PHASED IMPLEMENTATION OF A MULTIMODAL ACTIVITY-BASED TRAVEL DEMAND MODELING SYSTEM IN FLORIDA

Final Report

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16. Abstract

This report describes the technical background and methodologies underlying a comprehensive activity-based travel demand microsimulation model system that was developed for Florida. The various model components were estimated using the 2000 Southeast Florida Household Travel Survey data sets. The model system is capable of synthesizing a population and simulating activity-travel patterns at the level of the individual traveler using advanced statistical and econometric models of travel behavior. The model system recognizes time space constraints that influence activity and travel engagement in time and space. The model results are very promising and indicate that activity based models offer a strong framework for undertaking travel demand forecasting. The project resulted in the development of a software called FAMOS: The Florida Activity Mobility Simulator. This PC-based user-friendly software can be used to implement activity-based modeling in virtually any urban area. A companion report constitutes a users guide for the software.

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CHAPTER I

SUMMARY

Activity based travel analysis has been gaining increasing attention in travel demand research during the past decade. Activity and trip information collected at the person level aids in understanding the underlying behavioral patterns of individuals and the interactions among their activities and trips. This chapter is aimed at performing a comparison of activity and time use patterns across geographical contexts. Potentially, such a comparison would be able to shed light on the differences and similarities in travel behavior that exists between areas. To accomplish this objective, activity, travel, and time use information derived from surveys conducted in the San Francisco Bay Area and Miami area has been analyzed to identify differences in activity engagement patterns across different sample groups. In general, it was found that activity and time use patterns are quite comparable across the two areas as long as the commuting status and demographic characteristics of the individuals are controlled for. In addition, a comparison of the time-of-day distributions of various events such as wake-up time, sleeping time, time of departure and arrival at home, and work start and end times was performed. These events were considered important in defining the temporal constraints under which people exercise activity and travel choices. Once again, it was found that the distributions followed similar trends as long as one accounted for the commuting status and the demographic characteristics of the individual.

INTRODUCTION

Activity based travel analysis is increasingly being recognized as a powerful methodology to model human travel behavior. This approach recognizes that travel is derived from an individual's desire to perform an activity at a location away from the previous activity location. Recent research has argued that information on individual activity engagement behavior offers the potential to enrich our understanding of the complex and dynamic nature of travel executed by people (*1*). Pas (*2*) has identified several benefits of the activity based approach, namely, as an aid to the determination of: 1) the spatial and temporal constraints on activity and travel choice, 2) sequence of these activities in time and space, 3) the interactions between activity and travel decisions and the interactions between individuals, and 4) the structure of the household and the roles played by the members of the household.

Time use research is playing an increasingly important role in travel behavior research because of the recognition that many travel choices are governed by time, which is a limited resource that is consumed according to one's needs and preferences (*3*). Potentially, the explicit representation of time use in travel demand models will help explain people's travel choices over the course of a day (*4,5*).

Over the past several years, there have been several activity and time use data collection efforts conducted in the United States. However, within the context of activity and time use behavior, very little is known regarding geographic differences that may exist due to differing spatial contexts in which the behavior is revealed. A comparison of activity and time use data collected in different areas would offer valuable insights into similarities and differences in activity and time use behavior across regional contexts. Such insights would, in turn, help plan future activity and time use data collection studies, shed light on the potential use of activity models estimated in one area in another area, and perhaps most importantly, help explain differences in travel behavior across geographical contexts.

This chapter is aimed at providing a comparison of activity and time use behavior between two major metropolitan areas of the United States located on the two opposite coasts of the country, namely, San Francisco and Miami. In both of these areas, recent activity and time use data collection efforts were undertaken with a view to develop enhanced travel demand modeling systems. In this chapter, activity and time use patterns are compared for various behavioral indicators between the two samples. Based on the comparison, conclusions are drawn regarding similarities and differences in behavior across regional contexts.

FOCUS OF ANALYSIS

The discussions in the preceding section have illustrated the high level of interest among travel behavior researchers in the notions of activity engagement and time use (*6,7*). Over the past several years, activity and time use surveys have been conducted in select urban areas of the United States. Despite the recent surge in activity and time use studies, the number of urban areas in which activity and time use data is available is quite limited. At a recent conference on Activity Based Travel Forecasting, many urban areas and states that have not conducted activity and time use surveys expressed a strong need to understand variability in activity and time use behavior across geographical contexts (*8*). It was felt that an understanding of such variability would provide insights into the potential applicability of using activity based models developed in one area in another. Moreover, it was strongly felt that differences in travel behavior between geographical areas may possibly be explained by differences in activity engagement and time use patterns. However, due to the limited availability of comparable activity and time use data, systematic comparisons of behavior across geographical contexts have not generally been made.

Besides overall activity, travel, and time use patterns, travel behavior researchers have been interested in the notion of space-time prisms that define the spatio-temporal activity space within which individuals exercise their activity and travel choices (*9*). These prism extremities are defined by certain events in the course of a day that occur at various times of the day. Describing these temporal extremities would be very useful for developing models of individual space-time prisms; in turn enhancing the ability to accurately capture constrained behavioral mechanisms. Then, again, the question arises as to whether the space-time prism extremities are similar or different across urban areas.

If these distributions are very similar across urban areas, then it might be possible to develop generalizable models of space-time prism constraints. If the space-time prism extremities are very different between urban areas, that means that people in different geographical contexts have very different spatio-temporal constraints. Perhaps, these differences would then explain the variability in travel behavior across areas.

It was considered valuable to analyze the hypotheses discussed in this section by comparing activity and time use patterns and temporal prism extremities between two recent activity based travel and time use data sets.

DESCRIPTION OF SURVEYS

This section provides a brief description of the two surveys from which the activity-based time use and travel data sets were drawn. Various detailed reports on the surveys have been published and are available (*10, 11*). The intent of this section is merely to provide an overall synopsis of the nature of the surveys and the sample sizes that were available for this study.

San Francisco Bay Area

A two-day activity based time use and travel survey was conducted in the nine counties of the San Francisco Bay Area in 1996. Detailed information on both in-home and out-of-home activities and trips undertaken by an individual was recorded. While in–home activity information was requested only for those activities that were 30 minutes or longer in duration. However, a few respondents provided detailed information on all in-home activities. Information on all out-of-home activities was collected irrespective of their duration.

After extensive data checking, cleaning, and merging/organizing, the final data set obtained for use in this study included 7,982 persons residing in 3,827 households. Among the 7,982 persons, 4,331 were commuters and the remaining 3,651 persons were non-commuters. Full-time or part-time workers, irrespective of their school status and work location, were treated as commuters in this study.

Miami-Dade County

An activity-based travel behavior and time-use survey was conducted in the Miami-Dade County area of Florida in 1998. The survey collected detailed information on both in-home and out-of-home activities and on all travel associated with these activities. Unlike the San Francisco Bay Area survey, activity and travel behavior data was collected for only a one-day (24-hour) period in this survey. In addition, the sample consisted exclusively of commuters who were defined as individuals who commuted to a regular work or school location at least three days a week. Only one randomly selected commuter was chosen to participate from each household. Unlike the Bay Area survey, the Miami survey did not have any duration threshold for reporting of activities. All activities, regardless of their length, were recorded in the data set.

640 commuters provided detailed activity and trip information for the 24-hour survey period. The analysis in this study was, however, performed only on a sample of 589 commuters as the remaining respondents included full time students with no work. Even though the Miami-Dade County survey sample is considerably smaller than that of the San Francisco Bay Area survey, it was not considered a problem for the broad types of comparisons presented in this chapter.

SAMPLE PROFILE

This section provides a brief overview of the socio-economic and demographic characteristics of the two survey samples. A comparison of household characteristics is presented first followed by a comparison of person characteristics. At the person-level, comparisons are made while distinguishing between commuters and non-commuters.

Household Characteristics

The sample included 3,827 households from the Bay Area and 640 households from Miami. The average household size in the Bay Area is found to be 2.3 while that in Miami is substantially higher at 3.2 (Table 1). While the Bay Area survey average household size is quite comparable with census information, it was found that the Miami figure was substantially higher than the census figure (*12*). One possible reason for this is that the exclusive commuter-based sample from the Miami survey may favor the inclusion of larger households as opposed to smaller household sizes such as single-person students and retirees. Indeed, the Miami sample shows substantially higher percentages of households with three or more persons.

The income distributions are as expected with a large percentage of the households in both surveys comprising medium income households. In Miami, the percentage of low income households is found to be quite higher than that in San Francisco. However, this observation is tempered by the fact that these income values have not been corrected for cost-of-living differences.

TABLE 1 Comparison of Household and Person Characteristics

Household Attributes	San Francisco (3827)		Miami (640)
Household Size	2.3		3.2
1 person hhld	32.2%		12.8%
2 person hhld	34.5%		27.0%
3+ person hhld	33.3%		60.2%
Income			
Low (<30k)	15.8%		29.4%
Medium (30-75k)	44.4%		40.9%
High (>75k)	26.7%		19.7%
Vehicle Ownership	1.9		2.1
0 car hhld	5.6%		3.9%
1 car hhld	34.4%		21.9%
2 car hhld	39.4%		49.4%
3+ car hhld	20.5%		24.8%
% Vehicles≥commuters	86.4%		64.4%
Number of Workers	1.4		2.5
0 worker hhld	16.5%		--
1 worker hhlds	40.4%		23.4%
2 worker hhld	37.0%		38.0%
3+ worker hhld	6.0%		38.6%
Person Attributes	**Commuter (4331)**	**Non-commuter (3651)**	**Commuter (589)**
Age (years)	41.5	32.4	--
Young (≤29)	18.8%	54.0%	25.3%
Middle (30-49)	53.8%	14.5%	48.9%
Old (≥50)	27.4%	31.5%	22.3%
Employment Status			
Full time	81.5%	--	80.0%
Part time	12.1%	--	15.0%
Licensed	95.3%	48.6%	93.0%
Student	13.3%	44.8%	11.1%
Mode Choice (Journey to Work)			
Single Occupant Auto	68%	--	72%
Pool	13%	--	18%
Transit	8%	--	3%
Non-motorized	11%	--	5%

--: Not applicable

The average vehicle ownership is found to be 1.9 and 2.1 for the Bay Area and Miami samples respectively. Once again, these values must be compared with caution in light of the exclusive presence of commuters in the Miami sample. One would expect that car ownership levels in such households would be higher than in other households. 86 percent of the households in the San Francisco Bay Area survey have at least as many vehicles as the number of workers in the household indicating a rather high degree of car availability; the corresponding percentage is only 64 percent for the Miami sample. This difference in level of car availability per worker must be looked at in conjunction with the comparison in the number of workers per household. While the number of workers per household is only 1.4 in the Bay Area sample, it is 2.5 in the Miami sample. Once again, the exclusive presence of commuters in the Miami sample explains this rather large difference.

