possible choices for commuters (Refs 5, 6). In this section, commuter route decisions are observed in a real urban network, containing several feasible routes between each commuter's home and workplace. The goal of this section is to explore the repetition and variability of the commuters' route choices during the two-week survey period.

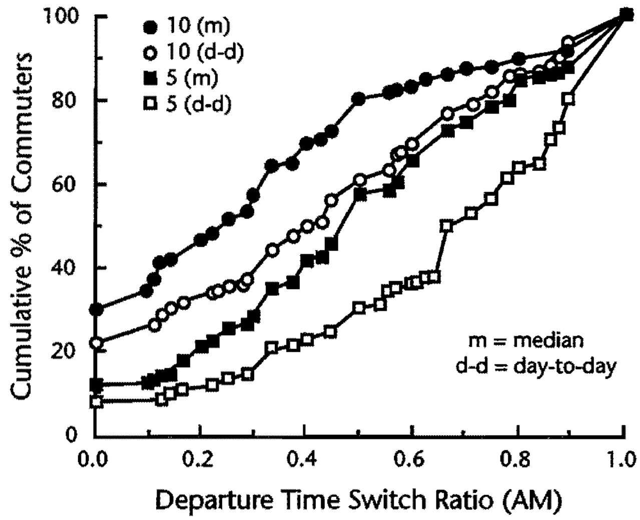


Figure 4.3 ***Cumulative distributions of departure time switch ratios for WSC case, by definition, AM commutes. Sample sizes are 176 for median and 170 for day-to-day (commuters included if had 3 or more switching opportunities***

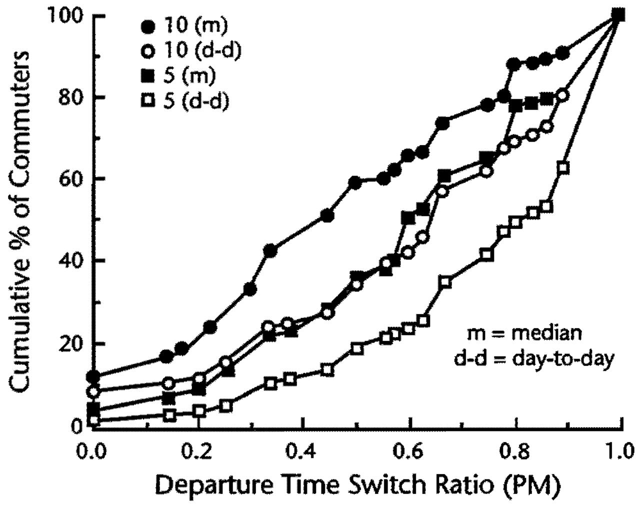


Figure 4.4 ***Cumulative distributions of departure time switch ratios for WEC case, by definition, PM commutes. Sample sizes are 147 for median and 145 for day-to-day (commuters included if had 3 or more switching opportunities)***

Three definitions of route switching are investigated here:

(1) mode (all days) switching: switching from a commuter's mode or most frequently used route,
(2) mode (days with no stops only) switching: same definition as (1) but considering only those days with no stops,
(3) day-to-day switching: switching from a commuter's previous day's route.

Note that a route is defined as a unique sequence of network nodes.

Table 4.4 summarizes the results of Dallas and Austin route switching analysis. As with departure time switching, route switching is more frequent during PM commutes than during AM commutes for all definitions except definition 2 for Dallas. Departure time switching is more frequent than route switching for AM and PM commutes in both cities. For definition 1, fewer than three in ten AM trips and two in five PM trips utilize a non-mode (i.e., other than the usual) route, showing that most commuters use a single route to commute. As expected, the percentage switches under definition 2 are all less than when trips contain stops, in both cities. Furthermore, the day-to-day definition captures more route switching than other definitions. The lower percentage of route switching compared with departure time switching is consistent with the results of commuting experiments (Ref 5).

Generally, Dallas has a larger percentage of switches than Austin in the morning and almost the same percentage of switches in the evening, under all definitions. The likely reasons are the city size difference and work start time constraint. In other words, there are more opportunities for commuters to switch routes to arrive at their workplace on time in Dallas. However, there does not appear to be much difference in evening route switching between these two cities, mostly because the home arrival time constraint is not as stringent during the evening.

As in the departure time analysis, route switch ratios were calculated for each commuter by dividing the number of actual switches by the number of possible switches, for each route switching definition (a ratio of 1.0 indicates a switch on every possible day). The cumulative distributions of the three route switching ratios for AM and PM trips are given in Figures 4.5 and 4.6, respectively.

When all days are analyzed, 30.4% (46% for Austin) of the users never switch from the mode route during AM commutes, while only 16.8% (15.5% for Austin) of them never switch during the PM commute; 17.5% of commuters in the morning and 32.4% in the evening switch from this mode with a frequency of more than one in two days. Furthermore, very little switching relative to the mode route occurs if only no-stop routes are considered, as 56.9% (78.6% in Austin) of the users never switch routes under these circumstances in the morning and 60.8% (64.3% for Austin) never switch routes in the evening. Only 8.4% of

Table 4.4 Results of route switching analysis. (percent of trips that are switches)

AM Trips

Definition		% Switches	Number of Trips
1. Mode (all days)	A	17.5	1,339
	D	26.6	1,725
2. Mode (days with no stops only)	A	6.5	1,002
	D	15.9	1,294
3. Day-to-Day	A	26.0	1,175
	D	36.9	1,528

PM Trips

Definition		% Switches	Number of Trips
1. Mode (all days)	A	36.1	1,312
	D	35.8	1,639
2. Mode (days with no stops only)	A	12.7	796
	D	13.0	1,050
3. Day-to-Day	A	53.2	1,148
	D	49.9	1,444

A: Austin D: Dallas

commuters in the morning and 5.2% in the evening have a switch ratio greater than 0.5 under this definition. Under the day-to-day definition, 31.4% (20.3% for Austin) of commuters in the morning and 52.7% (52.9% for Austin) in the evening have a switch ratio greater than 0.5. Clearly, the need to link one or more activities along the commute influences path selection, and causes a substantial amount of route switching, even for those who would not change routes otherwise.

By definition, the spatial aspect of trip chaining is strongly associated with the route choice, as commuters needing to make a stop on the way to work may have to deviate from their mode route. The chi-squared statistic was computed to test the hypothesis that the presence of a stop (or 'stop-influence') on a given commute is independent of whether that trip is a route switch (for the day-to-day definition, the presence of a stop on the current or the previous trip results in the 'stop-influence' on the current trip). For AM and PM trips, the results, which again are the same as for Austin, led to the rejection of the independence hypothesis with over 95% confidence for both route switching definitions, confirming that trips with stops or stop-influence have a higher likelihood of inducing a route switch. Table 4.5 summarizes the proportion of trips with stops conditional on the switch indicator, for AM and PM commutes. For both definitions, this proportion is much larger than the corresponding unconditional proportion. Almost 50% of all route switches in Dallas are stop-influenced, indicating the importance of trip chaining in route decisions. Again, the values for Dallas in Table 4.5 are all less than those for Austin, which suggests that other effects, such as the availability of more route choice opportunities and the longer commutes in Dallas, influence route switching.

JOINT ROUTE AND DEPARTURE TIME DECISIONS

A joint switch consists of both a departure time and route switches on a given commute. The analysis of joint switching provides a better understanding of temporal and spatial commuting behavior concurrently.

Four definitions for joint switching are investigated:

(1) median/mode switching: defined as a median departure time switch together with a mode (all days) route switch;
(2) median/mode (WSC or WEC) switching: defined as a median departure time with work start time or end time controlled together with a mode (all days) route switch;
(3) day-to-day switching: defined as a day-to-day departure time switch together with a day-to-day route switch; and
(4) day-to-day (WSC or WEC) switching: defined as a day-to-day with work start or end time controlled together with a day-to-day route switch.

The first two definitions capture switching from a routine trip, whereas the last two definitions would reflect changes from non-routine trips.

Results of the Dallas and Austin joint departure time and route switching analysis for AM and PM trips are presented in Table 4.6. More joint switching occurs during the evening commute, consistent with the higher PM switching frequencies for departure time and route separately. For the morning commute, the highest percentage of trips in which such joint switches take place is 31.5%, obtained using the 3-minute day-to-day departure time and the day-to-day route switching definitions. The lowest percentage is 4.4%, obtained with the 10-minute median departure time (work start controlled) and mode route definitions. For evening commutes, the highest percentage of trips in which joint switches take place is 46.6% (again for the 3-minute day-to-day departure time and the day-to-day route switching definitions). The lowest percentage is 16.9%, also for the 10-minute median departure time (work start controlled) and mode route definitions. Note that more than two

Table 4.5 ***Impact of trip chaining on route switching behavior of commuters. Proportion of trips with stop-influence given that trip is a switch. Unconditional proportion is given in parenthesis***

Switch Definition		AM	PM
1. Mode (all days)	D	0.475 (0.249)	0.700 (0.361)
	A	0.671 (0.252)	0.732 (0.393)
2. Day-to-Day	D	0.677 (0.358)	0.833 (0.506)
	A	0.801 (0.364)	0.854 (0.564)

A: Austin D: Dallas

in five evening commutes are joint 5-minute day-to-day switches. This variability at the individual level suggests a high potential for variable aggregate temporal and spatial demand patterns during the evening peak period, even for individuals traveling between work and home.

Compared with Austin, Dallas has a higher fraction of the morning commutes, and about the same fraction of the evening commutes that constitute joint switches. A possible explanation, as mentioned in the previous section, is that the larger size of the Dallas area offers greater opportunities for commuters to switch jointly in order to arrive the work place on time. However, the relatively less stringent nature of home arrival time constraints in the evening coupled with the desire to not remain at work longer than necessary in both cities tend to result in similar fractions of joint switches for the evening commutes.

Chi-squared tests were performed for the hypothesis that the joint switching patterns are similar between Dallas and Austin for the 3, 5, or 10 minutes switch threshold (total trips are divided into switch and no switch two categories for each threshold). Table 4.7 summarizes the test results, indicating that the null hypothesis can be rejected at the 1% level of confidence for all definitions during the morning commute. However, the null hypothesis cannot be rejected for all definitions during the evening commute.

Chi-squared statistics were computed for the hypothesis that the presence of a stop (or stop influence) on a given commute is independent of whether that trip is or is not a joint route and departure time switch. For both AM and PM trips, and in both Austin and Dallas, the results led to the rejection of the independence hypothesis with over 99.9% confidence for all joint switching definitions, confirming that trips with stops or stop-influence have a higher likelihood of inducing a switch. This result is not surprising in light of the interdependence between trip chaining and route choice detailed in the previous section.

Table 4.8 summarizes the proportion of trips with stops conditional on the various joint switch indicators. For all categories, this proportion is much larger than the corresponding unconditional proportion. At least 50% of all joint median/mode switches contain stops, and at least 64% of all joint day-to-day switches are

Table 4.6 ***Results of joint departure time and route switching analysis (WSC = work start controlled, WEC = work end controlled)***

Percent of AM Trips that are Joint Switches

Definition		Departure Time Switch Threshold (minutes) 3	5	10	Number of Trips
1. Median mode	A	12.2	10.0	7.2	1,329
	D	21.5	19.2	15.2	1,720
2. Median mode (WSC)	A	9.0	7.2	4.4	1,077
	D	15.8	13.3	10.5	1,275
3. Day-to-Day	A	21.2	19.3	15.3	1,167
	D	31.5	29.0	22.3	1,520
4. Day-to-Day (WSC)	A	17.5	15.5	11.6	965
	D	30.6	27.8	20.3	1,235

Percent of PM Trips that are Joint Switches

Definition		Departure Time Switch Threshold (minutes) 3	5	10	Number of Trips
1. Median mode	A	26.7	24.3	19.3	1,298
	D	28.7	26.3	21.8	1,633
2. Median mode (WSC)	A	24.8	22.3	16.9	961
	D	24.7	22.3	17.6	1,112
3. Day-to-Day	A	46.6	43.9	37.6	1,136
	D	44.6	42.8	37.6	1,434
4. Day-to-Day (WSC)	A	44.9	41.6	34.6	878
	D	40.6	38.0	31.7	1,047

A: Austin D: Dallas

influenced by stops. These results further amplify the need to consider trip chaining in the spatial and temporal framework of commuting behavior. From Table 4.8, we know that the values for Dallas are all smaller than the one for Austin in the morning. However, there appears to be little difference between Dallas and Austin in the evening. These findings are quite similar to those obtained for departure time switching and route switching separately.

Table 4.7 Testing results of joint switching analysis for Dallas and Austin

AM				
	Switch Threshold (minutes)			
Definition	3	5	10	Number of Trips
1. Median/Mode	R	R	R	1,720
2. Median/Mode (WSC)	R	R	R	1,275
3. Day-to-Day	R	R	R	1,520
4. Day-to-Day (WSC)	R	R	R	1,235

PM				
	Switch Threshold (minutes)			
Definition	3	5	10	Number of Trips
1. Median/Mode	NR	NR	NR	1,633
2. Median/Mode (WEC)	NR	NR	NR	1,112
3. Day-to-Day	NR	NR	NR	1,434
4. Day-to-Day (WEC)	NR	NR	NR	1,047

R: rejected at 1% level of significance
NR: cannot be rejected at 20% level of significance

Table 4.8 Impact of trip chaining on joint switching behavior of AM and PM commutes (uncontrolled work start/end). Proportion of trips with stops or stop-influence (for day-to-day) given that trip is a switch. Unconditional proportion is in parenthesis

AM Trips			
Threshold		Median/Mode	Day-to-Day
3 minute	D	0.520 (0.249)	0.653 (0.358)
	A	0.735 (0.252)	0.810 (0.364)
5 minute	D	0.509 (0.249)	0.648 (0.358)
	A	0.767 (0.252)	0.849 (0.364)
10 minute	D	0.505 (0.249)	0.656 (0.358)
	A	0.802 (0.252)	0.835 (0.364)

PM Trips			
Threshold		Median/Mode	Day-to-Day
3 minute	D	0.701 (0.361)	0.782 (0.506)
	A	0.723 (0.393)	0.847 (0.564)
5 minute	D	0.699 (0.361)	0.776 (0.506)
	A	0.718 (0.393)	0.850 (0.564)
10 minute	D	0.725 (0.361)	0.789 (0.506)
	A	0.724 (0.393)	0.843 (0.564)

A: Austin D: Dallas

CHAPTER 5. TRIP CHAINING AND SWITCHING FREQUENCY MODELS

INTRODUCTION

In this chapter, models are developed to relate trip chaining, route, departure time, and joint switching patterns to three types of factors:

(1) socio-economic characteristics;
(2) workplace conditions; and
(3) traffic system characteristics.

To provide useful insights into the potential transferability of the commuter behavior characteristics, comparisons are made with the results of a previous study conducted in Austin, Texas. The Poisson regression model, used to analyze trip chaining and three types of switching behavior is discussed first, along with the likelihood ratio test used in the comparison between Austin and Dallas. The subsequent sections present models relating daily stop, departure time switching, route switching, and joint switching frequency, respectively, to the commuter's attributes and traffic conditions.

METHODOLOGICAL BACKGROUND

Several mathematical models are developed to investigate the attributes that influence commuter behavior for both the morning and evening commutes. These models address, respectively, the following aspects of commuter behavior: daily stop frequency, daily departure time switching, daily route switching, and daily joint (route and departure time) switching. The Poisson regression model form is used for those four models because the dependent variables of concern are integer-valued variables, which are also equal to zero for a relatively large number of observations (commuters). Such situations cannot be handled satisfactorily by ordinary regression models.

The probability of commuter i making Z_i switches in t_i recorded days is given by the Poisson probability model:

$$P(Z_i) = \frac{\exp(-\lambda_i)\,\lambda_i^{Z_i}}{Z_i!}$$

Where $\lambda_i = E[Z_i]$. Let α_i denote the mean number of daily switches, that is, $\alpha_i = \lambda_i/t_i$. Herein, the Poisson parameter is defined as $\log \alpha_i = \log \lambda_i/t_i = \beta X_i$ or $\log \lambda_i = \beta X_i + \log t_i$, where β is a vector of estimable parameters and X_i is a vector of socio-economic and commuting characteristics for commuter i.

The vector of parameters can be estimated by the standard maximum likelihood method. The likelihood function is given by:

$$L(\beta) = \pi \frac{\exp(-\lambda)_i\,\lambda_i^{Z_i}}{Z_i!}$$

which yields the log-likelihood function:

$$\log L(\beta) = \sum_i \left[-\exp(\beta X_i + \log t_i) + Z_i(\beta X_i + \log t_i) - \log Z_i!\right]$$

with gradient and Hessian

$$\frac{\partial \log L}{\partial \beta'} = \sum_i \left[-X_i \exp\left(\beta X_i + \log t_i\right) + Z_i X_i\right]$$

$$\frac{\partial^2 \log L}{\partial \beta' \partial \beta} = \sum_i \left[-\left(X_i X_i'\right) \exp\left(\beta X_i + \log t_i\right)\right]$$

The standard Poisson regression model assumes an equal number of trials for all commuters. However, data were not available for all commuters for all days. Hence the model used here is a modified version of the standard Poisson model.

A detailed discussion of the theoretical background of the Poisson regression model can be found in Lerman and Gonzalez (Ref 11). Applications of the Poisson regression model are also described elsewhere (Refs 10, 12).

In order to compare commuter behavior characteristics in Austin and Dallas, the coefficient estimates obtained from the respective samples are tested for equality. The likelihood ratio test is used for this purpose. By estimating parameters for the same model specification for the two samples separately, as well as for a pooled sample combining observations from both samples (restricted model), one can calculate the test statistic. The null hypothesis is that the corresponding vector of parameters is the same over the two underlying populations, i.e., that the restriction (of equality of parameters) is a true one. The test statistic is χ^2 distributed with degrees of freedom equal to the number of restricted parameters, and can be expressed as

$$-2\left[L\left(\beta^r\right) - L\left(\beta^u\right)\right]$$

where $L(\beta^r)$ is the log likelihood value at convergence for the restricted model and $L(\beta^u)$ is the likelihood value at convergence for unrestricted model. In this case, $L(\beta^u)$ is taken as the sum of the respective sample likelihoods (at convergence) for the two cities.

DAILY STOP FREQUENCY

In this section, Poisson regression models are presented to characterize the trip-chaining behavior observed during the morning and evening commutes. Model comparisons between Dallas and Austin are summarized towards the end of the section.

Morning Commute

Table 5.1 indicates that all variables have plausible signs and reasonably significant t-statistic values. In addition, the change from the initial log likelihood value (under $\beta = 0$) to the final log likelihood value (at convergence) is quite satisfactory.

Generally speaking, AM stop frequency is clearly influenced by socio-economic variables, workplace attributes, and individual preferences. Other influential attributes in the model are average AM no-stop travel time and walk time from parked car to office. In terms of socio-economic variables, female commuters are more likely to make stops than males, which is consistent with other findings that gender affects multi-purpose travel behavior (Refs 10, 13). Commuters forty-five years and older have a lower propensity to make stops than other commuters. One workplace condition variable influences the average AM daily stop frequency of commuters. Low power job type commuters ("low-power" jobs correspond to schedule-driven jobs, such as clerical workers, registered nurses, teachers) make fewer stops than other commuters.

Commuters who prefer to arrive at work at least fifteen minutes before the official work start time are found to be less likely to make stops, since they want to have a larger buffer before work. In other words, they may avoid stops in the morning so as not to have to leave earlier than desired in the morning. The effect of the PAT (preferred arrival time) on stop frequency was found to be non-linear. Commuters with a PAT below 15 minutes exhibited no systematic trends. Above the 15-minute threshold, a linearly negative effect was found until the PAT reached 60 minutes, which defined the upper limit of the negative effect on stop frequency.

Average no-stop travel time is positively correlated with frequency of stops, while the walk time from parked car to office has a significant negative effect on the dependent variable in the model. Possible explanations for these two variables were addressed in previous work (Ref 10).

Table 5.1 *Estimation results for Poisson regression model of daily stop frequency for AM commute. Calibrated for those with at least three AM trips, Dallas*

AM Stop Frequency Model		
Independent Variable	**Estimated Coefficient**	**t-statistic**
Constant	-1.106	-5.70
Average AM no-stop travel time, in minutes	0.012	3.11
Gender (1 if male, 0 if female)	-0.427	-2.89
45 and over age indicator (1 if age ≥ 45)	-0.421	-2.71
Low power job type indicator (1 if yes)	-0.802	-4.18
Preferred arrival time, in min (0 if PAT≤15; [PAT-15] if 15<PAT≤60; and 45 if PAT>60)	0.019	3.86
Walk time from parked car to office, in min. (WALKTM if WALKTM≤10,10 if WALKTM>10)	-0.095	-4.69
Log-likelihood at zero	-921.99	
Log-likelihood at convergence	-230.27	
Number of observations	160	

Evening Commute

Table 5.2 contains the estimation results of the PM daily stop frequency model. Note that more stops are expected during the evening commute than during the morning because of fewer scheduling constraints in the evening (as shown in Chapter 3).

As in the AM daily stop frequency model, gender and the low power job type indicator decrease the expected number of stops of tripmakers. In contrast to the findings of the AM model, young commuters (≤ 29) make fewer PM stops than others. This could be an indication that older commuters require more stops for their household responsibilities. The home ownership indicator variable suggests that those who rent make more PM stops than those who own.

Two workplace variables, work end time and walk time indicators, are found to be important in this model. The negative sign of the work end time indicator suggests that those with work end time later than 5 PM are likely to make fewer stops than others. This implies that commuters with late work end times are more concerned about getting home than pursuing non-work stops. The other workplace variable, walk time from office to parked car, was also significant in the morning model. The main difference is that the effect of walk time is found to be dichotomous in the evening.

The traffic condition attribute, average no-stop travel time, increases the likelihood of making more stops along the PM commute, similarly to the morning stop frequency model.

Comparison with Austin Results

The likelihood ratio test is performed here to investigate the validity of stop frequency behavior transferability and to understand the underlying commuter stop frequency behavior between Austin and Dallas. Table 5.3 summarizes the test results of daily stop frequency behavior during the morning and evening commutes for the two samples.

It can be established through further statistical tests that socio-economic, commuter preference, and workplace condition variables have the same effects on morning stop frequency behavior in both cities, while the descriptor of traffic conditions (average no-stop travel time) has different effects (i.e. coefficient values) in each city. For evening stop frequency behavior, none of the coefficients of the explanatory variables exhibit significant differences between Austin and Dallas. This is a powerful result that suggests good transferability of the models of trip chaining frequency across Texas cities.

Table 5.2 *Estimation results for Poisson regression model of daily stop frequency for PM commute. Calibrated for those with at least three PM trips, Dallas*

PM Stop Frequency Model		
Independent Variable	**Estimated Coefficient**	**t-statistic**
Constant	-0.430	-4.96
Average PM no-stop travel time, in minutes	0.010	5.04
Gender (1 if male, 0 if female)	-0.569	-10.34
29 and under age indicator (1 if age $\leq$ 29)	-0.470	-5.31
Work end time (WET) past 5PM, in hours ([WET-5] if WET>5PM, 0 otherwise)	-0.193	-3.84
Low power job type indicator (1 if Yes)	-0.147	-2.27
Home ownership indicator (1 if renting, 0 otherwise)	0.237	4.20
High walk time from office to car, in min (1 if WALKTM$\geq$5 minutes)	-0.362	-6.23
Log-likelihood at zero	-683.91	
Log-likelihood at convergence	-393.56	
Number of observations	155	

Table 5.3 *Testing results of stop frequency behavior for Dallas and Austin*

	Daily Route Switching Behavior	
Test Summary	**AM**	**PM**
Similarity	socio-economic workplace condition commuter preference	socio-economic workplace condition traffic condition
Significant Difference	traffic condition	none

DEPARTURE TIME SWITCHING FREQUENCY

The model developed here postulates that the mean daily switching rate (or frequency) can be systematically related to the characteristics of the commuter and of the commuter environment.

Morning Commute

Table 5.4 presents the parameter estimation results of the daily departure time switching model for the morning commute. Note that only the day-to-day switching (with WSC or WEC) that exceeds a 10-minute threshold is considered in this model. The Table indicates that all variables are of plausible sign and reasonably significant t-statistic values. Generally speaking, AM departure time switching frequency is clearly influenced by workplace attributes, individual preference, and socio-economic variables. Other influential attributes in the model are the AM stop ratio (defined as number of trips with stops to total trips) and travel time variability. With regard to workplace characteristics, commuters with lateness tolerance at work and flexible work hours are likely to switch departure time more frequently than those without such tolerance and with regular or shift schedules. However, commuters with low power jobs have less propensity to switch than others. The AM stops ratio, which captures the effects of trip-chaining frequency, increases switch behavior up to a threshold.

One interaction variable, the high preferred arrival time indicator, captures the attributes of commuter preference and the workplace characteristics. Commuters with this indicator reveal more risk-seeking behavior than others do, with greater departure time switching in the AM. The other interaction term, the young male without lateness tolerance indicator, is a mixed effect of socio-demographic and workplace characteristics. It exhibits positive correlation with departure time switching. Only one traffic condition variable, the travel time variability indicator, has a significant effect on departure time switching. Those who experience travel time variability on the most often used commuting route, with a standard deviation (of the travel time) in excess of three minutes are likely to switch more frequently than others.

Table 5.4 *Estimation results for Poisson regression model of daily departure time switching frequency for Dallas AM commute (10-minute day-to-day definition, work start controlled)*

AM Departure Time Switching Model		
Independent Variable	Estimated Coefficient	t-statistic
Constant	-2.485	-8.998
Lateness tolerance at workplace (1 if ≥ 5 min)	1.371	4.910
Flexible work hours indicator (1 if yes)	0.428	4.205
Low power job type indicator (1 if yes)	-0.686	-5.530
AM stops ratio, if less than 0.75 (0 otherwise)	0.426	2.209
AM mode route travel time variability indicator (1 if std. deviation of tt ≥ 3 min)	0.245	2.210
High preferred arrival time indicator (1 if PAT ≥ 15 min and has no lateness tolerance)	0.932	3.378
Young male with no lateness tolerance indicator (1 if male, less than 45, and no latenesss tolerance)	0.517	3.390
Log-likelihood at zero	-777.16	
Log-likelihood at convergence	-271.40	
Number of observations	150	

Evening Commute

Table 5.5 contains the parameter estimation results of the PM departure time switching frequency model. Note that more departure time switching is expected during the evening commute than during the morning because of less stringent scheduling constraints in the evening.