In general, the differences found in the comparison of household characteristics between the two survey samples are consistent with expectations. Many of these differences are simply manifestations of the fact that the Miami sample consists exclusively of commuters while the San Francisco sample includes all types of households. In light of these differences, it was felt necessary to divide the San Francisco sample into commuters and non-commuters. In this way, comparisons between the Miami commuter sample and the San Francisco commuter sample may be made in a consistent fashion. Also, by isolating the San Francisco non-commuter sample, one can identify differences in activity and time use patterns between commuters and non-commuters. As such, in the remainder of this chapter, these distinct sample groups are considered separately.

Person Characteristics

A comparison of the person characteristics of commuters and non-commuters in the Bay Area sample and commuters in the Miami sample is also shown in Table 1. The age distribution for commuters appears quite comparable with nearly one-half of the individuals (both in San Francisco and Miami) in the middle age bracket. There is a substantially higher percent of younger people among non-commuters. Nearly 80 percent of the commuter respondents in both regions are full-time workers. As expected, the percent of licensed drivers among commuters is substantially higher than that of non-commuters. This is easily explained by the high preponderance of young people (including those less than driving age) in the San Francisco non-commuter sample. Consistent with the above is the finding that the non-commuter portion of the Bay Area sample consists largely of students.

In general, the commuter samples in both surveys are quite comparable with respect to their personal characteristics. Variables representing age, employment status, drivers license holding, and student status are all quite similar between the two commuter samples. As such, it was felt that performing comparisons of activity and time use patterns between these two samples would be appropriate. As expected, the Bay Area non-commuter sample is quite different from the commuter samples. In light of these differences, one would expect the non-commuters to have substantially different activity and time use patterns when compared with their commuter counterparts.

ACTIVITY AND TRIP FREQUENCY ANALYSIS

Performing a comparison of trip frequencies across the two survey samples is relatively straightforward considering that each survey collected information on all trips pursued by an individual. Daily averages of activity and trip frequencies for the Bay Area survey sample were obtained by averaging over the two-day survey period.

In order to provide for comparability across the data sets, the numerous activity categories available in the data sets (there were about 30-40 activity categories in each data set) were aggregated as shown in Table 2. The first part of the table shows the average activity frequencies for these 10 activity types across the various samples. A distinction is made between Bay Area survey sample commuters and non-commuters to facilitate comparison between the Bay Area survey and the Miami survey.

Statistical tests comparing mean frequencies across the samples were performed. As expected, the activity frequencies of the San Francisco commuters differed significantly from those of non-commuters. Interestingly, statistically significant differences were also found between the two commuter samples for a majority of the activity types. However, one must exercise caution when interpreting these statistical differences as they may not necessarily imply behavioral differences.

The average number of work and work related activities for commuters is 1.6 for the Bay Area and 1.8 per day for Miami-Dade County. This difference could be attributed to the multiple job profiles of the commuters in Miami-Dade County. It can also be noted that nearly 38% of the commuters in Miami-Dade County perform trips while at work, which results in a higher number of work activity episodes.

TABLE 2 Comparison of Activity Frequencies and Trip Rates

Characteristic	San Francisco Commuters (N=4331)	San Francisco Non-commuters (N=3651)	Miami Commuters (N=589)
Activity Frequencies (per day)			
Work/Work Related	1.6	--	1.8[a]
Eating/Meal Preparation	1.7	2.0[a]	2.5[a]
Shopping/Personal Business	0.6	0.7[a]	1.1[a]
Out of Home Entertainment	0.5	0.6[a]	0.3
In Home Entertainment	1.2	1.8[a]	1.0[a]
Personal care and Child care	1.2	1.2	2.6[a]
Sleep and Nap	1.0	1.1[a]	1.2[a]
In Home Maintenance/Other	0.7	1.1[a]	1.1[a]
Out of Home Other	0.4	0.4[a]	0.6[a]
School	0.1	0.7[a]	--
Travel (Total Trips)	4.8	3.5[a]	4.9[a]
Trip Rates (per day)			
Work/Work Related	1.3	--	1.4
Return Home	1.6	1.3[a]	1.4[a]
Meal (out-of-home)	0.4	0.2[a]	0.4
Shopping/Personal Business	0.5	0.6[a]	0.6[a]
Out of Home Entertainment	0.5	0.5[a]	0.3[a]
Child Care	0.1	0.1	0.4[a]
Out of Home Other	0.4	0.4[a]	0.5[a]
School	0.1	0.4[a]	--
Total Activities and Trips	13.9	13.1	17.1

[a]Statistically different from the San Francisco Commuters at the 95% confidence level
--: Not applicable

The average number of eating and meal preparation activities is 1.7 and 2.0 for commuters and non-commuters respectively in the Bay Area, while it is relatively higher at 2.5 episodes per day for commuters in Miami-Dade County. It is possible that some eating and meal preparation activities are shorter than 30 minutes and thus did not get reported in the Bay Area survey.

The average frequency of shopping and personal business activities for the Bay Area commuter sample is about 0.6 while that for the Miami sample is a little over one activity per day. The reasons for this are not immediately apparent and merit further investigation; perhaps the demographic differences between the two samples contribute, at least partially, to the differences in shopping and personal business activity engagement.

The in-home entertainment frequency averages a little over one episode per day for both commuter samples. Major differences are seen between the two survey samples with respect to personal and childcare. The Miami sample exhibits an average frequency of 2.6 activity episodes per commuter on personal and child care against 1.2 for the Bay Area sample. Much of this difference can be attributed to the higher average household size in the Miami-Dade County sample. It can also be hypothesized that a few of these activity types are in-home activities and may not have been reported in the Bay Area survey because of their relatively short duration.

With respect to travel, it is found that the commuter samples in both surveys exhibit very comparable overall trip rates. While the average number of trips per day in the Bay Area commuter sample is 4.8, the corresponding average in the Miami sample is 4.9. As expected, the non-commuter sample is considerably lower at 3.5 trips per day.

The trip rate for work and work related activities is found to be 1.3 in the Bay Area and 1.4 in the Miami area sample. Return-home trip frequencies are slightly higher for the Bay Area commuters when compared with the Miami area commuters. As transit usage in the Bay Area is considerably higher than that in the Miami area, it is possible that people undertake fewer multi-stop trip chains in the Bay Area than in Miami. The mode share to work for the Bay Area commuters is 80% auto, 9% transit, and the rest non-motorized modes. The share for the Miami sample is 90% auto and 3% transit.

The trip frequencies for out-of-home eat-meal activities, shopping and personal business activities are comparable across both samples. The trip frequency for childcare activities is much higher at 0.4 for the Miami commuter sample while it is 0.1 for the Bay Area sample.

Again, this could be attributed to the differences in household composition across the two samples.

The commuter sample in the Bay Area survey reported, on average, a total of about 14 episodes per day while non commuters reported about 13 episodes per day. The corresponding value in the Miami commuter sample is 17 episodes per day. As explained earlier, this is most likely due to differences in average household size and household composition between the two samples.

ANALYSIS OF TIME USE PATTERNS

The previous section focused on the frequencies with which people engage in various activities and trips. However, as there is increasing recognition in the literature on the role played by time use on activity engagement and travel behavior (*1*), it is of interest to compare time use patterns between different survey samples. Analyzing time use patterns can offer valuable insights into how people trade-off time between various activities and the amount of time that might be available for less mandatory activities after the mandatory activity durations are accounted for. This section focuses on time use patterns, first in the context of activity engagement and second, in the context of travel durations.

Activity Duration

Table 3 shows the activity duration distributions for the various survey samples by activity type. It should be noted that the two-day data in the Bay Area survey was averaged to obtain the daily values presented in the graphic. The average work duration for commuters is found to be about seven hours; this figure is consistent with expectations considering that a few commuters are part-time workers. This accounts for nearly 30 percent of the day. Sleep duration averages close to eight hours and accounts for another 30 percent of the day regardless of whether the person is a commuter or non-commuter.

The eating and meal preparation durations are also comparable across the two regions. In all of the sample classes, it is found that the eating and meal preparation duration averages about 1 ½ hours per day. It is interesting to note that even though the Bay Area survey may not have captured all of the eating and meal preparation episodes (because some of them may have been less than 30 minutes in duration), the overall activity durations are very similar.

TABLE 3 Activity and Travel Durations by Purpose

Characteristic	San Francisco Commuters (N=4331) hr:min	San Francisco Non-commuters (N=3651) hr:min	Miami Commuters (N=589) hr:min
Activities			
Work/Work Related	06:41 (28%)	00:00 (0%)[a]	07:00 (29%)[a]
Eating/Meal Preparation	01:24 (6%)	01:46 (7%)[a]	01:23 (6%)
Shopping/Personal Business	00:23 (2%)	00:34 (2%)[a]	00:24 (2%)
Out of Home Entertainment	00:46 (3%)	01:10 (5%)[a]	00:40 (3%)
In Home Entertainment	02:12 (9%)	03:46 (16%)[a]	01:51 (8%)[a]
Personal care and Child care	01:08 (5%)	01:16 (5%)[a]	01:24 (6%)[a]
Sleep and Nap	07:57 (32%)	09:23 (40%)[a]	07:56 (32%)
In Home Maintenance/Other	01:20 (6%)	02:27 (10%)[a]	01:05 (5%)[a]
Out of Home Other	00:21 (2%)	00:13 (1%)[a]	00:21 (1%)[a]
School	00:07 (1%)	02:21 (10%)[a]	00:00 (0%)[a]
Missing	00:07 (1%)	00:05 (0.5%)	00:15 (1%)
Travel	01:34 (7%)	00:59 (4%)[a]	01:41 (7%)[a]
Work/Work Related	00:29 (32%)	00:00 (0%)[a]	00:34 (34%)[a]
Return Home	00:34 (36%)	00:23 (39%)[a]	00:28 (28%)[a]
Meal (out-of-home)	00:05 (5%)	00:03 (5%)[a]	00:06 (6%)
Shopping/Personal Business	00:07 (8%)	00:08 (14%)[a]	00:10 (10%)[a]
Out of Home Entertainment	00:07 (8%)	00:08 (14%)[a]	00:06 (6%)
Child Care	00:01 (1%)	00:01 (2%)	00:06 (6%)[a]
Out of Home Other	00:09 (10%)	00:09 (16%)	00:10 (10%)
School	00:00 (0%)	00:06 (10%)	00:00 (0%)

[a]:significantly different from San Francisco commuters at the 95% confidence level

As expected, non-commuters exhibit the largest value for in-home entertainment duration. Non-commuters are likely to watch more TV and relax at home than commuters who spend 30 percent of the day at work. Among the commuter samples, it is found that the average in-home entertainment duration in the Bay Area is higher than in the Miami sample (2 hr 12 min vs. 1 hr 51 min). This difference merits further investigation, but one possible explanation is that the Miami commuters spend slightly more of their in-home time (and out-of-home time) on personal and child care responsibilities. The total time spent on such activities is 1 hr 24 min for the Miami sample compared to 1 hr 8 min for the Bay Area sample.

The statistical comparison of activity durations between the Miami and San Francisco commuter samples revealed no significant differences for eat meal/preparation, shopping/personal business, out of home entertainment, and sleep/nap activities. On the other hand, differences between the San Francisco commuter and non-commuter samples were found to be statistically different for all activity types.

Travel Duration

Average travel durations by purpose are also shown in Table 3. The average travel duration for work and work related activities in the Bay Area is 29 minutes as against 34 minutes in Miami-Dade County. The average return home travel duration for Miami commuters is 28 minutes when compared to 34 minutes for the Bay Area commuters. The corresponding average for the non-commuter sample is about 23 minutes.

The travel duration for childcare is considerably higher in the Miami area. As explained before, this can be attributed to the higher average household size. The travel durations for the other categories are comparable across the commuter samples.

In contrast to activity and trip frequency comparisons, the comparisons of time use (activity and travel durations) show greater similarities (from a statistical standpoint) across geographical contexts. The differences in time use between the samples may simply be a manifestation of the differences in socioeconomic and demographic characteristics of the study samples and the survey methods employed. These findings provide a first-cut indication that models based on concepts of time use may exhibit a greater potential to be applied in multiple geographic contexts as opposed to models based purely on activity/trip frequencies.

SPACE-TIME PRISM EXTREMITIES

The notion of space-time prisms is particularly appealing and useful in the context of the increasing interest in microsimulation approaches for travel demand forecasting (*13*). This involves the modeling of a series of choices that travelers make during the day including those related to activity type choice, activity duration, timing and scheduling, location and destination choice, and path choice. Considering that many of these choices are made under constrained conditions, one can argue that there is a finite spatio-temporal action space or space-time prism within which one can engage in activities and travel.

During the course of a day, there may be multiple prisms defining the spatio-temporal action space of an individual. In other words, various prisms during the day have important temporal extremities. From a spatial standpoint, one can conjecture that the home and work locations are potential anchors that constrain the potential range of destinations that a person can visit. Similarly, the temporal anchors or extremities might dictate how an individual schedules and plans his or her activities over the course of a day.

In the two data sets available for this study, time-of-day information is available for several key activities or events during the day. It is worth noting that the survey information provides data on the revealed behavior of individuals and does not necessarily correspond to theoretical extremities of individual space-time prisms. However, in the absence of information about theoretical temporal extremities of space-time prisms, it was considered useful to analyze information about observed temporal extremities. Such data may offer valuable insights into how and why people arrange their activities and allocate time to various activities in the manner that they exhibit.

In this chapter, six space-time prism temporal extremities are analyzed. They are:

1. Wake up time
2. First time of departure from home
3. Work start time (for commuters)
4. Work end time (for commuters)
5. Final time of arrival at home
6. Sleep time

This section is devoted to analyzing the distributions of these temporal extremities for the various sample groups. The first block, shown in Figure 1, focuses on the initial daily space-time prisms. The second block, shown in Figure 2, focuses on the temporal extremities that define the final space-time prisms of an individual's day. Each temporal extremity is discussed separately in the next several paragraphs. Note that, in the case of the Bay Area sample, the day-1 space-time prism extremities have been plotted.

Statistical comparisons were performed to compare temporal distributions between San Francisco and Miami commuters, and between San Francisco commuters and non-commuters. The χ^2 test was used to determine whether significant differences existed between these two sample pairs. Differences in distributions were found to be statistically significant for all space-time extremities for both sample pairs considered. However, it is noteworthy that the χ^2 values are higher for the comparisons between the San Francisco commuter and non-commuter samples, potentially indicating that commute status is more influential than geographic context in determining space-time prism extremities.

Wake Up Time

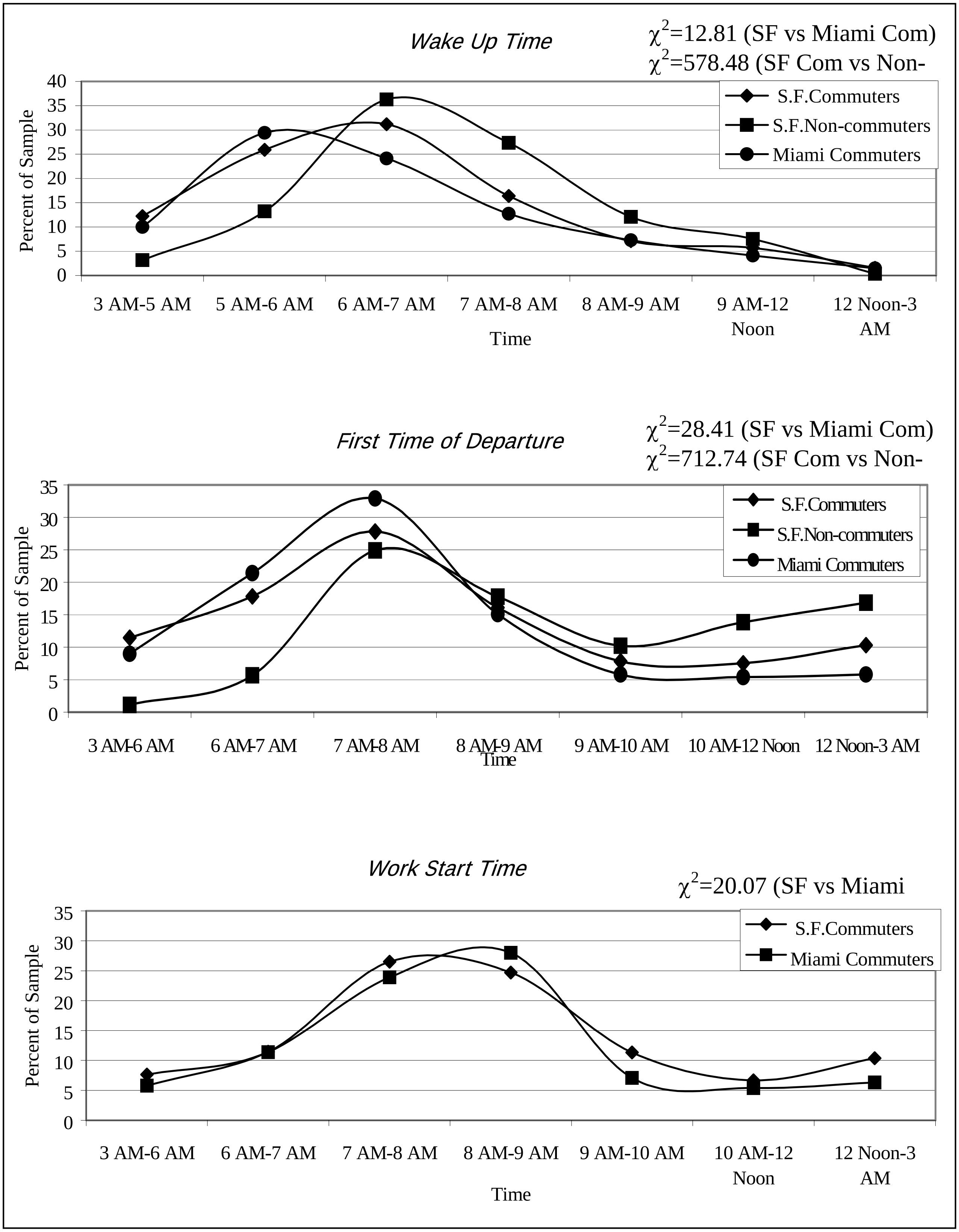
The first graph in Figure 1 shows a comparison of the wake-up time distributions for the three samples. The commuter sample in the Bay Area and Miami show a similar pattern. The distribution of wake-up times for the Miami commuter sample suggests that they wake up earlier compared to the Bay Area commuter sample. This difference may be attributed to several factors including household obligations (the Miami sample has larger household sizes) and the nature of the occupations in which they are employed.

First Time of Departure From Home

The second graph in Figure 1 shows the distributions of the first time of departure from home. As expected, these distributions are shifted to the right by about one hour when compared to the wake up time distributions. This time differential could be attributed to personal care, child care, and eating and meal preparation activities that are typical of morning before-work prisms.

The interesting finding in this graph is that the two commuter samples exhibit peaks at about the same time period, namely 7 AM to 8 AM. While this is quite plausible, considering that commuters often depart from home within this time band, it is not consistent with the differences exhibited by the wake up time distributions. In the previous graphic, it was found that the Miami commuters had a wake up time distribution that was earlier than the Bay Area commuter sample. In other words, it appears that the Miami commuter sample has a larger

FIGURE 1 Observed Temporal Extremities of Initial Daily Space-Time Prisms



morning before-work prism, possibly because they have more household obligations and responsibilities. As such, it may be conjectured that the temporal dimensions (extremities) of the prisms will be highly influenced by socio-demographic characteristics and household composition variables.

The Miami commuter sample exhibits the distribution with the greatest peak. The distribution for the Bay Area commuter sample is relatively flatter possibly because they have fewer household obligations (e.g., dropping child at school) and have occupations that offer greater degrees of flexibility with respect to work start times (see discussion in next subsection). As expected, non-commuters show the flattest distribution of all groups with a rather even distribution starting about 7 AM.

Work Start and End Times

Work start time distributions are plotted in the third graph of Figure 1 for the two commuter samples. As mentioned previously, it appears that possible differences in occupational make-up, work start time flexibility, and household obligations are contributing to substantially different patterns.

The work end time distributions are shown in the first graphic of Figure 2. In general, both commuter samples exhibit substantially flatter distributions as compared to their work start time distributions. It appears that there is greater flexibility in work end times than there is in work start times. In addition, the presence of part time workers who leave work earlier than others may contribute to the pattern seen in this graph.

The work end time generally represents the terminal extremity of the at-work space-time prism and is therefore quite important in the analysis of activity-travel patterns. Potentially, this extremity might dictate the extent to which a person pursues activities, and therefore requires personal (and flexible) transportation, during his or her stay at work.