Two workplace variables are found to be important in this model. The negative sign of the late work end time indicator suggests that those with late work end time (≥ 6:15 PM) are likely to switch departure time less frequently than those with earlier work end times. This implies that more commuters adjust their departure time to avoid traffic congestion during the peak hour. The other workplace variable is lateness tolerance at the workplace, which is also included in the final morning departure time switching frequency model specification. The parameter value implies that those who do not have to be at work on time are likely to switch departure time more frequently in the evening (a similar result was observed in Austin).

Commuters who make at least one routine stop (as defined in the previous chapter) along their PM commute are less likely to switch departure time on a daily basis. Such commuters typically have a longer total travel time (including the stop time, which is incurred almost daily), and many have to satisfy a constraint associated with the routine stop, thereby decreasing their propensity for departure time switching. Males over 44 years old and those commuters renting their home all tend to switch departure time less frequently. As in the morning departure time model, greater variation of the trip time on the usual (mode) route increases the likelihood of PM departure time switching.

Comparison with Austin Results

Table 5.6 summarizes the comparative test results of the model parameters calibrated for Austin and Dallas respectively, for both AM and PM commutes. Socio-economic, commuter preference, and workplace condition variables have similar effects on the morning departure time switching behavior in both cities, while the trip chaining factor (stops ratio ≤ 0.75) exerts a significant different influence on it. With regard to the evening departure time switching behavior, the socio-economic and workplace condition variables, as well as the routine stop factor all have the same degree of impact on both cities. No attributes exhibit significantly different effects on departure time switching behavior between Austin and Dallas for the evening commute.

ROUTE SWITCHING FREQUENCY

Morning Commute

The results of the AM daily model of route switching frequency (from the mode route, definition 1 in Chapter 4) are presented in Table 5.7. All variable coefficients are quite significant, with reasonably high t-statistics. The AM stops ratio, up to 0.75, the mode route travel time variability indicator, as well as the access indicator have a positive effect on the daily number of route switches for the AM commute.

Table 5.5 Estimation results for Poisson regression model of daily departure time switching frequency for Dallas PM commute (10-minute day-to-day definition, work end controlled).

PM Departure Time Switching Model		
Independent Variable	Estimated Coefficient	t-statistic
Constant	-0.694	-9.49
Lateness tolerance at workplace (1 if ≥ 5 min)	0.19	2.86
Late work end time indicator (1 if work end time≥6:15)	-0.260	-2.70
PM routine stopper indicator (1 if makes a routine stop on PM commute)	-0.486	-4.05
Coefficient of variation of non-stop PM travel time (std. dev. travel time/mean travel time)	0.52	3.67
Home ownership indicator (1 if renting, 0 other)	-0.338	-4.19
Male over 44 indicator (1, if male and over age 44)	-0.233	-2.46
Log-likelihood at zero	-524.0	
Log-likelihood at convergence	-322.4	
Number of observations	134	

Table 5.6 Testing results of departure time switching behavior for Dallas and Austin

Daily Route Switching Behavior		
Test Summary	AM	PM
Similarity	socio-economic workplace condition commuter preference	socio-economic workplace condition routine stop
Significant Difference	trip-chaining factor	none

This indicates that commuters are likely to engage in more route switching when they make more stops (but only up to a threshold) along the commute. However, as the stops ratio exceeds 0.75, its effects become negative, as users with routine daily stops tend to follow the same route everyday. Those commuters who have several alternate routes available, have a medium length commute, but who experience high travel time variability on their most frequently traveled route, tend to make more route switches. The results also indicate that male commuters with lateness tolerance at the workplace are less likely to switch route, probably because their behavior is not much restricted by the work start time.

Evening Commute

The estimation results of the model of daily route switching frequency for the PM commute are shown in Table 5.8. As for the AM model, the number of route switches increases as the stops ratio increases up to a point and then decreases after that. Two traffic system attributes, the late PM peak hour indicator and the medium travel time indicator, exert a positive influence on route switching. To avoid traffic congestion, commuters with work end times between 5:46 and 6:15 apparently make more route switches than others. Commuters who normally experience medium travel times on their mode route tend to switch more than others.

Comparison with Austin Results

The comparative test results of daily route switching behavior for Austin and Dallas during the morning and evening commutes are presented in Table 5.9. Again, the socio-economic, workplace condition, and routine stop variables all have similar contribution to the AM and PM route switching behavior in both cities. Only one variable, the trip chaining factor (stops ratio ≤ 0.75), has a different influence on AM route switching behavior in Austin and Dallas.

Table 5.7 ***Estimation results for Poisson regression model of daily mode route switching frequency for Dallas AM commute (all days definition)***

AM Route Switching Model		
Independent Variable	**Estimated Coefficient**	**t-statistic**
Constant	-1.85	-23.26
AM stops ratio, if less than 0.75 (0.75 if ≥ 0.75)	1.12	5.494
Additional AM stops ratio over 0.75 ([ratio-0.75], if ratio ≥ 0.75)	-3.89	-4.501
Males with lateness tolerance indicator (1 if male and has over 5 min tolerance)	-0.32	-5.197
AM mode route travel time variablity and access indicator (1 if std. deviation of tt ≥ 3 min, additional routes are available, and avg. tt is between 15 & 30 minutes)	1.05	5.802
Log-likelihood at zero	-980.99	
Log-likelihood at convergence	-286.60	
Number of observations	165	

Table 5.8 ***Estimation results for Poisson regression model of daily mode route switching frequency for Dallas PM commute (all day definition)***

PM Route Switching Model		
Independent Variable	**Estimated Coefficient**	**t-statistic**
Constant	-1.888	-18.41
PM stops ratio, if less than 0.75 (0.75 if ≥ 0.75)	1.502	7.61
Additional PM stops ratio over 0.75 ([ratio-0.75], if ratio ≥ 0.75)	-2.272	-3.43
Late PM peak hour indicator (1 if work end is between 5:46 and 6:15)	0.287	2.56
PM mode route medium length travel time indicator (1 if average tt is between 20 and 30 minutes)	0.390	3.88
Log-likelihood at zero	-726.94	
Log-likelihood at convergence	-305.57	
Number of observations	162	

Table 5.9 ***Testing results of route switching behavior for Dallas and Austin***

Daily Route Switching Behavior		
Test Summary	AM	PM
Similarity	socio-economic workplace condition routine stop	workplace condition routine stop
Significant Difference	trip-chaining factor	none

JOINT ROUTE AND DEPARTURE TIME SWITCHING FREQUENCY

Morning Commute

The models presented consider a joint switch to consist of a day-to-day route switch and a 10-minute day-to-day departure time switch (with controlled work start or end times), as described in Chapter 4. Table 5.10 shows the attributes included in the specification of the AM joint switching frequency model, along with the corresponding coefficient estimates and t-values. As in the AM route switching model, the trip-chaining variable is also significant in the joint switching model, with the same sign. The lateness tolerance at the workplace indicator and the high preferred arrival time indicators included in the AM departure time switching model are also significant explanatory variables here. The commuters with median travel time with high variance on the mode route are likely to make more joint switches than others.

Evening Commute

Table 5.11 presents the estimation results of the PM day-to-day joint switching frequency model. Most of the independent variables included in the two individual PM switching models are also captured here, such as stops ratio, additional stops ratio, lateness tolerance at workplace, and coefficient of variation of travel time. Although the form of the peak period work end time indicator is a little different than the two individual PM switching models, it reveals the same finding that commuters tend to switch routes and departure times to avoid the delay they may encounter. The only significant socioeconomic variable, the age indicator, shows that middle-aged commuters are likely to make more joint switches than others.

Comparison with Austin Results

The test results of daily joint switching behavior for Austin and Dallas during the morning and evening commutes are presented in Table 5.12. As described in previous sections, the socioeconomic, workplace condition, and routine stop variables have a similar effect on the AM and PM route switching behavior in both cities. Again, the trip chaining factor (stops ratio ≤ 0.75) has a different effect on AM route switching behavior in Austin, as compared with Dallas. For the evening departure time switching behavior, no attributes were found to be significantly different between Austin and Dallas.

Table 5.10 Estimation results for Poisson regression model of daily joint switching frequency for Dallas AM commute (10-minute day-to-day [WSC] departure time and day-to-day route definition)

AM Joint Switching Model

Independent Variable	Estimated Coefficient	t-statistic
Constant	-3.980	-15.12
AM stops ratio, if less than 0.75 (0.75 if ≥ 0.75)	1.327	5.09
Additional AM stops ratio over 0.75 ([ratio-0.75], if ratio ≥ 0.75)	-5.543	-3.35
Lateness tolerance at workplace (1 over 5 minutes)	1.215	4.35
High preferred arrival time indicator (1 if PAT>15 min and has no lateness tolerance)	1.220	4.45
AM mode route travel time variability indicator (1 if std. dev. of tt ≥ 3 min and average tt is between 15 and 30 minutes)	1.057	6.85
Log-likelihood at zero	-1103.5	
Log-likelihood at convergence	-253.4	
Number of observations	150	

Table 5.11 Estimation results for Poisson regression model of daily joint switching frequency for Dallas PM commute (10-minute day-to-day [WEC] departure time and day-to-day route definition)

PM Joint Switching Model		
Independent Variable	Estimated Coefficient	t-statistic
Constant	-2.372	-17.89
PM stops ratio, if less than 0.75 (0.75 if ≥ 0.75)	0.952	4.84
Additional PM stops ratio over 0.75 ([ratio-0.75], if ratio ≥ 0.75)	-3.135	-5.21
Lateness tolerance at workplace (1 over 5 minutes)	0.148	1.61
PM peak period work end time indicator (1 if work end time is between 5:15 and 6:15)	0.363	3.82
Coefficient of variation of non-stop PM travel time (std. deviation of travel time/mean travel time)	0.875	4.57
Age indicator (1 if age is between 30 and 60)	0.350	3.72
Log-likelihood at zero	-792.11	
Log-likelihood at convergence	-283.84	
Number of observations	141	

Table 5.12 Testing results of joint switching behavior for Dallas and Austin

Daily Joint Switching Behavior		
Test Summary	AM	PM
Similarity	socio-economic workplace condition routine stop commuter preference	socio-economic workplace condition routine stop
Significant Difference	trip-chaining factor	none

CHAPTER 6. COMPARISONS OF WAVES ONE AND TWO

INTRODUCTION

This chapter serves two purposes. One is to compare the behavior, including trip chaining, departure time, and route decisions from the first wave survey, with behavior revealed by the second wave survey, conducted approximately one year after the first. This is presented in the first two sections. The other purpose, addressed in the third section, is to analyze the repetition and variability of the behavior of those commuters who participated in both waves. The first section presents the exploratory analysis of trip chaining, departure time, and route decisions for waves one and two, along the lines of the analysis presented in Chapter 4. The second section presents Poisson regression models similar to those presented in Chapter 5 to characterize the trip chaining, departure time, and route switching behavior observed during the second wave survey. The final section describes the changes in behavior that might have taken place over time (about one year) for those participants in both waves.

TRIP CHAINING BEHAVIOR, TRIP SCHEDULING, AND ROUTE DECISIONS VARIABILITY

The number of AM and PM stops made in wave one and wave two is given in Tables 6.1 and 6.2. The number of stops is smaller in wave two because of the smaller sample size. In a chi-square test for independence, the null hypothesis that the relative frequency distributions of observed stops are similar in both waves is rejected at the 5% level of significance for morning trips (chi-square value of 10.27, 3 df, p = 0.016) and could not be rejected at the 20% level of significance for evening trips (chi-square value of 4.242, 3 df, p = 0.236). The results indicate that the distributions of number of stops during the evening commute for waves one and two exhibit no significant difference. Table 6.3 shows the frequency distributions of the activity types at stops made by wave one and wave two commuters. Over 50% of all AM stops for both waves are serve passenger or personal business activities. Personal business is the predominant activity pursued at stops during the commuting portion of the day, accounting for 33.6% of all AM and PM stops made in wave one and 27% in wave two. A chi-square test for independence led to rejecting the null hypothesis that the frequency distribution of purpose of stops in wave one is similar to the distribution in wave two at the 1% level of significance (chi-square value of 19.72, 4 df, p = 0.001) during the morning and at the 5% level of confidence (chi-square value of 9.896, 4 df, p = 0.042) during the evening commute. The results indicate that there are significant differences in the purposes of stops between wave one and wave two both in the morning and evening commutes. However, while statistically significant, it is not clear that these differences are practically meaningful. In particular, most of the discrepancies between the two waves could be explained by a greater number of "other" responses in wave 2, accounting for the small reductions in responses in the other categories. Given the subjective and sometimes ambiguous interpretation of these purposes, an increase in "other" may simply be a reflection of semantic interpretation rather than any real change in travel behavior.