Final Time of Arrival at Home

The second graph in Figure 2 shows the distributions of final arrival time at home after undertaking all out-of-home activities during the day. The two commuter samples show rather even distributions without clear peaks. As expected, both commuter segments show most final home-arrival times in the evening distributed between 5 PM and 8 PM with gradual decreases as one proceeds later into the night. However, it is found that both the commuter samples exhibit a sudden surge in final arrival times between 10 PM and 3 AM. This is possibly due to the returning home of part-time (or evening shift) workers.

The Bay Area non-commuters show a peak in the 2 PM – 4 PM range. This may represent a convergence of activities including bringing children home from school, finishing shopping, and completing personal business and other errands. As expected, the distribution then shows a very gradual and uniform decreasing trend.

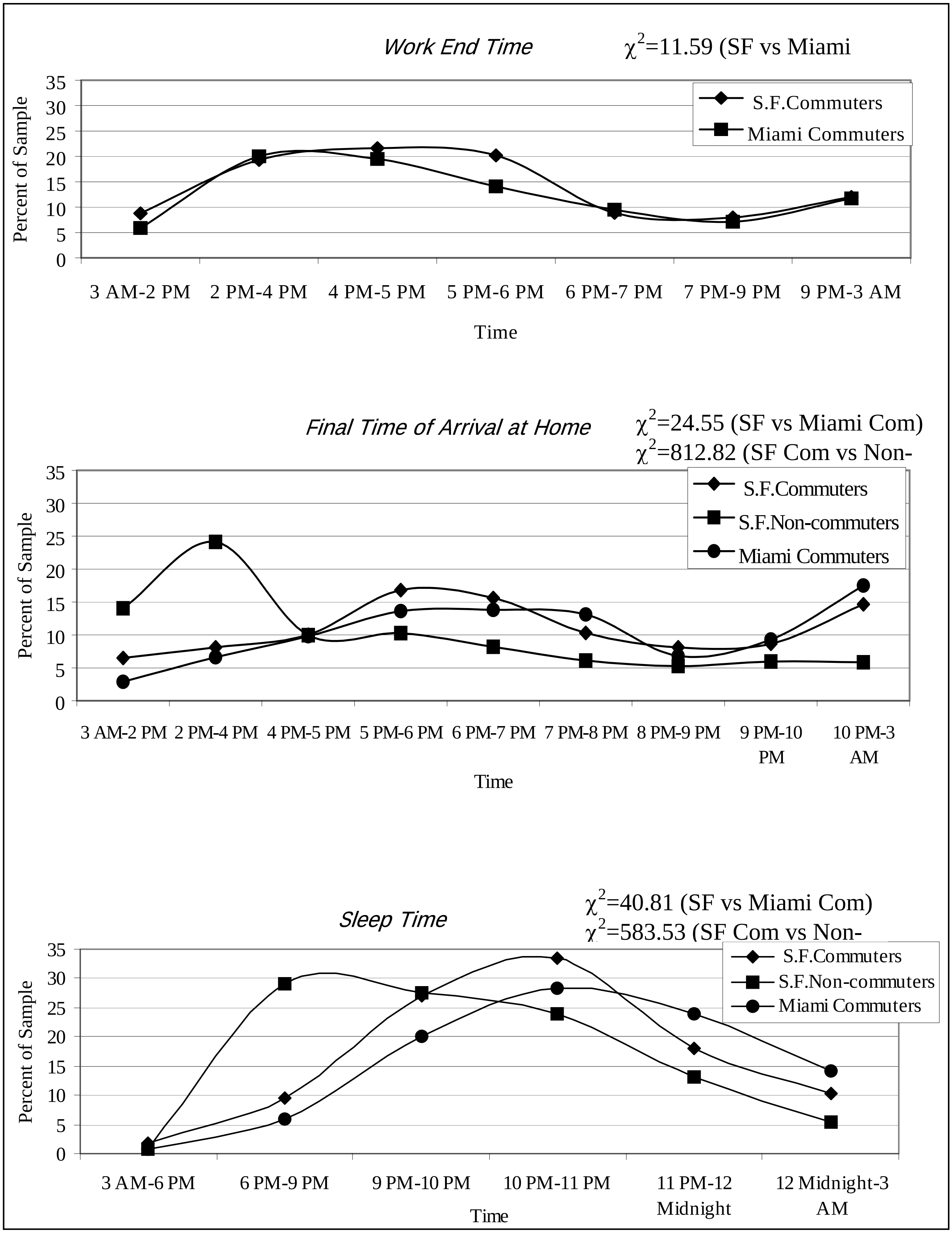
The final arrival time at home often represents the initial temporal extremity of the evening at-home (and post-work for commuters) prism. It may dictate the types of in-home activities that a person may be able to engage in and shows the extent to which an individual is prone to engage in activities outside the home during the evening hours. These tendencies may be dependent on personal and household socio-demographic characteristics.

Sleep Time

The final graph in Figure 2 shows the distributions of sleep times for all of the sample groups considered in this chapter. The non-commuters in the Bay Area sample are found to have a relatively flat distribution that exhibits earlier sleeping times than the commuter samples. Nearly 30 percent of the non-commuters are found to sleep in the 6 PM – 9 PM time span. The corresponding percentages for the commuter samples are between 5 and 10 percent.

The two commuter samples exhibit noticeable differences in their distributions of sleep times. Both samples show peaks in the 10 PM – 11 PM range. However, the peak in the Bay Area commuter sample is much more well-defined and the Miami commuter sample distribution is clearly shifted to the right. In other words, the Miami commuter sample appears to exhibit relatively later sleeping times when compared with the Bay Area commuter sample.

FIGURE 2 Observed Temporal Extremities of Final Daily Space-Time Prisms



Nearly 13 percent of the Miami commuter sample report sleeping in the time span of 12 midnight – 3 AM. Almost 24 percent of the Miami commuter sample report sleeping in the 11 PM – 12 midnight range and the corresponding percentage of the Bay Area commuter sample is 17 percent. Again, it is hypothesized that the nature of the occupational make-up of the sample and the household composition (i.e., household obligations) play an important role in explaining these differences.

The sleep times represent the terminal extremity of the at-home prism and represent the end point by which time a person must conclude his or her activities, whether in-home or out-of-home. As such, it is a key temporal point in the daily activity schedule of a person.

CONCLUSIONS

In this study, detailed activity and trip information from activity-based time use and travel surveys conducted in the Miami-Dade county area of Florida and the San Francisco Bay Area of California was used to perform a coast-to-coast comparison of activity and time use patterns. The Bay Area survey included both commuters and non-commuters while the Miami survey included only commuters. Much of the comparisons presented in the chapter consider differences and similarities that exist between three distinct sample groups: Miami commuters, Bay Area commuters, and Bay Area non-commuters.

Within the context of this study, emphasis was placed on exploring differences and similarities in behavior from a qualitative and behavioral standpoint. However, certain statistical tests were performed to identify significant differences in activity and time use patterns. Most activity and trip frequencies were found to be statistically different across the samples, but there was a greater level of similarity across samples in time use measures. It was also found that the travel durations in these survey samples compared very well with those reported by Robinson and Godbey (*14*) from the Americans' Use of Time project. Considering the greater level of similarity in time use, one might conjecture that time use based models of travel demand exhibit greater potential for adaptation in multiple geographic contexts than do models of activity/trip frequency. As this chapter constituted an exploratory analysis and did not involve model development and estimation, further work is needed to confirm or reject this hypothesis.

In addition to a comparison of activity and time use patterns, the chapter reported on a comparison of temporal space-time prism extremities across sample groups. Space-time prisms represent spatio-temporally constrained action spaces within which individuals plan and schedule their activities, undertake trips, and fulfill their daily needs and preferences for activity engagement. Even though the concept of a prism is very appealing, it is difficult to develop an operational model of individual space-time prisms. As a first step in that direction, it was considered useful to examine observed temporal extremities of space-time prisms for the various sample groups.

The space-time prism distributions for both regions followed expected trends, but there were statistically significant differences across the samples. While the exact reasons for these differences are not immediately apparent, it is hypothesized that these differences occur due to differences in occupational make-up of the sample and household composition (and therefore household obligations).

Future work in this area should focus on developing and comparing models of activity engagement, time use, and travel behavior for different geographic areas. Such a model development and comparison exercise will help explain the differences and similarities that exist between areas and the potential for using models developed in one area in another area. In addition, there are numerous other activity and time use survey data sets that have been collected in the recent past. Further comparisons across survey samples should be undertaken to add to the body of evidence on differences and similarities in activity and time use patterns across geographical contexts.

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DATA QUALITY AND TRANSFERABILITY - II
CHAPTER II

SUMMARY

Human activity scheduling and sequencing are important aspects of activity-travel behavior that can have important implications for the development of activity-based travel demand modeling systems. Trip chaining patterns, and therefore trip characteristics, are directly influenced by the scheduling and sequencing of activities during the course of a day. This chapter provides an in-depth comparative analysis of activity stop placement and sequencing behavior for commuter samples drawn from two geographic areas in the United States – Miami, Florida and San Francisco Bay Area, California. Comparisons between the areas show that activity sequencing exhibits the greatest similarities during the at-work period when commuters are presumably constrained by work schedules. While some differences in activity sequencing were found in the before-work period, dramatic differences in activity placement and sequencing were found in the after-work period. In this period, it was found that Miami commuters are far more prone to undertake activities while on the way home from work and less prone to undertake activities in separate trip chains after returning home from work. These differences may be partially attributed to socio-economic, household, and commute characteristics (e.g., mode to work) that influence people's activity engagement patterns. Models of activity sequencing behavior should reflect these differences and account for the factors that contribute to these differences so that they are sensitive to changes in socio-economic and transportation system characteristics.

INTRODUCTION

Activity-based approaches to travel demand analysis focus on numerous aspects of activity engagement behavior that drive individual travel decisions (Axhausen and Garling, 1992). These include, but are not necessarily limited to, the type, location, timing, duration, and sequencing of activities over the course of a certain time period (typically, a day or several days). Recent research in activity-based approaches to travel analysis has devoted considerable attention to unraveling and explaining these various aspects of activity engagement behavior with a view to obtaining a better understanding of decision processes that govern travel demand (Damm, 1982; Kitamura, 1988; Bowman and Ben-Akiva, 2001).

This chapter focuses on analyzing and understanding the activity sequencing and stop-making behavior of individuals over the course of a day. In order to obtain additional insights regarding similarities and differences in activity sequencing across different contexts, comparisons are made between two geographical areas in which recent and detailed activity and travel data are available. Analyses and comparisons are presented in this chapter exclusively for samples of commuters who work outside the home on a regular basis. This is done in order to provide a focused discussion and because activity sequencing patterns of commuters tend to be structured around the relatively rigid work schedules. This tends to provide a meaningful basis for performing comparisons of activity sequencing patterns across different geographical contexts.

Several research studies in the recent past have underscored the importance of analyzing and developing models of activity sequencing behavior (Doherty and Miller, 2000; Ettema and Timmermans, 1997). Wilson (1998) uses sequence-alignment methods to analyze activity patterns. Hamed and Mannering (1993), Bhat (1998), and Bhat, et. al. (1999) developed models of activity stop generation and organization to better understand the scheduling of stops during different periods of the day. Chen, et. al. (1999) adopted an interactive programming approach to develop a daily activity itinerary for an individual. Being able to model activity sequencing behavior is particularly useful in the context of microsimulation approaches to activity-travel modeling where the entire activity-travel pattern of each individual is being simulated over the course of a day (Kitamura, et. al., 1997, 2000). Insights into activity scheduling preferences and sequencing behavior can also aid in the development of rule-based algorithms and heuristic approaches that are behaviorally sound and allow the identification of preferred activity-travel patterns over less preferred ones (see e.g., Pendyala, et. al., 1997, 1998).

It must be recognized, however, that activity sequencing and stop-making behavior can not be viewed in isolation. Various aspects of activity engagement behavior undoubtedly influence the sequencing of activities. For example, the frequency of activity engagement (Ma and Goulias, 1999) is likely to influence the scheduling and sequencing of activities over the course of a day. Similarly, there is a large and growing body of literature on time use research that clearly shows the linkages between time use and activity engagement (Bhat and Koppelman, 1999). It is conceivable that the amount of time spent at various activities will determine how the activities can be scheduled and sequenced over the course of a day, particularly for commuters who may be constrained by work schedules. Models of activity time allocation have been developed to capture the effects of time use on activity engagement behavior (see e.g., Kuppam and Pendyala, 2000; Kitamura, 1984; Golob, 1998). As such, patterns of activity placement and sequencing presented in this chapter should be interpreted while keeping these possible interlinkages in mind.

In this chapter, activity sequencing behavior is analyzed for commuter samples drawn from two surveys, namely, the 1996 San Francisco Bay Area activity survey and the 1998 Miami activity survey of commuters. The observed placement of various non-work activity stops in relation to the work activity is examined first. This is followed by a more in-depth analysis of activity sequences undertaken by commuters within the various periods of the day. Differences and similarities in activity placement and sequencing behavior between the two survey samples are discussed together with possible reasons that explain the differences and similarities found. Such comparisons are gaining increasing attention as they provide valuable insights into the types of similarities and differences in activity engagement patterns that need to be reflected in activity-based model systems (Sermons and Koppelman, 2001).

A note is due here regarding the nature of the geographic regions being compared in this chapter. In general, both Miami and the San Francisco Bay Area exhibit substantial similarities. Both of the regions are quite comparable in size and represent large metropolitan areas. They are regions with dense central business districts that represent major employment centers and have large numbers of commuters living in lower density suburban areas. The population is quite diverse, both economically and ethnically, in both areas. In addition, both regions enjoy favorable weather throughout the year. Besides these broad similarities, there are several key differences that are noteworthy as well. Both regions experience substantial peak period congestion; however, congestion tends to be worse in the San Francisco Bay Area than in Miami. Also, both areas have multimodal transportation systems with a significant presence of transit and rail. However, transit usage in the San Francisco Bay Area is considerably greater than in the Miami area. It is in the context of these similarities and differences that the comparisons in this chapter should be interpreted.

The next few sections provide some background information about the concept of activity sequencing and scheduling, the two surveys from which data have been drawn, and socio-demographic characteristics of the commuter samples included in the analysis. Following these sections, there are two sections devoted to analyzing and comparing activity placement and activity sequencing patterns of commuters. Finally, conclusions and directions for future research are highlighted in the last section.

ACTIVITY SCHEDULING AND SEQUENCING

Activity sequencing and scheduling behavior has important implications for travel demand analysis. Even when two individuals perform the same number of out-of-home non-work activities, the manner in which they link, sequence, and schedule their activities can lead to different travel patterns (Kwan, 1999). For example, consider two commuters who engage in two out-of-home non-work activities in the day, namely, shopping and personal business. Depending on how they schedule and sequence these activities, the number of trips they undertake (and therefore travel times, vehicle miles traveled, and cold/hot starts) may be very different. In other words, the two individuals may adopt different trip chaining patterns. Consider the following possibilities:

Person 1: Home → Work → Shop → Personal Business → Home (4 trips)

Person 2: Home → Work → Personal Business → Work → Home → Shop → Home (6 trips)

Many other trip chaining possibilities that accommodate different activity sequencing and scheduling patterns are also conceivable. While the first person performs both non-work activities on the way home in an efficient multiple-stop chain, the second person performs one activity while at work (perhaps in the lunch hour) and the second activity after returning home from work. By doing so, the second person has undertaken two additional trips. Thus the implications of activity sequencing (and trip chaining) on trip generation are very clear. Considering that determination of the number of trips undertaken by individuals in a study area is the first step in the traditional urban transportation modeling and forecasting procedures, it would be useful to have activity sequencing and scheduling behavior effectively captured and represented in travel demand models (Garling, et. al., 1994).

The notion of activity sequencing and its impact on travel demand takes on added significance in the context of transportation policy analysis (Pendyala, et. al., 1997; Wang, 2001). Accurate prediction of the impact of various travel demand management strategies, transportation control measures, and transportation investment decisions on travel demand calls for a deep understanding of how activity sequencing and trip chaining patterns are altered by the proposed measures.

Activity sequencing and scheduling has often been seen in the context of tour formation and trip chaining (Bowman and Ben-Akiva, 2001; Wen and Koppelman, 1999, 2000). Indeed, the close correspondence between activity sequencing and trip chaining or tour formation is particularly true in the case of out-of-home activity engagement. Generally, knowledge of the out-of-home activity sequence will provide information on the trip chaining pattern and vice versa. Even though activity sequencing and trip chaining (tour formation) may be considered synonymous, this chapter uses the term activity sequencing to recognize that the activity sequence is the fundamental driving force underlying trip chain formation.

Also, within the context of this chapter, an important distinction is made between activity scheduling behavior and activity sequencing behavior. Activity scheduling refers to the behavioral process that an individual uses to develop an activity agenda, say for an entire day. The activity sequence is the observed outcome of the activity scheduling process. In most household activity-travel surveys, one obtains information about the activity sequencing behavior (i.e., the outcome) rather than the activity scheduling behavior (i.e., the process). However, it is envisaged that insights about the scheduling process can be obtained by studying the observed activity sequences in depth.

This chapter examines the placement and sequencing of out-of-home activities in relation to the work activity for samples of commuters. The work activity is generally non-discretionary in nature and tends to have limited flexibility in the time-space continuum. Given the limited flexibility associated with work locations and work timings, one may postulate that there are several specific periods in the day in which commuters can place their non-work activities. These periods may be likened to space-time prisms that define the spatio-temporal action space in which individuals may undertake activities (Pendyala, et. al., 2001). While the space dimension is not considered in this chapter, the time dimension is considered so as to define specific periods vis-à-vis the work activity in which activities may be undertaken. Consider the following temporal events in a day (for a typical commuter):

1. Wake up time
2. First departure from home
3. Work start time
4. Work end time
5. Final home arrival
6. Sleep time

These six temporal events define various periods, some of which are linked to the work activity, as follows:

1. Initial at-home stay
2. Before work
3. At work
4. After work
5. Final at-home stay

The first and last periods are exclusively reserved for in-home activities and are therefore not considered within the scope of this chapter which focuses on the placement and sequencing of out-of-home activities. Then, there are three other periods in which out-of-home activities may be undertaken – before, at, or after work. In this chapter, the 'before work' and the 'at work' periods are not broken down further, but the 'after work' period is broken down into two further possibilities because of the high prevalence of non-work activity engagement in the 'after work' period. First, stops (activities) undertaken 'on the way home from work' are considered.

Second, activities undertaken in separate chains following the return home from work are considered. Thus, an after work pattern of 'work → shop → home' falls into the first category, while an after work pattern of 'work → home → shop → home' falls into the second category. Such a distinction did not have to be made during the before work period, because of the lower prevalence of non-work activity engagement in that period. While the periods considered here do not necessarily represent the actual time dimension of the space-time prisms within which commuters may pursue activities, they represent potentially constrained periods in which commuters must undertake their activities. In this chapter, activity placement and sequencing patterns are studied in detail in the context of each of the four periods – before work, at work, on way home from work, and post-return home.

With the recent spate of activity and time use data collection efforts around the country, there has been growing interest in comparing activity and time use patterns across geographic contexts (Gangrade, et al., 2000). In the previous chapter comparing commuter samples drawn from the same two survey data sets, it is found that overall activity durations and time allocation patterns (i.e., the time spent on each activity type) are very similar (Gangrade, et. al., 2000). It is found that time use patterns and activity durations show greater similarities than activity and trip frequencies. In a subsequent chapter, it is found that the distributions of temporal vertices (end points) associated with various space-time prisms are virtually identical between the Miami and San Francisco Bay Area commuter samples (Pendyala, et. al., 2001). For example, it was found that the observed distributions of first time of departure from home and final time of arrival at home are very similar for the two commuter samples. The predicted prism vertices (estimated using stochastic frontier models) associated with these events are also found to show very similar distributions between the two samples.

Then, the question arises: if the overall activity duration and time allocation patterns and the locations of temporal vertices are very similar across geographical contexts, then how do patterns of activity sequencing and stop-scheduling that occur within the various prisms (periods) compare? This is the broad research question that this chapter attempts to answer. In other words, while many of the temporal measures of activity engagement behavior (activity durations, time allocation, travel durations, and temporal vertices of prisms) show substantial similarities across geographical contexts, not much is known about differences and similarities with respect to specific activity sequences and stop-patterns that commuters pursue within various periods (prisms) of the day. This chapter sheds light on this question by comparing both stop making behavior and activity sequencing patterns across commuter samples. Within the context of this chapter, differences and similarities in stop making and sequencing behavior are examined in light of socio-economic, demographic, and mode-to-work characteristics of the commuter samples. It is certainly possible that spatial, land use, and cultural aspects of the two regions play an important role in explaining similarities and differences in activity sequencing patterns. However, in the absence of detailed information about these aspects, an examination of their role is beyond the scope of this chapter.