Table 6.1 Number of AM stops (%) made in wave one and wave two

Number of stops	0	1	2	≥3	Total
Wave 1	1,294	360	63	7	1,724
	(75.1)	(20.9)	(3.7)	(0.4)	(100)
Wave 2	698	154	26	10	888
	(78.6)	(17.3)	(3.0)	(1.1)	(100)

Table 6.2 Number of PM stops (%) made in wave one and wave two

Number of stops	0	1	2	≥3	Total
Wave 1	1,050	419	127	42	1,638
	(64.1)	(25.6)	(7.8)	(2.6)	(100)
Wave 2	556	219	56	33	864
	(64.4)	(25.3)	(6.5)	(3.8)	(100)

Table 6.3 Activity types of stops made in wave 1 and wave 2 during morning and evening commutes

Activity Type	AM frequency	%	PM frequency	%
Serve passenger	132*	27.4	100	12.9
	(51)**	(21.7)	(46)	(10.6)
Personal business	177	36.8	246	31.6
	(75)	(32.0)	(107)	(24.7)
Food/Social/Recreational	77	16.0	127	16.3
	(29)	(12.3)	(83)	(19.2)
Shopping	16	3.3	146	18.8
	(20)	(8.5)	(90)	(20.8)
Other	79	16.4	159	20.4
	(60)	(25.5)	(107)	(24.7)
TOTALS	481	100.0	778	100.0
	(235)	(100.0)	(433)	(100)

*Wave 1; **Wave 2

Table 6.4 Average and standard deviation of duration of all stops for the trip to work, by activity type (in minutes), for wave one and wave two

	AM Commutes	
Activity Type	Wave 1 average (std dev)	Wave 2 average (std dev)
Serve passenger	4.4 (4.5) n=132	2.4 (3.2) n=51
Personal business	8.1 (14.4) n=177	9.7 (21.5) n=75
Food/Social/Recreational	15.2 (26.6) n=76	22.8 (31.0) n=29
Shopping	8.1 (7.1) n=16	4.9 (3.6) n=20
Other	46.9 (58.4) n=77	62.3 (66.5) n=60
ALL TYPES	14.5 (30.9) n=478	22.8 (44.2) n=235

Table 6.4 shows the average duration of all stops, by activity type, for waves one and two for AM commutes. Similar information is presented in Table 6.5 for PM commutes. The average durations in wave two are greater than in wave one, except for the serve passenger and shopping activities in the morning and personal business activity in the evening. The results indicate that wave two commuters tended to stop longer, on the average, than wave one commuters for the trips to work and to home. Again, this may be due to certain stops being classified as "other" in wave 2.

The analysis results for departure time switching are presented in Table 6.6. Under all definitions and thresholds (described in Chapter 4), departure time switching for the evening trips is more frequent than for the morning trips in both waves. The day-to-day definition yields the highest percentage of switches while the median (WSC or WEC) definition results in the lowest. Wave two has higher percentages of trips switching departure time than wave one has for the day-to-day definitions (definitions 3, 4) during both morning and evening commutes. However, the percentages of AM median departure time switching are lower for the AM and almost the same for the PM commutes in wave two. To test the independence of wave one and wave two, chi-square tests were performed on the presence of 3-, 5-, and 10-minute switches, respectively. The results of the tests are shown in Table 6.7. The null hypothesis, that the overall median switching pattern is similar between wave one and wave two, can be rejected at the 10% level of significance for the morning trips, but not at the 5% level. The corresponding hypothesis cannot be rejected (at the 10% level) for the evening trips. In general, the results are not very definitive, suggesting that changes in the overall pattern, if present, are of rather small magnitude.

Table 6.5 ***Average and standard deviation of duration of all stops for the trip to work, by activity type (in minutes), for wave one and wave two***

	PM Commutes	
Activity Type	**Wave 1 average (std dev)**	**Wave 2 average (std dev)**
Serve passenger	8.0 (12.1) n=99	9.8 (15.4) n = 46
Personal business	18.9 (37.8) n=246	13.4 (26.8) n = 107
Food/Social/Recreational	79.4 (91.7) n=124	92.7 (89.2) n= 83
Shopping	18.0 (15.0) n=144	19.7 (21.0) n= 90
Other	63.6 (57.4) n=155	66.1 (68.1) n = 107
ALL TYPES	36.1 (56.9) n=768	42.6 (63.2) n = 433

Table 6.6 ***Results of wave one and wave two departure time switching analysis (WSC = work start controlled; WEC = work end controlled)***

Percent of AM Trips that are Departure Time Switches

		Switch Threshold (minutes)			
Definition		**3**	**5**	**10**	**Observed Trips**
1. Median	W-1	69.7	58.6	38.8	1,720
	W-2	63.9	53.3	35.0	888
2. Median (WSC)	W-1	61.7	50.2	31.0	1,275
	W-2	59.2	46.8	27.4	682
3. Day-to-Day	W-1	78.7	69.5	49.1	1,520
	W-2	83.2	72.4	51.3	760
4. Day-to-Day (WSC)	W-1	75.7	65.4	42.5	1,235
	W-2	80.2	67.6	44.4	615

Percent of PM Trips that are Departure Time Switches

		Switch Threshold (minutes)			
Definition		**3**	**5**	**10**	**Observed Trips**
1. Median	W-1	75.8	68.4	55.2	1,633
	W-2	75.6	69.1	54.9	864
2. Median (WEC)	W-1	70.1	62.3	48.5	1,112
	W-2	69.4	62.2	45.9	614
3. Day-to-Day	W-1	86.6	81.7	70.0	1,434
	W-2	89.4	84.3	74.5	737
4. Day-to-Day (WEC)	W-1	82.7	76.4	62.3	1,047
	W-2	85.5	78.5	65.9	516

W-1: wave one W-2: wave two

Table 6.7 ***Tests results of wave one and wave two departure time switching analysis (WSC = work start controlled; WEC = work end controlled)***

AM

Definition	Switch Threshold (minutes)		
	3	5	10
1. Median	R	R	R*
2. Median (WSC)	NR	NR	R*
3. Day-to-Day	R	NR	NR
4. Day-to-Day (WSC)	R	NR	NR

PM

Definition	Switch Threshold (minutes)		
	3	5	10
1. Median	NR	NR	NR
2. Median (WEC)	NR	NR	NR
3. Day-to-Day	R*	R*	R
4. Day-to-Day (WEC)	NR	NR	NR

R: rejected at 5% level of significance
R*: rejected at 10% level of significance
NR: cannot be rejected at 10% level of significance

The results of the route switching analysis for the two waves are summarized in Table 6.8. As noted in Chapter 4, route switching is less frequent than departure time switching for AM and PM commutes in both waves. Moreover, route switching is more frequent during PM commutes than during AM commutes for all definitions except definition 2 for wave one. The lower percentage of switches for definitions 1 and 2 indicates that most commuters use one single route to commute. When trips contain no stops (definition 2), even more commuters (more than eight out of ten trips) use a mode route to commute, indicating the influence of trip chaining on route switching. Comparing wave one with wave two, wave two has a higher percentage of switches than wave one during the evening commute. From the results of chi-square tests as shown in Table 6.9, the null hypothesis that the route switching pattern between waves one and two are similar cannot be rejected at the 10% level of confidence for most definitions except mode (definition 2) for the morning and day-to-day for the evening commutes.

Although there are discrepancies between the two waves in the trip chaining behavior, including the frequency, purpose, and duration of the stops, these differences may not be practically meaningful because of the smaller sample size of wave two. Nevertheless, the importance of trip chaining in commuting behavior and the higher frequency of trip chaining in the PM commute were clearly confirmed by the wave two results. These results are consistent with the findings stated in Chapter 3. The results regarding changes in overall departure time and route switching between the two waves are not entirely conclusive. However, they do suggest a slight increase in switching frequency in the second wave, though the differences in the overall switching pattern between the two waves are rather small.

TRIP CHAINING AND SWITCHING FREQUENCY MODELS FOR WAVE TWO

In this section, Poisson regression models similar to those presented in the preceding chapter for the wave one data are developed for the wave two sample, for both morning and evening commutes. These models address, as before, daily stop frequency, daily departure time switching, and daily route switching.

Daily Stop Frequency

Table 6.10 presents the parameter estimation results of the daily stop frequency model for the AM commute for wave two. The attributes included in the specification are similar to those in the corresponding model for wave one, capturing the influence of socio-economic variables, workplace attributes, individual preferences, and average AM no-stop travel time on trip chaining in connection with the AM commute. The main difference in model specification between the two waves is that the walk time from the car park to the office, which had a significant effect in wave one, appears to be statistically insignificant in wave two (t-statistic = -0.32). Comparing the parameter estimates between waves, the absolute coefficient values of gender and preferred arrival time in wave two are greater than those in wave one, while those of age ≥ 45 and low power job type indicators are not. The results indicate that gender and PAT variables, on the average, have a larger influence on AM stop frequency in wave two. For example, in wave two, males make fewer stops, while commuters with low power jobs make more stops, on average.

Table 6.8 Results of wave one and wave two route switching analysis (percent of trips that are switches)

AM Trips

Definition		% Switches	Number of Trips
1. Mode (all days)	W-1	26.6	1,725
	W-2	23.9	888
2. Mode (days with no stops only)	W-1	15.9	1,294
	W-2	12.3	698
3. Day-to-Day	W-1	36.9	1,528
	W-2	37.1	760

PM Trips

Definition		% Switches	Number of Trips
1. Mode (all days)	W-1	35.8	1,639
	W-2	38.4	864
2. Mode (days with no stops only)	W-1	13.0	1,050
	W-2	15.5	556
3. Day-to-Day	W-1	49.9	1,444
	W-2	56.4	737

Table 6.9 Tests results of wave one and wave two route switching analysis (percent of trips that are switches)

Definition	AM Trips	PM Trips
1. Mode (all days)	NR	NR
2. Mode (days with no stops only)	R	NR
3. Day-to-Day	NR	R

R: rejected at 5% levels of significance
NR: cannot be rejected at 10% levels of significance

Table 6.10 Estimation results for Poisson regression model of daily stop frequency for AM commute of wave two. Calibrated for those with at least three AM trips

AM Stop Frequency Model

Independent Variable	Estimated Coefficient	t-statistic
Constant	-1.450	-10.98
Average AM no-stop travel time, in minutes	0.015	3.54
Gender (1 if male, 0 if female)	-0.826	-7.66
45 and over age indicator (1 if age ≥ 45)	-0.268	-2.15
Low power job type indicator (1 if yes)	-0.318	-2.46
Preferred arrival time, in min (0 if PAT ≤ 15; [PAT-15] if 15 < PAT ≤ 60; and 45 if PAT > 60)	0.028	11.27
Log-likelihood at zero	-582.89	
Log-likelihood at convergence	-215.86	
Number of observations	117	

The estimation results of the daily stop frequency model for the PM commute in wave two are shown in Table 6.11. As in the AM daily stop frequency model, the specification is essentially similar to the wave one model. However, the walk time, included in the model specification of wave one, is not statistically significant in wave two, as in the AM stop frequency model. The work end time variable is not statistically significant either and therefore is excluded from the specification. Comparison between waves indicates that gender and the low power job type indicator have the opposite interpretation as in the AM model. However, the age ≤ 29 indicator and no stop travel time have the same results identified in the AM model. It should be noted that the comparison results are quite limited in terms of commuter behavior, probably because of the small sample size for wave two.

Departure Time Switching Frequency

Table 6.12 presents the estimation results of the daily departure time switching model for the morning commute in wave two. As for wave one, the definition of switching adopted in this model consists of day-to-day switching subject to a 10-minute threshold, controlling for the work start time (i.e., WSC). The specification is essentially the same as for wave one. The main difference is that the "young male without lateness tolerance" indicator, significant in the wave one model, is not included in wave two because it is not significant. Comparing the parameters between the two waves, only the coefficients of the lateness tolerance at the workplace indicator and the high PAT indicator exhibit meaningful differences. Other parameters have almost the same magnitudes in both waves.

Table 6.13 contains the estimation results of the departure time switching frequency model for the PM commute in wave two. Only the home ownership indicator is included in both waves. Other variables, significant in the wave one model, are not included in wave two because of the lack of sufficient statistical significance of their estimated parameters. The individual and socio-economic attributes have negative correlation with the dependent variable. Commuters having low power jobs and who rent their homes make fewer departure time switches than other commuters. As in the morning departure time model, the traffic condition attribute "mode route travel time indicator" increases the likelihood of PM departure time switching. Another trip-chaining factor, the "additional PM stops ratio over 0.75," exhibits a negative correlation with the dependent variable.

Route Switching Frequency

The parameter estimation results of the daily AM route switching frequency model in wave two are presented in Table 6.14. The AM stops ratio up to 0.75 and the additional AM stops ratio are both included in both waves. The average AM no-stop travel time and the gender indicator are introduced instead of the "males with lateness tolerance" indicator and the AM mode route travel time, both of which were included in wave one but found insignificant in the wave two model specification. Similar to the findings in the AM route switching frequency model for wave one, males switch route less frequently than females do.

The estimation results of the PM route switching frequency model for wave two are shown in Table 6.15. As in the morning route switching model, the number of route switches increases as the stops ratio increases up to a point and then decreases as the ratio increases. Two traffic system attributes included in wave one, the late PM peak hour indicator and the medium travel time indicator, are dropped out of the specification because of their relatively poor statistical significance.

Table 6.11 ***Estimation results for Poisson regression model of daily stop frequency for PM commute of wave two. Calibrated for those with at least three PM trips***

PM Stop Frequency Model		
Independent Variable	Estimated Coefficient	t-statistic
Constant	-0.799	-6.68
Average PM no-stop travel time, in minutes	0.010	1.86
Gender (1 if male; 0 if female)	-0.406	-4.80
29 and over age indicator (1 if age ≤29)	-0.615	-3.10
Low power job type indicator (1 if yes)	-0.417	-3.56
Home ownership indicator (1 if renting; 0 otherwise)	0.803	9.37
Log-likelihood at zero	-429.65	
Log-likelihood at convergence	-244.25	
Number of observations	116	

Table 6.12 Estimation results for Poisson regression model of daily departure time switching frequency for AM commute of wave two (10-minute day-to-day definition, work start controlled)

AM Departure Time Switching Model		
Independent Variable	Estimated Coefficient	t-statistic
Constant	-1.467	-6.52
Lateness tolerance at workplace (1 if ≥ 5 min)	0.369	1.86
Flexible work hours indicator (1 if yes)	0.303	1.24
Low power job type indicator (1 if yes)	-0.748	-2.67
AM stops ratio, if less than 0.75 (0 otherwise)	0.510	1.40
AM mode route travel time variability indicator (1 if std. deviation of tt ≥ 3 min)	0.249	1.19
High preferred arrival time indicator (1 if PAT ≥ 15 min and has no lateness tolerance)	0.644	2.14
Log-likelihood at zero	-247.95	
Log-likelihood at convergence	-135.23	
Number of observations	81	

Table 6.13 Estimation results for Poisson regression model of daily departure time switching frequency for Dallas PM commute of wave two (10-minute day-to-day definition, work end controlled)

PM Departure Time Switching Model		
Independent Variable	Estimated Coefficient	t-statistic
Constant	-0.352	-3.41
Additional PM stops ratio over 0.75 ([ratio-0.75], if ratio ≥0.75)	-4.527	-1.46
PM mode route travel time variability (1 if average tt is between 15 & 30 minutes)	0.215	1.34
Home ownership indicator (1 if renting; 0 other)	-0.199	-1.17
Low power job type indicator (1 if yes)	-0.458	-2.38
Log-likelihood at zero	-190.53	
Log-likelihood at convergence	-154.95	
Number of observations	83	

PAIRWISE COMPARISON BETWEEN WAVES ONE AND TWO

This section presents some results of how commuters' behavior changes over time for the participants in both waves (which are one year apart). These participants form the panel portion of the survey, for which repeated paired observations are available and which therefore allow the observation of change over time for the same individuals (rather than in aggregate over independent cross-sections).

Average Travel Time

Table 6.16 shows the comparison of the average travel times (including stoptime, i.e., the time spent pursuing activities at intermediate stops along the way) of all trips, trips without stops, and trips with stops, between waves one and two for the panel participants. The results show that the average travel times for all three trip types in wave two are longer than those in wave one during both morning and evening commutes. The average travel time in wave two

Table 6.14 Estimation results for Poisson regression model of daily mode route switching frequency for Dallas AM commute of wave two (all days definition)

AM Route Switching Model		
Independent Variable	Estimated Coefficient	t-statistic
Constant	-1.85	-10.29
AM stops ratio, if less than 0.75 (0.75 if ≥ 0.75)	1.12	4.37
Additional AM stops ratio over 0.75 ([ratio-0.75], if ratio ≥ 0.75)	-3.89	-0.96
Average AM no-stop travel time, in minutes	0.022	3.13
Gender (1 if male; 0 if female)	-0.416	-2.61
Log-likelihood at zero	-568.13	
Log-likelihood at convergence	-177.68	
Number of observations	122	

Table 6.15 Estimation results for Poisson regression model of daily mode route switching frequency for PM commute of wave two

PM Route Switching Model		
Independent Variable	Estimated Coefficient	t-statistic
Constant	-1.888	-8.97
PM stops ratio, if less than 0.75 (0.75 if ≥ 0.75)	2.208	5.41
Additional PM stops ratio over 0.75 ([ratio-0.75], if ratio ≥ 0.75)	-4.295	-1.81
Late PM peak hour indicator (1 if work end is between 5:46 and 6:15)	0.238	1.06
PM mode route medium length travel time indicator (1 if average tt is between 20 and 30 minutes)	0.160	0.86
Log-likelihood at zero	-264.22	
Log-likelihood at convergence	-118.99	
Number of observations	75	

Table 6.16 Comparison of travel time between waves one and two (include stoptime)

AM	Wave one		Wave two	
	Mean (std. dev.)	Sample size	Mean (std. dev.)	Sample size
All Trips	26.32 (22.18)	226	29.93 (22.65)	248
Trips w/o stops	21.07 (12.05)	181	25.18 (14.38)	200
Trips with stops	44.91 (38.49)	45	49.71 (36.39)	48

PM	Wave one		Wave two	
	Mean (std. dev.)	Sample size	Mean (std. dev.)	Sample size
All Trips	48.20 (68.62)	224	49.91 (61.53)	246
Trips w/o stops	24.01 (15.08)	139	26.01 (12.50)	161
Trips with stops	87.76 (97.85)	85	95.18 (87.04)	85

is also longer than in wave one when the stop-time is excluded, as shown in Table 6.17. These differences between the two waves are statistically significant (using a two-sided, two sample t-test) for all definitions of the average travel times. This could partly be attributed to the reconstruction activities along HWY 75.

Stop Patterns

Four types of stop patterns are defined to analyze the pairwise trip chaining behavior revealed in both waves:

(1) no-no pattern: a commuter makes no stops on the same weekday (e.g., Mondays) of both waves;
(2) stop-stop pattern: a commuter makes stop(s) on the same weekday of both waves;
(3) no-stop pattern: a commuter makes no stop(s) in wave one and stop(s) in wave two on the same weekday; and
(4) stop-no pattern: a commuter makes stop(s) in wave one but makes no stops in wave two on the same weekday.

The results of the pairwise daily trip chaining analysis are shown in Table 6.18, which presents the number of participants (and corresponding percentage of the overlap sample) whose behavior follows each of the above four patterns. From the weekday analysis, commuters have fewer no-no patterns on Friday than on other weekdays, and generally more of them tend to make stops along the commute on Friday.

The pairwise analysis clearly brings out changes at the individual tripmaker level that are otherwise masked when making aggregate comparisons. In particular, it can be noted that, say on Monday, six commuters (or 14.3%) who did not stop in the AM in wave one did make at least one stop in wave two (no-stop pattern). However, another five commuters (or 11.9%) who made a stop in wave one did not do so in wave two. The net difference between the two waves is one additional commuter making a stop in wave two. The net difference of only one commuter is actually the result of 11 commuters (more than one quarter of the sample) making a change between the two waves. Similar results were noted for the other days and for the PM commute. Such results have important methodological implications on the definition and measurement of change over time and highlight the importance of panel surveys for such analyses.

Departure Time Switching Analysis

The results of departure time switching analysis for the panel sample in the two waves are shown in Table 6.19. Only the day-to-day and median definitions (without controlling for the work start or end times) are discussed. A higher percentage of trips in wave two correspond to switches in departure time during the morning commute, while almost the same percentage of evening commuting trips in both waves involved a change in departure time under both day-to-day and median definitions. To test the similarity of the switching fractions for the panel participants between the two waves, chi-square tests were performed based on the presence of a 3-, 5-, and 10-minute switch, respectively. The results for the two waves indicate that the above null hypothesis cannot be rejected even at the 40% level of significance for the evening trips under both definitions. However, switching patterns during the AM commute exhibit significant differences (at the 10% level of significance) between the two waves, especially for the day-to-day definition (Table 6.20).

The AM and PM rates of day-to-day departure time switching in both waves are summarized in Tables 6.21 and 6.22, and shown in Figures 6.1 and 6.2. These figures contain the aggregate switch rates for four days of each wave (June 19 to June 22, 1990 and April 30 to May 3, 1991) for the panel participants. For the AM commute, the switching rate is systematically higher in wave two than in wave one, except for the 3-minute threshold on day one. Nevertheless, the PM departure time switching rates remain almost the same between wave one and wave two. The results are consistent with those of Table 6.19. It is quite probable that the increase in departure time switching in the morning commute is a reflection of the need to accommodate the additional delays and uncertainty in trip time introduced by the reconstruction activities in the commuting corridor.

Differences in Departure Time Between Waves

To capture the difference in departure times between the two waves for the panel participants, two types of departure time differences are defined as followed:

(1) median shift: a commuter's median departure times in the two waves are different,
(2) daily switch: a commuter's departure time in wave two is different from that in wave one on the same weekday (subject to a minimum threshold of 3, 5, or 10 minutes).

Table 6.17 Comparison of travel time between waves one and two (exclude stoptime)

AM

	Wave one		Wave two	
	Mean (std. dev.)	Sample size	Mean (std. dev.)	Sample size
All Trips	22.85 (13.22)	226	26.45 (14.36)	248
Trips w/o stops	21.70 (12.05)	181	25.18 (14.38)	200
Trips with stops	27.47 (16.52)	45	31.61 (13.19)	48

PM

	Wave one		Wave two	
	Mean (std. dev.)	Sample size	Mean (std. dev.)	Sample size
All Trips	27.90 (16.27)	224	30.12 (15.80)	246
Trips w/o stops	24.01 (15.08)	139	26.01 (12.50)	161
Trips with stops	34.27 (16.20)	85	37.92 (18.34)	85

Table 6.18 Results of pairwise trip-chaining analysis: number (and percent) of panel participants exhibiting each stop pattern between the two waves

AM

Stop Pattern	Day of Week				
	Mon.	Tue.	Wed.	Thu.	Fri.
No-no	29	28	31	29	25
	(69.0)	(70.0)	(75.6)	(69.0)	(59.5)
Stop-stop	2	3	3	6	4
	(4.8)	(7.5)	(7.3)	(14.3)	(9.5)
No-stop	6	5	3	4	7
	(14.3)	(12.5)	(7.3)	(9.5)	(16.7)
Stop-no	5	4	4	3	6
	(11.9)	(10.0)	(9.8)	(7.1)	(14.3)

PM

Stop Pattern	Day of Week				
	Mon.	Tue.	Wed.	Thu.	Fri.
No-no	21	22	19	21	18
	(50.0)	(56.4)	(45.2)	(50.0)	(43.9)
Stop-stop	8	6	10	7	12
	(19.0)	(15.4)	(23.8)	(16.7)	(29.3)
No-stop	7	5	6	9	9
	(16.7)	(12.8)	(14.3)	(21.4)	(22.0)
Stop-no	6	6	7	5	2
	(14.3)	(15.4)	(16.7)	(11.9)	(4.9)

The results of the analysis of departure time differences are presented in Table 6.23. Commuters are making their trips at different times in wave two relative to the earlier wave, for both morning and evening commutes, under all definitions. Departure time shifts for the evening commute are more pervasive than for the morning trip, under both definitions and all thresholds. The departure times in wave two are at least five minutes earlier or later than the departure times in wave one for more than three out of four trips, while the differences of median departure times between the two waves are within five minutes for half of the commuters. Tables 6.24 and 6.25 present the extent of daily pairwise departure time switches on a weekday basis. It appears that commuters switch less in the AM and more in the PM on Monday and Friday.

Table 6.19 Results of wave one and wave two departure time switching analysis

AM

Percent of Trips that are Departure Time Switches

	Survey	Switch Threshold (minutes)			Considered trips
		3	5	10	
Day-to-Day	wave 1	75	65	44	178
	wave 2	81	73	55	190
Median	wave 1	55	45	32	227
	wave 2	61	53	35	250

PM

Percent of Trips that are Departure Time Switches

	Survey	Switch Threshold (minutes)			Considered trips
		3	5	10	
Day-to-Day	wave 1	88	77	66	177
	wave 2	85	77	66	188
Median	wave 1	67	59	46	226
	wave 2	65	60	47	246

Table 6.20 Test results of wave one and wave two departure time switching analysis

AM

	Switch Threshold (minutes)		
	3	5	10
Day-to-Day	NR*	R	R
Median	NR*	R	NR

PM

	Switch Threshold (minutes)		
	3	5	10
Day-to-Day	NR	NR	NR
Median	NR	NR	NR

R: can be rejected at 10% levels of significance

NR*: cannot be rejected at 15% levels of significance

NR: cannot be rejected at 40% levels of significance

Table 6.21 Results of day-to-day departure time switching rate analysis

AM

Threshold	wave	Tue.	Wed.	Thu.	Fri.
3 min	wave 1	0.81	0.79	0.67	0.74
	wave 2	0.71	0.80	0.86	0.85
5 min	wave 1	0.67	0.66	0.58	0.67
	wave 2	0.68	0.68	0.72	0.78
10 min	wave 1	0.40	0.45	0.38	0.53
	wave 2	0.49	0.52	0.55	0.67

Table 6.22 Results of day-to-day departure time switching rate analysis

PM

Threshold	wave	Tue.	Wed.	Thu.	Fri.
3 min	wave 1	0.93	0.91	0.82	0.86
	wave 2	0.82	0.89	0.79	0.89
5 min	wave 1	0.83	0.81	0.66	0.77
	wave 2	0.75	0.83	0.71	0.78
10 min	wave 1	0.62	0.74	0.61	0.66
	wave 2	0.64	0.72	0.63	0.65