There are potentially several other types of analyses about activity sequencing and activity scheduling that merit investigation. These are beyond the scope of this chapter, but are identified here so as to complete the discussion on activity scheduling and sequencing. First, it would be interesting to analyze day-to-day variability in activity sequencing and scheduling. The two-day data available from the 1996 San Francisco Bay Area survey may prove useful in this context, even though one would ideally like to have even more than two days of data to analyze day-to-day variability. Second, considering that rich activity-based surveys include detailed in-home activity information, analysis of activity sequencing and scheduling patterns should include explicit consideration of the scheduling of activities inside home. This will help identify relationships between the scheduling of activities outside home and the scheduling of activities inside home. Substitution and complementarities among in-home and out-of-home activities can also be analyzed through such an effort. Third, comparisons of activity sequencing and scheduling behavior across various socio-demographic market segments should be undertaken. Fourth, comparisons of activity sequencing and scheduling behavior should be undertaken across household members within the same household. This will help in the development of models of activity allocation, intra-household travel relationships, and intra-household activity prioritization. Such models would, in turn, prove valuable in the development of robust and comprehensive household activity-travel model systems (Veldhuisen, et. al., 2000).

SURVEY DESCRIPTIONS

This section provides a brief description of the two surveys from which the activity-based time use and travel data sets were drawn. More detailed descriptions of the surveys may be obtained from various reports that specifically describe the survey efforts (Pendyala, 1997; NuStats Research and Consulting, 1999).

San Francisco Bay Area

A two-day activity based time use and travel survey was conducted in the nine counties of the San Francisco Bay Area in 1996. Detailed information on both in-home and out-of-home activities and trips undertaken by a sample of individuals was recorded. In-home activity information was requested only for those activities that were 30 minutes or longer in duration. However, many respondents provided detailed information on all in-home activities, regardless of duration. On the other hand, information on all out-of-home activities was collected, regardless of duration.

After extensive data checking, cleaning, and merging/organizing, the final data set obtained for use in this study included 7,982 persons residing in 3,827 households. Among the 7,982 persons, 4,331 were commuters and the remaining 3,651 persons were non-commuters. Full-time or part-time workers, irrespective of their school status, were treated as commuters in this study.

Miami-Dade County

An activity-based travel behavior and time-use survey was conducted in the Miami-Dade County area of Florida in 1998. The survey collected detailed information on both in-home and out-of-home activities and on all travel associated with these activities. Unlike the San Francisco Bay Area survey, activity and travel behavior data was collected for only a one-day (24-hour) period in this survey. In addition, the sample consisted exclusively of commuters who were defined as individuals who commuted to a regular work or school location at least three days a week. Only one randomly selected commuter was chosen to participate from each household. Unlike the Bay Area survey, the Miami survey did not have any duration threshold for reporting of in-home activities. All activities, regardless of their length, were recorded in the data set.

640 commuters provided detailed activity and trip information for the 24-hour survey period. The analysis in this study was, however, performed only on a sample of 589 commuters as the remaining respondents included full time students with no work activity. Given the relatively smaller sample size of the Miami survey, detailed comparisons by socio-economic and demographic market segment could not be undertaken within the context of this study. As such, comparisons presented in this chapter are sample-wide comparisons that facilitate the identification of hypotheses regarding the factors that potentially contribute to differences and similarities in activity stop-placement and sequencing behavior.

SAMPLE DESCRIPTIONS AND COMPARISON

This section provides a brief overview of the socio-economic and demographic characteristics of the two survey samples. A comparison of household characteristics is presented first followed by a comparison of person characteristics. At the person-level, comparisons are made while distinguishing between commuters and non-commuters.

Household Characteristics

The sample included 3,827 households from the Bay Area and 640 households from Miami. The average household size in the Bay Area is found to be 2.3 while that in Miami is substantially higher at 3.2 (Table 1). While the Bay Area survey average household size is quite comparable with census information, it was found that the Miami figure was substantially higher than the census figure. One possible reason for this is that the exclusive commuter-based sample from the Miami survey may favor the inclusion of larger households as opposed to smaller household sizes such as single-person students and retirees. Indeed, the Miami sample shows substantially higher percentages of households with three or more persons.

The income distributions are as expected with a large percentage of the households in both surveys comprising medium income households. In Miami, the percentage of low income households is found to be higher than that in San Francisco. However, this observation is tempered by the fact that these income values have not been corrected for cost-of-living differences. The average vehicle ownership is found to be 1.9 and 2.1 for the Bay Area and

TABLE 1 Comparison of Household and Person Characteristics

Household Attributes	San Francisco (3827)	Miami (640)
Household Size	2.3	3.2
1 person hhld	32.2%	12.8%
2 person hhld	34.5%	27.0%
3+ person hhld	33.3%	60.2%
Income		
Low (<30k)	15.8%	29.4%
Medium (30-75k)	44.4%	40.9%
High (>75k)	26.7%	19.7%
Vehicle Ownership	1.9	2.1
0 car hhld	5.6%	3.9%
1 car hhld	34.4%	21.9%
2 car hhld	39.4%	49.4%
3+ car hhld	20.5%	24.8%
% Vehicles≥commuters	86.4%	64.4%
Number of Workers	1.4	2.5
0 worker hhld	16.5%	--
1 worker hhld	40.4%	23.4%
2 worker hhld	37.0%	38.0%
3+ worker hhld	6.0%	38.6%
Person Attributes	Commuter (4331)	Commuter (589)
Age (years)	41.5	--
Young (≤29)	18.8%	25.3%
Middle (30-49)	53.8%	48.9%
Old (≥50)	27.4%	22.3%
Employment Status		
Full time	81.5%	80.0%
Part time	12.1%	15.0%
Licensed	95.3%	93.0%
Student	13.3%	11.1%
Mode Choice (Work Trip)		
Single Occupant Auto	68%	72%
Pool	13%	18%
Transit	8%	3%
Non-motorized	11%	5%

--: Not applicable

Miami samples respectively. Once again, these values must be compared with caution in light of the exclusive presence of commuters in the Miami sample. One would expect that car ownership levels in such households would be higher than in other households. 86 percent of the households in the San Francisco Bay Area survey have at least as many vehicles as the number of workers in the household indicating a rather high degree of car availability; the corresponding percentage is only 64 percent for the Miami sample. This difference in level of car availability per worker must be looked at in conjunction with the comparison in the number of workers per household. While the number of workers per household is only 1.4 in the Bay Area sample, it is 2.5 in the Miami sample. Once again, the exclusive presence of commuters in the Miami sample explains this rather large difference.

In general, the differences found in the comparison of household characteristics between the two survey samples are consistent with expectations. Many of these differences are simply manifestations of the fact that the Miami sample consists exclusively of commuters while the San Francisco sample includes all types of households. In light of these differences, it was felt necessary to divide the San Francisco sample into commuters and non-commuters. In this way, comparisons between the Miami commuter sample and the San Francisco commuter sample may be made in a consistent fashion. As such, in the remainder of this chapter, only the commuter sample groups from these two surveys are considered.

Person Characteristics

A comparison of the person characteristics of commuters in the Bay Area sample and commuters in the Miami sample is also shown in Table 1. The age distribution for commuters appears quite comparable with nearly one-half of the individuals (both in San Francisco and Miami) in the middle age bracket. Nearly 80 percent of the commuter respondents in both regions are full-time workers. As expected, the percent of licensed drivers among commuters is quite high.

It is found that the two commuter samples show different modal splits for the journey to work. While the Miami area shows only 8 percent of the commuters using transit or non-motorized modes, the San Francisco Bay Area sample shows nearly 20 percent of the commuters using transit or non-motorized modes. It should be noted that the higher usage of alternative modes of transportation in the Bay Area sample may contribute to differences in activity sequencing and scheduling patterns between the two areas. One may conjecture that, in general, the flexibility afforded by the automobile facilitates undertaking multi-stop chains with greater ease than can be undertaken on transit or non-motorized modes.

In general, the commuter samples in both surveys are quite comparable with respect to their personal characteristics. Variables representing age, employment status, drivers license holding, and student status are all quite similar between the two commuter samples. As such, it was felt that performing comparisons of activity and time use patterns between these two samples would be appropriate. Gangrade, et. al. (2000) have shown that non-commuter activity and travel characteristics are quite different from those of commuters. Then it may be conjectured that the activity scheduling and sequencing patterns of non-commuters would be very different from those of commuters. Comparisons between commuters and non-commuters are left for future research.

PRISM-BASED ACTIVITY PLACEMENT BEHAVIOR

As mentioned in the previous section, various non-work stops may be performed during different periods of the day. In this section, the placement of four types of non-work activities is compared between the two geographic areas. In the case of the San Francisco Bay Area, only the first day of activity and travel information (from the two-day survey) was used for analysis. The four activities considered include eat meal, shopping, personal business (including serve child), and social recreation (including entertainment). The question being addressed in this comparison is: how do commuters in San Francisco Bay Area and Miami differ with regard to the participation and placement of non-work activity stops vis-à-vis the work activity?

Table 2 shows the stop scheduling pattern for eat meal activities. The first four columns in the table indicate when an eat-meal activity has been undertaken. If an X appears in the column, it means that an eat-meal activity has been undertaken in that period. The percent valid column provides the percent of those who actually undertook an eat-meal activity in the various stop-making patterns. The percent of total provides the percentage calculated on the entire sample. Percentages smaller than 0.05 percent appear as zero in this and all other tables in the chapter.

TABLE 2 Comparison of Out of Home Eat Meal Activity Placement

				San Francisco		Miami	
Before Work	While at Work	On way Home	Post Return Home	% Valid* N=1034	% Total N=4331	% Valid* N=187	% Total N=589
					76.1		68.3
X				9.1	2.2	7.0	2.2
	X			54.5	13.0	56.1	17.8
		X		12.6	3.0	18.2	5.8
			X	8.3	2.0	6.4	2.0
Subtotal				84.5	20.2	87.7	27.8
X	X			1.9	0.5	2.7	0.8
X		X		1.3	0.3	1.6	0.5
X			X	0.4	0.1	0.5	0.2
	X	X		5.2	1.2	4.3	1.4
	X		X	4.3	1.0	2.1	0.7
		X	X	1.3	0.3	1.1	0.3
Subtotal				14.4	3.4	12.3	3.9
X	X	X		0.5	0.1	0.0	0.0
X	X		X	0.2	0.0	0.0	0.0
	X	X	X	0.4	0.1	0.0	0.0
Subtotal				1.1	0.2	0.0	0.0
X	X	X	X	0.1	0.0	0.0	0.0
				100	100	100	100

*Valid includes sample of individuals who engaged in at least one eat meal stop

In Table 2, it is seen that a larger percent of commuters in the San Francisco area do not pursue an eat-meal activity outside home. Whereas 76 percent of commuters did not pursue an eat-meal activity outside home in the San Francisco sample, the corresponding percent in the Miami sample is 68 percent. Among those who pursue an eat-meal activity outside home, more than one-half schedule it while at work (54.5 percent in San Francisco and 56.1 percent in Miami). This is consistent with expectations that a majority of the commuters would undertake an eat-meal activity during the lunch period at work. Among those who actually undertake an eat-meal activity outside home, the percent who undertake one, two, three, and four activities respectively (that is the percent of valid in the subtotal rows) are quite similar across the two samples.