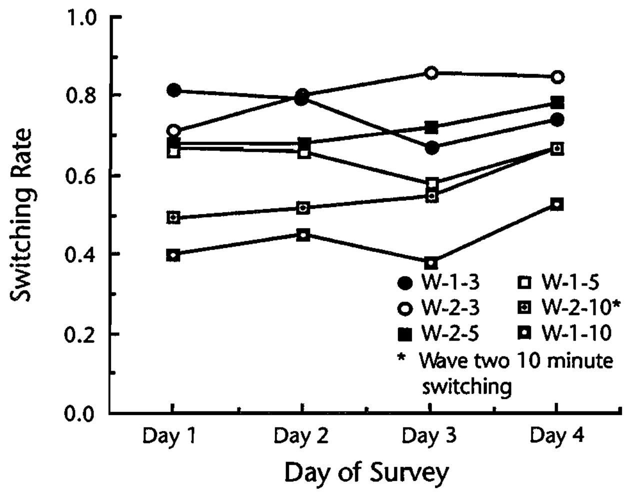


Figure 6.1 ***Daily AM departure time switch rate exhibited by commuters: day-to-day definition (uncontrolled work end). Day 1 is June 17, 1990, for wave one and is April 30, 1991, for wave two***

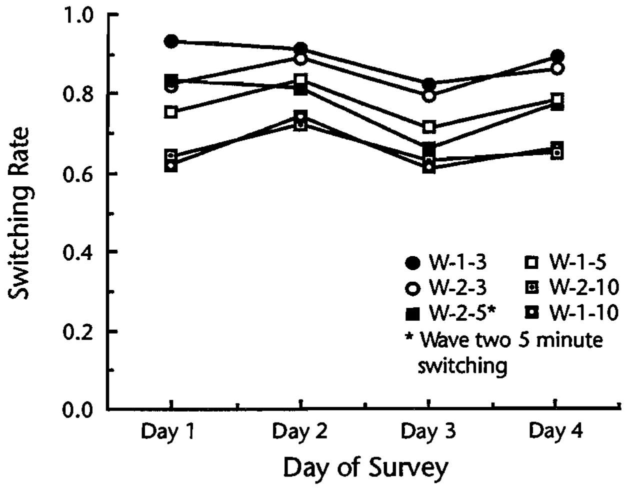


Figure 6.2 ***Daily PM departure time switch rate exhibited by commuters: day-to-day definition (uncontrolled work end). Day 1 is June 17, 1990, for wave one and is April 30, 1991, for wave two***

Route Switching Analysis

Table 6.26 presents the results of a comparison of route switching between the two waves for the panel participants. The fraction of trips that are switches, under both the day-to-day and mode (all days) definitions, are shown for each wave. About the same percentage of trips constitute route switches for both waves during the morning and evening commutes under the two definitions. Chi-square tests indicate that the null hypothesis (i.e., that overall route switching patterns between the two waves are similar) cannot be rejected at any reasonable level of significance for the morning and evening trips under both definitions (Table 6.27). The rates of day-to-day route switching in both waves are shown in Table 6.28 for the morning and evening commutes. Figure 6.3 shows that the switching rates are rather similar between waves one and two, consistent with the results shown in Table 6.26.

Table 6.23 ***Summary of departure time difference between wave one and wave two***

AM

	Threshold (minutes)			
	3	5	10	
Daily Switch	87.8†	78.0	62.0	205*
Median Shift	72.4††	55.0	42.8	41**

PM

	Threshold (minutes)			
	3	5	10	
Daily Switch	91.2	87.0	75.0	204
Median Shift	90.0	78.7	66.0	40

†: fraction of daily trips
††: fraction of commuters
*: number of trips
**: number of commuters

Route Differences Between the Two Waves

Two types of route differences are investigated here:

(1) Mode shift: a commuter's mode or most frequently used routes in waves one and two are different;
(2) Daily switch: the commuter's route on a given weekday in wave two is different from that in wave one for the corresponding weekday.

Note that a route is defined as a unique sequence of network nodes. Table 6.29 presents the results of the route change analysis. As shown, there are more route differences for the evening commute than for morning trips, under both definitions. The routes in wave two are different from those in wave one for more than six out of ten trips, while over 60 percent of commuters have different mode routes in both waves for the evening commute.

Table 6.24 Results of pairwise day-to-day departure time switching analysis (switch threshold: 5 minutes)

AM

Switching Pattern	Day of Week				
	Mon.	**Tue.**	**Wed.**	**Thu.**	**Fri.**
No Switch	13	6	6	8	12
	(31.0)	(15.0)	(14.6)	(19.5)	(29.3)
Switch	29	34	35	33	29
	(69.0)	(85.0)	(85.4)	(80.5)	(70.7)

PM

Switching Pattern	Day of Week				
	Mon.	**Tue.**	**Wed.**	**Thu.**	**Fri.**
No Switch	3	6	6	9	2
	(7.1)	(15.4)	(14.3)	(22.0)	(5.0)
Switch	39	33	36	32	38
	(92.9)	(84.6)	(85.7)	(78.0)	(95.0)

Table 6.25 Results of pairwise day-to-day departure time switching analysis (switch threshold: 10 minutes)

AM

Switching Pattern	Day of Week				
	Mon.	**Tue.**	**Wed.**	**Thu.**	**Fri.**
No Switch	18	16	15	13	16
	(42.9)	(40.0)	(36.6)	(31.7)	(39.0)
Switch	24	24	26	28	25
	(57.1)	(60.0)	(63.4)	(68.3)	(61.0)

PM

Switching Pattern	Day of Week				
	Mon.	**Tue.**	**Wed.**	**Thu.**	**Fri.**
No Switch	7	10	11	15	7
	(16.7)	(25.6)	(26.2)	(36.6)	(17.5)
Switch	35	29	31	26	33
	(83.3)	(74.4)	(73.8)	(63.4)	(82.5)

Table 6.26 Results of wave one and wave two route switching analysis

Percent of Trips that are Route Switches

AM

	Survey	Switch (%)	Considered Trips
Day-to-Day	W-1	33.7	184
	W-2	31.1	196
Mode	W-1	19.6	235
	W-2	18.4	250

PM

	Survey	Switch (%)	Considered Trips
Day-to-Day	W-1	49.7	179
	W-2	51.3	193
Mode	W-1	34.2	228
	W-2	34.0	246

Table 6.27 ***Test results of wave one and wave two route switching analysis***

Definition	AM	PM
Day-to-Day	NR	NR
Mode	NR	NR

NR: cannot be rejected at 50% levels of confidence

Table 6.28 ***Results of day-to-day route switching rate analysis***

Time	Wave	Tue.	Wed.	Thu.	Fri.
AM	wave 1	0.34	0.31	0.39	0.30
	wave 2	0.32	0.34	0.30	0.33
PM	wave 1	0.52	0.45	0.51	0.51
	wave 2	0.52	0.57	0.53	0.45

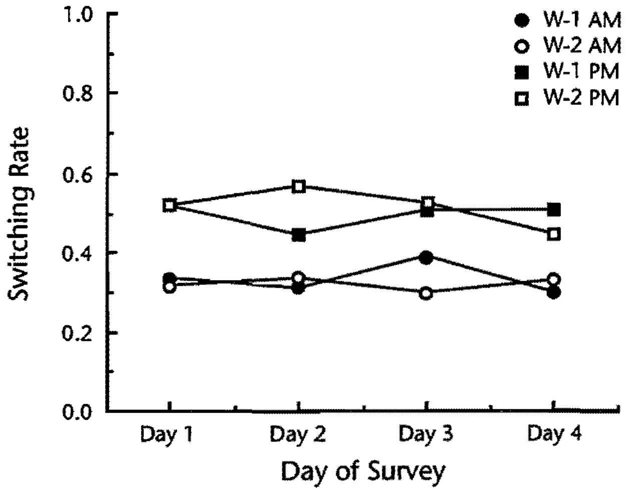


Figure 6.3 ***Daily route switch rate exhibited by commuters: day-to-day definition (uncontrolled work end). Day 1 is June 17, 1990, for wave one and is April 30, 1991, for wave two***

Table 6.29 ***Summary of route change between wave one and wave two***

AM		
Percent of Switches		
Daily Switch	61.3†	212*
Mode Shift	45.6††	43**

PM		
Percent of Switches		
Daily Switch	66.7	206
Mode Shift	62.1	42

†: fraction of daily trips
††: fraction of commuters
*: number of trips
**: number of commuters

CHAPTER 7. DAY-TO-DAY SWITCHING MODELS

INTRODUCTION

This chapter describes the development of models of the day-to-day switching behavior of individual commuters. Whereas the Poisson regression models related the switching frequency over the observation period to various characteristics of the trip and the commuters, the models presented here are intended to relate the decision to change one's departure time and/or route on the next day's commute to commuter's recent and accumulated experience with the facility, external information supply, and other pertinent characteristics. These models are part of the user decisions component of the framework for the dynamic analysis of commuting systems described in the companion report (Ref 3). This chapter then describes the development of the models used in the application of this framework described in that report.

The general form of these day-to-day switching models is based on previous work (Refs 4, 5, 6). These models are based on the notion of bounded rationality, and are of the multinomial probit form because the latter is suitable for capturing dynamic effects through flexible assumptions on the structure of the variance-covariance of the error terms. A recently developed multinomial probit (MNP) model parameter estimation program, allowing general specifications and a relatively large number of choice alternatives, was used to obtain the parameter estimates.

The structure of this chapter is as follows. The next section discusses the conceptual background of the bounded rational model. Section three briefly presents the general estimation procedure. Sections four and five describe the model specifications and estimation results for departure time and route switching decisions, respectively.

THE BOUNDED RATIONALITY MODEL

The contents in this section are based largely on the research of Mahmassani (Ref 14). Previous studies have confirmed that arrival time is of major concern to commuters, and have suggested that an indifference band of tolerable "schedule delay" (defined as the difference between the actual arrival time and the preferred arrival time [PAT] for a given commuter) is the primary mechanism governing the day-to-day responses of commuters to congestion. In their daily commute, tripmakers are assumed to maintain the same choice as long as the outcome does not fall outside the tolerable range (i.e., deviation from PAT is smaller than the indifference band). Otherwise, if the previous outcome is considered unacceptable, commuters will adjust the previous decision through some mechanism. Thus, let PAT_i denote the preferred arrival time at the workplace of commuter i, i = 1,.... N. This quantity reflects inherent preferences and risk attitudes of each commuter, as well as the characteristics of the workplace. Let AT_{it} denote the arrival time of commuter i on day t. The bounded rational character of the decision process is operationalized using Simon's satisficing rule (Refs 15, 16) whereby the user does not switch departure time and/or route so long as the corresponding schedule delay, termed ESD_{it} when it corresponds to early arrival at the workplace (relative to the PAT) and LSD_{it} for late arrival, remains within the user's indifference band as follows:

$$\delta_{it} = -1, \text{ if } 0 \le ESD_{it} \le EBD_{it} \text{ or } -LBD_{it} \le LSD_{it} \le 0$$

$$\delta_{it} = 1, \text{ otherwise}$$

$$\lambda_{it} = -1, \text{ if } 0 \le ESD_{it} \le EBR_{it} \text{ or } -LBR_{it} \le LSD_{it} \le 0$$

$$\lambda_{it} = 1, \text{ otherwise}$$

with

$$SD_{it} = PAT_i - AT_{it} = ESD_{it}, \text{ if } SD_{it} > 0;$$
$$= LSD_{it}, \text{ if } SD_{it} < 0,$$

As noted ESD_{it} denotes the early-side schedule delay and LSD_{it} the late-side schedule delay; δ_{it} and λ_{it} are the departure time and route switching decision indicator variables, respectively, with δ_{it} equal to 1 when user i switches departure time after the commute on day t (i.e., for the commute on day t + 1), and $\delta_{it} = -1$, otherwise. The variable λ_{it} has a similar definition, but for route switching only. There are four possible combinations of departure time and route choice decisions, corresponding to the combinations of values for the pair (δ_{it}, λ_{it}). For example, (–1,–1) denote that both departure time and route will not be changed on the next day. Note that EBD_{it} and LBD_{it} are the respective departure time indifference bands of tolerable schedule delay corresponding to early and late arrivals for day t and EBR_{it} and LBR_{it} denote the early-side and late-side indifference bands governing route switching.