In general, the distribution of eat-meal activity stop placement appears to be rather similar across the two geographic areas but for one noteworthy difference. This difference is seen in the first group who pursue only one eat-meal activity outside home in the day. The percent of

Miami commuters who undertake an eat-meal activity on the way home from work is considerably larger than the corresponding percentage for the San Francisco sample. The reasons behind this difference are not immediately apparent. One possible reason is that a larger percent of Miami commuters are auto users for the journey to work. Then, they have greater flexibility to pursue an outside eat-meal activity on the way home.

Table 3 shows the distribution of stop placement for shopping activities. Once again, it is found that a larger percentage of Bay Area commuters do not undertake any shopping activity outside home during the day. For both areas, the percent of commuters who do not undertake any shopping activity is larger than the percent of those who do not undertake any eat-meal activity suggesting the more discretionary nature of the shopping activity.

TABLE 3 Comparison of Out of Home Shopping Activity Placement

				San Francisco		Miami	
Before Work	While at Work	On way Home	Post Return Home	% Valid* N=728	% Total N=4331	% Valid* N=131	% Total N=589
					83.2		77.8
X				14.3	2.4	14.5	3.2
	X			19.9	3.3	17.6	3.9
		X		34.2	5.7	49.6	11.0
			X	20.1	3.4	9.2	2.0
Subtotal				88.5	14.8	90.9	20.1
X	X			1.5	0.3	1.5	0.3
X		X		1.2	0.2	1.5	0.3
X			X	1.2	0.2	0.0	0.0
	X	X		2.9	0.5	3.1	0.7
	X		X	1.2	0.2	0.8	0.2
		X	X	2.6	0.4	0.8	0.2
Subtotal				10.6	1.6	7.7	1.7
X	X	X		0.4	0.1	0.0	0.0
X		X	X	0.1	0.0	0.0	0.0
	X	X	X	0.3	0.0	1.5	0.3
Subtotal				0.8	0.1	1.5	0.3
				100	100	100	100

*Valid includes sample of individuals who engaged in at least one shopping stop

In general, the distributions of shopping stop placement are quite similar between the two areas. Nearly 90 percent of those who actually undertake a shopping activity (percent of valid) do so only in one period in both areas. However, while 20 percent of all commuters in the Miami sample undertake shopping in one period, the corresponding percent for the Bay Area is less at 15 percent. Nearly 10 percent of those who undertake shopping activities (percent of valid) do so in two time periods with a slightly higher percent in the Bay Area than in Miami.

There are two noteworthy differences here. First, Miami commuters show a much larger propensity to place a shopping activity stop on the way home from work. Second, Bay Area commuters show a larger propensity to place shopping activities after returning home in the post-return home period (when compared with Miami commuters). Whereas nearly 50 percent of those who undertake a shopping activity in Miami did so on the way home (11 percent of all commuters), the corresponding percentage for the Bay Area is only 34 percent (6 percent of all commuters). On the other hand, whereas 20 percent of those who undertake a shopping activity in the Bay Area did so after returning home (3.4 percent of all commuters), the corresponding percentage for the Miami area is only 9 percent (2 percent of all commuters). Similarly, if one looks at the patterns involving shopping activities in two periods, those patterns that involve shopping in the post-return home period show larger percentages in the Bay Area sample than in the Miami sample.

There are several possible explanations for this. First, Miami commuters are in larger households with potentially greater household obligations (child and household care). As such, they may show a greater tendency to complete out-of-home activities prior to returning home so that they may tend to their household obligations (and not leave home again) once they have reached home. Second, Bay Area commuters have higher incomes and the higher incomes may be contributing to some post-return home discretionary shopping. Third, once again, the mode choice to work may be influencing the way in which non-work activities may be undertaken. As nearly 20 percent of the commuters in the Bay Area do not use the automobile for the trip to work, they may be constrained to pursue their shopping activity after returning home in separate home-based trip chains that involve the use of the automobile.

In Table 4, comparisons are provided with regard to the placement of personal business and child care stops. These two purposes had to be combined because of the very low frequency of serve child activities in the San Francisco sample. There are some very clear differences between the two samples in this table that can be strongly attributed to the larger household sizes (and greater number of children) in the Miami sample. First and foremost, whereas over 27 percent of all Miami commuters pursue these stops (personal business or serve child), only 13 percent of all Bay Area commuters do so.

TABLE 4 Comparison of Personal Business / Childcare Activity Placement

				San Francisco		Miami	
Before Work	While at Work	On way Home	Post Return Home	% Valid* N=592	% Total N=4331	% Valid* N=163	% Total N=589
					86.3		72.3
X				26.0	3.6	23.3	6.5
	X			22.0	3.0	20.2	5.6
		X		24.3	3.3	28.2	7.8
			X	10.3	1.4	2.5	0.7
Subtotal				82.6	11.3	74.2	20.6
X	X			3.5	0.5	4.9	1.4
X		X		5.9	0.8	14.1	3.9
X			X	1.7	0.2	0.6	0.2
	X	X		1.7	0.2	1.8	0.5
	X		X	0.8	0.1	0.0	0.0
		X	X	1.9	0.3	3.7	1.0
Subtotal				15.5	2.1	25.1	7.0
X	X	X		0.3	0.0	0.0	0.0
X		X	X	0.8	0.1	0.6	0.2
	X	X	X	0.5	0.1	0.0	0.0
Subtotal				1.6	0.2	0.6	0.2
X	X	X	X	0.2	0.0	0.0	0.0
				100	100	100	100

*Valid includes sample of individuals who engaged in at least one personal business or childcare stop

Among those who pursue a personal business or serve child activity during the day, the first major difference can be seen in the post-return home period. 10 percent of Bay Area commuters who undertake a personal business or serve child activity only in one period do so in the post-return home period. The corresponding percent for the Miami sample is only 2.5 percent, indicating that Miami commuters tend to finish their personal business and serve child activities prior to returning home.

Another major difference can be seen in the group that pursues these activities in two time periods. Serve child activities tend to occur in pairs, e.g., drop a child in the morning before work and pick up a child in the afternoon after work. The greater prevalence of children in the Miami commuter sample clearly contributes to the difference seen in the row corresponding to activity engagement both before work and on the way home. Among those who pursue at least one of these activities, only 6 percent of Bay Area commuters do so before work and on the way home. The corresponding percentage for the Miami sample is 14 percent. Clearly, this result confirms earlier findings that household lifecycle and structure greatly influence the placement and sequencing of activities (Stopher and Metcalf, 1999).

Finally, Table 5 shows the placement of social recreation-entertainment activity stops. About 20 percent of the commuters in both samples pursue at least one such stop. Once again, the major difference between the two samples is that San Francisco commuters are more prone to pursue such activities in the post-return home period while Miami commuters are more prone to pursue them on the way home from work. Once again, household structure and mode to work differences may be contributing to this tendency. Among those who pursue at least one social-recreation stop, nearly 10 percent of Bay Area commuters do so in two time periods. The corresponding percent for the Miami sample is only 4.4 percent. Household constraints and lower income levels may be contributing to this lower discretionary activity participation tendency among Miami commuters.

Thus, it can be seen that activity placement and stop-making behavior, though showing broad similarities across the two commuter samples, exhibit a few distinct differences that are most likely attributable to socio-economic characteristics, household structure and lifecycle, and modal constraints. Commuters who have modal flexibility (auto) and greater household and income constraints are found to show a greater propensity to pursue activities on the way home from work (as in the case of Miami commuters) while those who have less modal flexibility and less household and income constraints are found to show a greater tendency to pursue activities in the post-return home period after returning home from work (as in the case of Bay Area commuters). These tendencies should be captured in models of activity scheduling and stop-making behavior.

TABLE 5 Comparison of Out of Home Social Recreation Activity Placement

				San Francisco		Miami	
Before Work	While at Work	On way Home	Post Return Home	% Valid* N=728	% Total N=4331	% Valid* N=131	% Total N=589
					82.9		80.6
X				13.6	2.3	12.3	2.4
	X			10.7	1.8	10.5	2.0
		X		36.7	6.3	53.5	10.4
			X	27.7	4.7	18.4	3.6
Subtotal				88.7	15.1	94.7	18.4
X	X			0.5	0.1	0.0	0.0
X		X		1.8	0.3	0.9	0.2
X			X	1.8	0.3	0.0	0.0
	X	X		2.2	0.4	0.9	0.2
	X		X	0.7	0.1	0.0	0.0
		X	X	3.6	0.6	2.6	0.5
Subtotal				10.6	1.8	4.4	0.9
X	X	X		0.1	0.0	0.0	0.0
X		X	X	0.5	0.1	0.0	0.0
	X	X	X	0.1	0.0	0.9	0.2
Subtotal				0.7	0.1	0.9	0.2
				100	100	100	100

*Valid includes sample of individuals who engaged in at least one social recreation or entertainment stop

ACTIVITY SEQUENCING BEHAVIOR

Recent research in activity scheduling and activity pattern generation has attempted to generate overall daily activity and travel itineraries for individuals (e.g., Chen, et. al., 1999; Kitamura, et. al., 1997; Wen and Koppelman, 1999; Wen and Koppelman, 2000). Activity based approaches are aimed at providing detailed depictions of daily activity engagement and trip making patterns so that the inter-linkages among activities and trips undertaken over the course of a day can be effectively captured. However, in making comparisons of activity sequencing patterns between two commuter samples, it was felt that comparing entire daily sequences would be a formidable task. The number of possible sequences pursued by individuals is generally huge and bringing out differences or similarities would be difficult. In addition, as this chapter focused exclusively on commuter samples, it was felt that the work activity provided effective breakpoints for comparing portions of daily activity sequences in a coherent framework. Therefore, comparisons of activity sequences in this chapter are done using the same period-based approach adopted in the previous section. Activity engagement sequences are isolated in each period and compared between the two areas. Possible inter-linkages across patterns in different periods are also discussed within this context.

Table 6 shows the activity sequencing pattern distributions followed by commuters in the two geographic areas prior to arrival at work. Each and every pattern starts at home and ends at work. A distinction is made among sequences that involve no stop (a journey directly from home to work), one stop (between home and work), two stops, three stops, four stops, or five or more stops. In the case of sequences that involve two or more stops, temporary return home sojourns are also included. Once again, as in the previous section, valid sample refers to commuters who actually undertook at least one non-work stop in the sequence while the total refers to the entire sample of commuters.