The indifference bands are latent terms, internal to each individual, and therefore cannot be observed nor measured directly. Instead, they will be inferred given actual observations of commuters' decisions to switch or not in response to experienced traffic conditions and exogenous information. To capture the dynamics of the decision process, the specification and estimation of the indifference bands and their daily variation is an essential task, which requires the time series of switching decisions made of individual commuters. Such data are available from the first wave survey of commuter behavior. For estimation purposes, the indifference bands are treated as random variables, distributed over days and across commuters with systematically varying mean values as illustrated in Figure 7.1. The commuter is assumed to have separate components corresponding to early and late arrivals at the workplace and have different indifference bands for departure time and route. The early and late components can be expressed in more compact form as a single indifference band by introducing an additional indicator variable W_{it} as follows:

$$IBD_{it} = W_{it}\,EBD_{it} + (1 - W_{it})\,LBD_{it}$$
$$IBR_{it} = W_{it}\,EBR_{it} + (1 - W_{it})\,LBR_{it}$$

That is,

$$\begin{aligned} IBD_{it} &= W_{it}\left(f_e(X_i, Z_{it}, \theta_{it}) + \varepsilon_{it,e}\right) + (1 - W_{it})\left(f_l(X_i, Z_{it}, \theta_{it}) + \varepsilon_{it,l}\right) \\ &= W_{it} f_e(X_i, Z_{it}, \theta_{it}) + (1 - W_{it}) f_l(X_i, Z_{it}, \theta_{it}) + W_{it}\varepsilon_{it,e} + (1 - W_{it})\varepsilon_{it,l} \end{aligned}$$

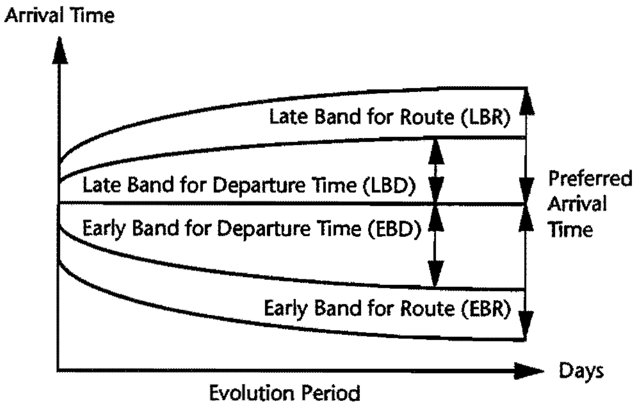


Figure 7.1 ***Early-side and late-side indifference bands for departure time and route (Ref 17)***

where W_{it} is a binary indicator variable, equal to 1 if $SD_{it} = ESD_{it} > 0$ (early-side), or to 0 if $SD_{it} = LSD_{it} < 0$ (late-side); $f_e(\cdot)$ and $f_l(\cdot)$ are the systematic components of the departure time bands for early and late arrivals, respectively. The vector of user characteristics X_i and the vector of performance characteristics Z_{it} capture user i's experience up to day t, and θ is a vector of parameters to be estimated.

Let $\varepsilon_{it} = W_{it}\,\varepsilon_{it,e} + (1 - W_{it})\,\varepsilon_{it,l}$,
and

$$f(X_i, Z_{it}, \theta_{it}) = W_{it} f_e(X_i, Z_{it}, \theta_{it}) + (1 - W_{it}) f_l(X_i, Z_{it}, \theta_{it})$$

The route indifference band can be derived in the same way. Therefore, the previous equations can be rewritten as:

$$\begin{aligned} IBD_{it} &= f(X_i, Z_{it}, \theta_{it}) + \varepsilon_{it} \\ IBR_{it} &= h(X_i, Z_{it}, \theta_{it}) + \tau_{it} \end{aligned} \qquad (1)$$

The random terms ε_{it},. and τ_{it},. i = 1, ... T, are assumed to be jointly normally distributed, over days and across commuters, with zero means and general covariance matrix Σ, or MVN (0, Σ) and the Σ can be expressed as follows:

$$\begin{bmatrix} \Sigma_{\varepsilon} & \text{cov} \\ \text{cov} & \Sigma_{\tau} \end{bmatrix}$$

The expression of Σ (joint) is given by:

$$\begin{array}{cccccc}
\sigma_D^2 & \cdots & \gamma_D & \gamma_{DR} & \cdots & 0 \\
. & \cdots & . & . & \cdots & . \\
. & \cdots & . & . & \cdots & . \\
\gamma_D & \cdots & \sigma_D^2 & . & \cdots & \gamma_{DR} \\
\gamma_{DR} & \cdots & . & \sigma_R^2 & \cdots & \gamma_R \\
. & \cdots & . & . & \cdots & . \\
. & \cdots & . & . & \cdots & . \\
0 & \cdots & \gamma_{DR} & \gamma_R & \cdots & \sigma_R^2
\end{array} \quad (2T \times 2T)$$

where σ_D^2 and σ_R^2 are the respective variances of the departure time and route bands, γ_D and γ_R are serial correlation terms (for the same commuter, from day to day) for departure time and route, respectively, and γ_{DR} is a correlation term between the departure time and route bands on the same day for a given commuter (contemporaneous correlation).

The probability of an outcome (δ_{it} , λ_{it}) for user i, after the commute on day t, is given by:

The details of the estimation procedure are described by Mahmassani (Ref 14) and Tong (Ref 17).

ESTIMATION PROCEDURE

The calculation of the choice probability of a sequence of daily departure time and/or route decisions requires the evaluation of the multidimensional integral of the multinormal density function, which is not tractable analytically. No closed form solution can be obtained when the number of alternatives exceeds three. Approaches to solve this problem fall in three general categories:

(1) numerical integration;
(2) numerical approximation; and
(3) Monte Carlo simulation.

The Clark approximation is used in the most widely available MNP estimation program, CHOMP (Ref 18). However, the Clark approximation has been shown to be unreliable beyond a certain number of alternatives. On the other hand, Monte Carlo simulation, while more accurate, is considerably more intensive computationally for accurate model estimation, particularly in scalar computing environments.

Fortunately, these computational issues have become of less concern with advances in computing hardware. A new MNP model estimation program based on a vectorized Monte Carlo simulation procedure and on new implementations of quasi-Newton nonlinear optimization procedures

$$\begin{aligned}
\Pr(\delta_{it},\lambda_{it}) &= \Pr\begin{pmatrix} \delta_{it}\left[W_{it}\left(ESD_{it}-EBD_{it}\right)+\left(1-W_{it}\right)\left(-LSD_{it}-LBD_{it}\right)\right]\geq 0, \\ \text{and } \lambda_{it}\left[W_{it}\left(ESD_{it}-EBR_{it}\right)+\left(1-W_{it}\right)\left(-LSD_{it}-LBR_{it}\right)\right]\geq 0 \end{pmatrix} \\
&= \Pr\begin{pmatrix} \delta_{it}\varepsilon_{it}\leq \delta_{it}\left[\left|SD_{it}\right|-f\left(X_i,Z_{it},\theta_{it}\right)\right] \\ \text{and } \lambda_{it}\tau_{it}\leq \lambda_{it}\left[\left|SD_{it}\right|-h\left(X_i,Z_{it},\theta_{it}\right)\right] \end{pmatrix}
\end{aligned}$$

The likelihood of a sequence of decisions ((δ_{it}, l_{it}), t = 1,...T) for an individual i is thus given by:

$$\Pr\left(\left(\delta_{it},\lambda_{it}\right),t=1,\ldots T\right)=\Pr\begin{pmatrix} \delta_{it}\ \varepsilon_{it}\leq \delta_{it}\left[\left|SD_{it}\right|-f\left(X_i,Z_{it},\theta_{it}\right)\right] \text{ and} \\ \lambda_{it}\ \tau_{it}\leq \lambda_{it}\left[\left|SD_{it}\right|-h\left(X_i,Z_{it},\theta_{it}\right)\right], \\ t=1,\ldots\ldots,T \end{pmatrix}$$

has recently been developed at The University of Texas at Austin. It allows the calibration of MNP models with general specifications and a relatively large number of choice alternatives accurately and efficiently in a supercomputing environment (Refs 19, 20). This code was used in this study to obtain accurate and meaningful parameter estimates.

DEPARTURE TIME

Model Specification

In this section, a detailed presentation of the mathematical specification and estimation results is given. The analysis focuses only on the day-to-day dynamics of commuter departure time decisions for morning commutes without intervening stops (trip-chaining).

The specification of the joint indifference band for the departure time switching model consists of the following items:

- initial range of tolerable schedule delay
- socio-economic characteristics of the commuter
- dynamic effects
- myopic term

The definitions of the elements of the indifference band are summarized in Table 7.1.

The joint model specification can then be expressed as shown below.

To simplify the estimation, we only discuss the case where the early and late bands have the same variance in S_e. Also, since the data base from wave one survey includes 10 working days, estimations are performed for 5, 6, 7, and 8 consecutive decision days in order to study the day-to-day decisions.

Estimation Results

The estimation results for 5 days, 6 days, 7 days, and 8 days (consecutive) with the error structure described above are shown in Table 7.2. The initial band for late-side is smaller than that for the early-side, as evidenced by the respective magnitudes of a_1 and a_2 (23.25 and 17.94, respectively, for the five-day estimates). As such, these estimates, based on actual survey data, confirm the earlier finding obtained by Tong (Ref 17) using data from laboratory-like experiments.

The parameters that capture socio-economic effects are a_3 through a_6, the estimated values of which show the correct signs and reasonable magnitudes; a_3 and a_4 suggest that older commuters will tend to tolerate greater schedule delays than younger ones. The estimates of a_5 and a_6 suggest that female commuters have a wider indifference band than males. Again, the late-side attributes' parameters are all greater than the early-side, which may imply that the commuters are expanding the late-side indifference bands more cautiously than the early-side bands in response to the frustration that they are likely encountering through their commuting experience. This can also be viewed as confirming that commuters are indeed more sensitive to late arrivals than to early ones (Ref 17).

The parameters that capture the dynamic effect of commuters' "learning" through previous experience are a_7, a_8 for the early-side and a_9, a_{10} for the late-side. Commuters tend to engage in less departure time switching after experiencing conditions that require them to switch on the previous t days. In other words, to the extent that previous switching is an indication of inability to find a feasible alternative, it is natural to expect the indifference band to increase, resulting in less switching. This result is identical to the earlier findings obtained by Mahmassani and Chang (Ref 21).

The shorter-term effect of adjustment in response to the most recently experienced travel time change in connection with a departure time change is captured by parameter a_{11}, the estimated value of which shows the correct sign and reasonable magnitude. Namely, commuters will be induced to tolerate greater schedule delay associated with a particular departure time decision if they have recently experienced a substantial increase in travel time resulting from a small adjustment in departure time.

The estimates of the variance terms σ^2 and γ for departure time are all significant at reasonable confidence level, which confirms the need to explicitly incorporate serial correlation in the error specification. We can see that the value of σ (theta 1) in the five-day case is larger than for any of the other alternatives.

$$
\begin{aligned}
IB_{it} = \big[& W_{it} * a_1 + (1 - W_{it}) * a_2 && \text{Initial Bands} \\
& + W_{it} * a_3 * AGE_i + (1 - W_{it}) * a_4 * AGE_i && \text{Socio-economic Component} \\
& + W_{it} * a_5 * GENDER_i + (1 - W_{it}) * a_6 * GENDER_i && \\
& + W_{it} * a_7 * NFAIL_{it} ** a_8 && \text{Dynamic Component} \\
& + (1 - W_{it}) * a_9 * NFAIL_{it} ** a_{10} && \\
& + W_{it} * a_{11} * l_{it} * \Delta TR_{it} / \Delta DT_{it} \big] && \text{Myopic Component} \\
& + \varepsilon_{it} && \text{Unobserved Component}
\end{aligned}
$$

Table 7.1 The indifference band elements and definitions

Element	Definition
AGE_i	The age of commuter i=1; if <18; 2, if [18,29]; 3, if [30,44]; 4, if [45,60]; 5, if.. > 60
$GENDER_i$	The gender of commuter i; = 1, if male; 0 otherwise
$NFAIL_{it}$	The number of unacceptable early and late arrivals till day t
ΔTR_{it}	The difference between travel times of commuter i on day t and t-1
ΔDT_{it}	The departure time that commuter i has adjusted between day t and t-1
W_{it}	A binary indicator variable, equal to 1 if $SD_{it} > 0$ (early-side); or = 0 if $SD_{it}<0$ (late-side)
I_{it}	A binary indicator variable equal to 0 if $DT_{it} = DT_{it} -1$; otherwise 1
$a_1,a_2...a_{11}$	Parameters to be estimated, plus other parameters included in the variance-covariance matrix
ε_{it}	Error term for commuter i on day t

Table 7.2 Estimated parameters for four cases

	Five days		Six days		Seven days		Eight days	
	Parameters	t Value	Parameters	t Value	Parameters	t Value	Parameters	t Value
Constant (e)	23.25	2.40	23.24	3.98	23.28	3.09	23.26	2.51
Constant (l)	17.94	5.13	17.89	2.18	17.87	5.37	17.82	4.08
Age (e)	7.35	5.49	7.44	3.74	7.64	2.21	7.61	4.85
Age (l)	4.41	2.87	4.30	2.12	4.58	3.74	4.51	5.68
Gender (e)	-5.51	-3.65	-5.62	-4.80	-5.62	-5.12	-5.59	-3.74
Gender (l)	-6.56	-2.97	-6.64	-2.06	-6.60	-2.36	-6.57	-2.66
nfail (e)	5.13	2.70	6.04	5.07	5.04	3.30	5.49	5.23
exp (e)	0.34	3.35	0.95	2.25	1.13	4.50	1.16	4.02
nfail (l)	3.41	3.85	5.10	4.58	3.90	4.69	4.36	2.73
exp (l)	0.11	2.19	0.53	5.12	0.79	2.52	0.78	5.96
Ratio	3.84	3.46	4.80	3.52	3.60	2.84	4.17	2.98
Theta 1	16.98	2.72	15.22	3.06	15.37	3.78	15.38	3.44
Theta 2	9.97	4.56	9.17	5.20	9.13	5.45	9.13	5.18
Log-likelihood	-425.21		-508.69		-597.36		-680.45	

Examining the value of γ (theta 2) reveals that the covariance terms are generally much smaller than the variance terms. Therefore, their influence is relatively small compared with the variance terms. It should be noted that all the covariance terms have positive signs which may indicate the positive correlation between the unobserved disturbances, as expected.

ROUTE DECISIONS

Model Specification

As in the previous section, the following analysis focuses only on the day-to-day dynamics of commuters' route decisions in the morning without intervening stops (trip-chaining). The detailed specification of the route switching model for capturing the day-to-day dynamics of the joint indifference band variation consists of the following three items:

(1) initial range of tolerable schedule delay;
(2) dynamic effects; and
(3) unobserved component.

The joint model specification can then be expressed as:

$$\begin{aligned} IB_{it} = \big[& W_{it} * c_1 + (1 - W_{it}) * c_2 && \text{Initial Bands} \\ & + W_{it} * c_3 * STDTR_{it} && \text{Dynamic Component} \\ & + (1 - W_{it}) * c_4 * STDTR_{it} && \\ & + W_{it} * c_5 * NFAIL_{it} && \text{Dynamic Component} \\ & + (1 - W_{it}) * c_6 * NFAIL_{it} \big] && \\ & + \tau_{it} && \text{Unobserved Component} \end{aligned}$$

The definitions of the various elements of the indifference band are shown in Table 7.3.

Only the case of the same variance and covariance in Σ_τ is discussed, that is, $\sigma_2{}^2 = \sigma_4{}^2$ and $\gamma_2 = \gamma_5 = \gamma_{25} = \gamma_{52}$, to simplify the estimation. Also, the estimations of consecutive 5, 6, 7, and 8 days are performed in order to study the day-to-day decisions.

Estimation Results

Table 7.4 presents the estimation results for the first prototype of consecutive 5 days, 6 days, 7 days, and 8 days with the error structure assumed previously. The initial band for late-side is smaller than that of the early-side (31.16 and 24.96, respectively, in the 5-day estimation), which confirms the earlier finding by Tong (Ref 17).

The parameters that capture the dynamic effect of commuters' "learning" through previous experience are c_3 and c_5 for early-side and c_4 and c_6 for late-side. All commuters are reluctant to continue switching route in response to the experienced higher travel time fluctuation, since c_3 and c_4 all have positive signs. This result is consistent with the earlier findings obtained by Tong (Ref 17). Commuters tends to engage in less route switching in response to the more frequent switches experienced on previous t days. This result is identical to the previous findings obtained for the departure time model.

The estimates of the σ_2 and γ for route switching models are all significant at reasonable confidence level, which confirms the need to incorporate the serial correlation. The covariance terms are positive signs indicating the positive correlation between the unobserved disturbances, as expected.

Comparing the results for route with those for departure time, the mean indifference band for departure time switching is much smaller than that for route switching, both for early and late side components ($23.25 < 31.16$ and $17.94 < 24.96$). The results indicate that when a commuter switches route, he/she is very likely to switch departure time as well. These estimates confirm the earlier finding by Stephan (Ref 22).

Table 7.3 The indifference band elements and definitions

Element	Definition
STDTR_{it}	The standard deviation of travel time up to day t
NFAIL_{it}	The number of unacceptable early and late arrivals till day t
W_{it}	A binary indicator variable equal to 1 if $SD_{it} > 0$ (early-side); or = 0 if $SD_{it} < 0$ (late -side)
$c_1, c_2 \ldots c_6$	Parameters to be estimated, plus other parameters included in the variance-covariance matrix
τ_{it}	Error term for commuter i on day t

Table 7.4 Estimated parameters for four cases

	Five days		Six days		Seven days		Eight days	
	Parameters	t Value	Parameters	t Value	Parameters	t Value	Parameters	t Value
Constant (e)	31.16	6.03	30.68	4.17	30.53	4.90	27.22	5.62
Constant (l)	24.96	5.40	24.79	7.89	25.00	4.40	18.76	9.61
stdtr (e)	3.41	7.22	6.55	7.68	6.14	7.81	8.87	9.21
stdtr (l)	8.92	4.05	5.38	7.57	7.52	5.67	4.37	5.67
nfail (e)	4.17	6.38	2.98	7.70	3.45	3.54	8.95	5.29
nfail (l)	3.19	4.91	5.91	4.39	5.27	4.08	9.13	8.03
Theta 1	20.18	8.17	21.50	10.69	21.29	4.06	17.74	4.16
Theta 2	21.75	8.36	16.58	6.40	4.50	4.48	5.89	5.09
Log-likelihood	-135.29		-174.84		-227.81		-233.12	

CHAPTER 8. CONCLUSION

This chapter summarizes the major findings of this report and discusses possible applications and future research needs in the area of commuter behavior. The first section provides a summary of the key findings of the exploratory analysis, the stop and switching frequency models, and day-to-day dynamic departure time and route choice models. The second section highlights applications of the findings and avenues for future investigation of commuting behavior.

SUMMARY OF FINDINGS

This report presented the analysis of commuter behavior revealed from a two-wave trip diary survey conducted in Dallas, Texas. The first wave included two partially overlapping survey periods (subwaves); the second wave was conducted about a year later in an attempt to capture long-term effects of the reconstruction activity on commuter patterns. Since a similar survey was conducted in Austin, Texas, in 1990, comparisons were also made with the results of that study to provide valuable insights into the underlying commuter behavior, the comparability of behavioral patterns between the two cities, and the possible transferability of behavioral insights and models across cities. The analysis focused on three major aspects of commuting behavior: trip chaining, departure time, and route choice. These decision components were studied in terms of the variation which they exhibited in the individual commuting patterns over the study period. Mathematical models were presented, relating the frequency of stops along the commutes to the characteristics of the commuters, the work environment, and the urban network. Similar models of the frequency of departure time and of route switching were also presented. Finally, models of the day-to-day decisions of departure time and route were developed. These models form the core of the user decisions component in the overall framework for modelling commuting traffic networks developed in the study (Ref 3).

Exploration of the trip-chaining behavior observed during the commutes revealed several important findings. First, commuters pursued many non-work stops during commuting trips, thereby confirming that trip chaining is an essential characteristic of commuting in this area. Second, differences in the frequency, purpose, duration, and variability of stops were observed between the morning and the evening commutes. In general, commuters tended to make stops more frequently in the evening than in the morning, possibly a reflection of constrained arrival times at the workplace and flexible arrival times at home, or an indication of more shops being open in the evening. The differences in trip chaining behavior between morning and evening trips undoubtedly result in differences in route selection and trip scheduling decisions of commuters. Remarkably similar results were observed in both Dallas and Austin.

The stop frequency model revealed that socio-economic and workplace characteristics of the commuter, commuter preference, and traffic system attributes (no-stop travel time) are the principal attributes influencing the stop frequency behavior exhibited by the commuters in Dallas. Comparative tests between Austin and Dallas during the morning and evening commutes indicated that overall socio-economic, workplace condition, and commuter preference attributes have similar effects in the two cities, whereas traffic system conditions (no-stop travel time) have a different influence in Austin and Dallas on AM stop frequency. For the evening, no attributes were found to be significantly different between Austin and Dallas.

The analysis applied both a "day-to-day" and a "deviation from normal" approach to switching behavior (Ref 10). In general, commuters tend to change departure times, routes, or both more frequently in the morning than evening, possibly a reflection of a constrained arrival time at workplace compared to a flexible arrival time at home. This phenomenon results in a different overall switching pattern in the morning between the two cities, but a very similar overall switching pattern in the evening. Generally, Dallas exhibits a higher percentage of switches than Austin in the morning and almost the same percentage of switches in the evening for departure time, route, and joint switching. Probable reasons include a city size effect and work start time constraints. There are more opportunities for commuters to switch in order to arrive at their workplace on time in Dallas. However, there is not much difference in the frequency of evening switches between the two cities, mostly because the corresponding home arrival time limitation is not particularly stringent for many commuters. Route and departure time decisions were shown to be interdependent and the lower percentage of route switching compared with departure time switching in both cities is consistent with the results of commuting experiments and field study (Refs 5, 10).

The characteristics of the commuter, his/her workplace, and the traffic system, along with the commuter's trip-chaining patterns, are all important determinants of the departure time and route switching behavior exhibited by the Dallas commuters. The trip-chaining variable (stops ratio), workplace variables (lateness tolerance at workplace or work end time indicator), and commuting trip time variability are significant explanatory variables in all reported morning and evening switching models. The preferred arrival time is included only in the morning departure time and joint switching models. Socio-economic variables such as gender, age, and interaction variables containing gender also display explanatory power.

The comparative tests of daily departure time switching behavior during the morning commute show that socio-economic, commuter preference, and workplace condition variables have similar effects on AM departure time switching behavior in both cities, while the trip chaining variable exhibits a different effect on it. For the evening departure time switching behavior, the routine stop factor also has the same effect in both cities, as do the socio-economic and workplace condition variables. No attributes exhibit significantly different effects on evening departure time switching behavior between Austin and Dallas.

The comparative tests of daily route switching behavior between Austin and Dallas also indicate that the socio-economic, workplace condition, and routine stop variables all exert a similar effect on route switching behavior in both cities, for both AM and PM commutes. Trip chaining has a different influence on route switching in the AM in Austin (as compared with Dallas). No factors have significantly different effects on PM route switching behavior between the two cities. Similar conclusions were reached with regard to joint (route and departure time) switching decisions.

Comparisons between the two survey waves were conducted, suggesting an increase in congestion and a slight increase in AM switching behavior and daily variability, most probably because of the reconstruction activities. The pairwise analysis at the individual tripmaker level brings out changes that are otherwise masked when making aggregate comparisons, thereby highlighting the importance of panel surveys for such analyses. Many commuters included in both waves exhibited modified individual patterns between the two periods.

A dynamic model of a commuter's decision to change departure time or route on a given day, given his/her experience with congestion in the facility, was developed. The model focuses only on morning commutes without intervening stops (no trip-chaining). Unlike the previous "laboratory-like" experiments, actual survey data were used to develop and calibrate this model. A recently developed probit model estimation technique (Refs 19, 20) was applied. Several conclusions can be obtained from this study:

1. Estimation results for the models generally confirmed the underlying assumptions.
2. It was found that commuters are more sensitive to late arrivals than to early arrivals.
3. In the departure time model, older commuters tend to tolerate greater schedule delays than do younger ones. Also, female commuters exhibit a wider mean indifference band than male commuters. The greater propensity for departure time switching of young males is consistent with the estimation results of the above mentioned switching frequency models (Ref 10).
4. Commuters are inclined to tolerate greater schedule delay (associated with a particular departure time decision) if they have recently experienced a substantial increase in travel time resulting from a small adjustment in departure time.
5. Commuters are reluctant to continue switching route in response to greater experienced travel time fluctuation, which is consistent with the earlier findings obtained by Tong (Ref 17).
6. The mean indifference band for departure time switching is much smaller than that for route switching, both for early and late side components, indicating that when a commuter switches route, he/she is very likely to switch departure time as well. These estimates confirm the earlier finding by Stephan (Ref 22).

7. Commuters tend to increase their indifference band (i.e., switchless) in response to more failures; this is true for both departure time and route models.
8. The estimates of the variance and covariance terms are all statistically significant in both departure time and route models, which confirms the need to incorporate the serial correlation in the specification.

APPLICATIONS AND IMPLICATIONS

This report has provided several useful contributions to the body of knowledge on commuting behavior. The primary contribution is that a weekly based survey (rather than traditional approaches in the form of cross-sectional home or phone interview surveys documenting a single day of travel) provides a more complete image of commuting patterns. Furthermore, this report has provided an opportunity to examine the transferability of commuter behavior and to share the substantive insights from two similar surveys, a minor one in Austin and a more extensive one in Dallas. Importantly, this report has tested the commuting behavior framework (indifference bands) developed in laboratory-like experiments by using "real world" data and applying a new estimation technique.

The exploratory analysis itself serves an important purpose by pointing to the limitations of current planning and travel demand models which treat the work trip as a stable and repetitive phenomenon. Moreover, the interdependence of trip chaining and the choice of route and departure time indicates that transportation planners should treat trip chains as the basic unit of tripmaking in travel demand models. From a travel demand management perspective, the participation of the individuals in non-work activities during the work commute is a detriment to ride-sharing or transit initiatives, since these options provide less flexibility in meeting stop needs. Significant modal shifts may not be possible without the provision of personal business and shopping opportunities (and possibly day-care) in proximity to major employment centers or park-and-ride transit facilities.

This report has also provided a few insights regarding the potential for in-vehicle guidance and other information systems. Route and departure time switching were shown to be already taking place in actual systems, implying that users may be willing to shift commuting patterns if they would benefit from these changes. This suggests a potential market for in-vehicle guidance systems. The higher frequency of departure time switching relative to route switching suggests that real-time information systems are likely to have significant impacts not only on path selection but also on trip timing. As shown in the simulation results of Mahmassani and Jayakrishnan (Ref 23), the potential benefits achievable through peak spreading by departure time shifts can greatly exceed those achievable by route guidance alone. The variability of evening commutes observed in the analysis suggests that the evening commute could be used to initially test and evaluate real-time information.

The frequency models could be used to forecast the expected number of stops or the expected rate of departure time and route switches given the attributes of a set of commuters and their work and travel environments. However, the primary value of these models lies in the behavioral insights they have generated. The day-to-day switching models developed in this report considered only the non-stop morning trips. The interaction of trip chaining with the other two decisions during commutes needs to be examined in order to further refine the insights learned here.

The topic of commuter behavior is becoming increasingly important. As the problem of urban congestion worsens, and as issues of energy consumption and air quality attainment attract further attention, travel behavior in general and commuter decisions in particular play a critical role in developing and analyzing travel demand management schemes.

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