In Table 6, it can be seen that 84 percent of Bay Area commuters directly went to work from home. The corresponding percent in Miami is lower at 74 percent. Very interesting differences are brought out by examining the valid samples, that is the commuters who undertook at least one stop before arrival at work. At the aggregate level, the percentages look quite similar. About 55 to 60 percent of valid commuters undertake one stop, about 20 percent undertake two stops, and so on. However, these aggregate-level similarities mask some very clear differences at the more disaggregate level.

Among commuters who make exactly one stop, the Miami sample shows a heavy emphasis on two types of stops, namely, child care and other errands. About 44 percent of the valid commuters are found to have one-stop sequences involving these two types of activities. The corresponding percentage for the Bay Area sample is only about 20 percent. In comparing the Bay Area and Miami valid commuter samples, it is found that the Bay Area sample shows larger percentages of commuters undertaking work-related, eat-meal, shopping, personal business, and social recreation activities prior to work than the Miami sample.

TABLE 6 Comparison of Out of Home Activity Sequencing Before Work

Sequence	San Francisco % Valid* N=706	San Francisco % Total N=4331	Miami % Valid* N=152	Miami % Total N=589
No Stop		83.7		74.2
One Stop (Subtotal)	56.9	9.3	59.9	15.4
Home-Work Related-Work	4.7	0.8	0.0	0.0
Home-Eat Meal-Work	9.8	1.6	4.6	1.2
Home-Shop-Work	5.4	0.9	3.3	0.8
Home-Personal Bsns-Work	10.6	1.7	6.6	1.7
Home-Soc Recn-Work	6.4	1.0	0.7	0.2
Home-Childcare-Work	6.2	1.0	21.7	5.6
Home-Other-Work	13.9	2.3	23.0	5.9
Two Stops (Subtotal)	23.7	3.9	19.7	5.1
Home-Work Related-Home-Work	2.3	0.4	0.0	0.0
Home-Shop-Home-Work	2.4	0.4	0.7	0.2
Home-Shop-Non home-Work	1.4	0.2	0.7	0.2
Home-Personal Bsns-Home-Work	2.0	0.3	0.0	0.0
Home-Personal Bsns-Non home-Work	2.4	0.4	0.7	0.2
Home-Soc Recn-Home-Work	4.1	0.7	2.0	0.5
Home-Soc Recn-Non home-Work	1.6	0.3	0.0	0.0
Home-Eat Meal-Non home-Work	2.0	0.3	2.0	0.5
Home-Childcare-Non home-Work	1.4	0.2	4.6	1.2
Other	4.1	0.7	9.2	2.4
Three Stops	9.5	1.5	11.8	3.1
Four Stops	5.0	0.8	2.6	0.7
Five or more Stops	5.0	0.8	5.9	1.5
	100	100	100	100

*Valid includes sample of individuals who made at least one stop before work

A very similar pattern unfolds if one were to examine the two-stop sample. Among those who undertake a stop prior to work (i.e., the valid sample), it is found that the Miami sample is much more heavily oriented towards the bottom two patterns (that involve child care and other) whereas the San Francisco Bay Area sample is much more uniformly distributed across various activity types in the sequence. While the total percentage of valid commuters who undertake two stops prior to work is very similar (at about 20 percent) across the two geographic areas, the types of stops that they tend to sequence in the pattern are very different. Income and household structure differences may be contributing to these divergent sequencing patterns between the two areas. Also, the potential influence of modal constraints can be seen in the pattern distributions. In the two-stop making samples, it is found that a larger percent of San

Francisco Bay Area commuters return home prior to departing to work (for example, see the pattern Home → Shop → Home → Work). This seems to be a common thread throughout the two-stop making sample.

Distributions of activity sequencing patterns undertaken by the commuter samples while at work are shown in Table 7.

TABLE 7 Comparison of Out of Home Activity Sequencing While at Work

	San Francisco		Miami	
Sequence	% Valid* N=1390	% Total N=4331	% Valid* N=200	% Total N=589
No Stop		67.9		66.0
One Stop (Subtotal)	67.8	21.8	63.0	21.4
Work-Work Related-Work	4.0	1.3	3.5	1.2
Work-Eat Meal-Work	39.9	12.8	40.0	13.6
Work-Return Home-Work	12.2	3.9	9.0	3.1
Work-Shop-Work	4.9	1.6	3.0	1.0
Work-Personal Bsns-Work	3.2	1.0	2.0	0.7
Work-Soc Recn-Work	2.4	0.8	1.0	0.3
Work-Childcare-Work	0.2	0.1	2.0	0.7
Work-Other-Work	0.9	0.3	2.5	0.8
Two Stops (Subtotal)	15.3	4.9	16.5	5.6
Work-Work Related-Eat Meal-Work	1.0	0.3	1.5	0.5
Work-Work Related-Return Home-Work	1.1	0.3	0.0	0.0
Work-Work Related-Non home-Work	1.7	0.6	2.5	0.8
Work-Eat Meal-Work Related-Work	1.3	0.4	1.0	0.3
Work-Eat Meal-Non home-Work	2.4	0.8	2.5	0.8
Work-Shop-Non home-Work	2.2	0.7	1.5	0.5
Work-Personal Bsns-Non home-Work	2.2	0.7	3.5	1.2
Work-Soc Recn-Non home-Work	1.2	0.4	0.5	0.2
Work-Childcare-Non home-Work	0.0	0.0	2.0	0.7
Other	2.2	0.7	1.5	0.5
Three Stops	8.6	2.7	7.5	2.5
Four Stops	4.1	1.3	4.0	1.4
Five or more Stops	4.2	1.4	9.0	3.1
	100	100	100	100

*Valid includes sample of individuals who made at least one stop while at work

It is found that the distributions here are quite similar between the two areas. This is consistent with expectations because it is likely that work schedule constraints do not allow much flexibility to undertake a myriad of activity sequencing patterns (other than to eat lunch during the lunch period). In both areas, it is found that about two-thirds of the samples do not undertake any activity while at work. About 40 percent of the valid commuters eat meal outside home and work while 10 percent of the valid commuters return home (possibly to eat lunch) in both areas. As expected, minor but important differences are seen with respect to patterns that involve child care. A larger percent of Miami commuters pursue patterns that involve child care or other errands. Interestingly, a larger percentage of Miami commuters (9 percent of valid) pursued activity sequences with five or more stops. A closer examination of these sequences showed that many of the stops included work-related activities suggesting that the types of occupations represented in the Miami commuter sample may be different from those in the San Francisco Bay Area sample.

Table 8 brings out some of the most dramatic differences between the San Francisco Bay Area and the Miami commuters. Activity sequencing on the way home from work is very different for these two samples. Whereas 77 percent of commuters in the San Francisco sample do not engage in any activity on the way home, only 46 percent of Miami commuters exhibit that pattern. A majority of Miami commuters stop on the way home for one or more activities whereas less than a quarter of Bay Area commuters do so.

In comparing the sub-samples of commuters who stop on the way home, there are some major differences. First and foremost, the percent of valid commuters who undertake multi-stop tours on the way home (greater than two stops between work and home) is much larger in Miami (40 percent) than in San Francisco (15 percent). These constitute complex tours that involve an array of personal business and other errands. An examination of the percentages in the percent of total columns indicate that whereas 20 percent of all commuters in Miami undertake activity sequences involving three or more stops between work and home, only 3.5 percent of Bay Area commuters do so. These are rather large differences that can partially be explained by differences in demographic or work mode choice characteristics.

TABLE 8 Comparison of Out of Home Activity Sequencing On Way Home From Work

Sequence	San Francisco % Valid* N=993	San Francisco % Total N=4331	Miami % Valid* N=318	Miami % Total N=589
No Stop		77.1		46.0
One Stop (Subtotal)	67.2	15.4	43.7	23.6
Work-Work Related-Home	5.0	1.2	0.0	0.0
Work-Eat Meal-Home	6.2	1.4	2.5	1.4
Work-Shop-Home	18.7	4.3	9.7	5.3
Work-Personal Bsns-Home	9.4	2.1	3.1	1.7
Work-Soc Recn-Home	18.4	4.2	11.0	5.9
Work-Childcare-Home	2.7	0.6	7.5	4.1
Work-Other-Home	6.6	1.5	9.7	5.3
Two Stops (Subtotal)	17.4	4.0	16.4	8.8
Work-Work Related-Non home-Home	1.4	0.3	0.0	0.0
Work-Eat Meal-Non home-Home	3.1	0.7	2.2	1.2
Work-Shop-Non home-Home	3.6	0.8	3.1	1.7
Work-Personal Bsns-Non home-Home	2.4	0.6	2.2	1.2
Work-Soc Recn-Non home-Home	4.8	1.1	2.5	1.4
Work-Childcare-Non home-Home	0.5	0.1	1.6	0.8
Other	1.5	0.3	4.7	2.5
Three Stops	10.7	2.4	16.7	9.0
Four Stops	3.2	0.7	6.6	3.6
Five or more Stops	1.5	0.3	16.7	9.0
	100	100	100	100

*Valid includes sample of individuals who made at least one stop on way home after work

Looking at the one and two stop sequencing patterns, it is found that Miami commuters are more heavily oriented towards child care and other errands while the Bay Area commuters are more heavily oriented towards shopping, personal business, and social recreation. An examination of one-stop sequencing patterns shows that close to 50 percent of valid commuters in the Bay Area sample include either shopping, personal business, or social recreation as their stop. The corresponding percentage for Miami is only about 24 percent.

Finally, Table 9 presents the activity sequencing distributions during the post-return home period. If a commuter undertakes activities within this period, it means that the commuter returned home from work (with or without a stop on the way), engaged in in-home activities for some duration, and then went out again before finally returning home for the day. Here again, there are some striking differences between the two areas that may at least partially be explained by differences in socio-demographic, household, and commute characteristics.

TABLE 9 Comparison of Out of Home Activity Sequencing During the Post Return Home Period After Work

Sequence	San Francisco % Valid* N=727	San Francisco % Total N=4331	Miami % Valid* N=55	Miami % Total N=589
No Stop		83.2		90.7
One Stop (Subtotal)	70.8	11.9	49.1	4.6
Home-Work Related-Home	4.1	0.7	0.0	0.0
Home-Eat Meal-Home	14.9	2.5	9.1	0.8
Home-Shop-Home	14.7	2.5	12.7	1.2
Home-Personal Bsns-Home	5.5	0.9	7.3	0.7
Home-Soc Recn-Home	23.4	3.9	16.4	1.5
Home-Childcare-Home	1.0	0.2	3.6	0.3
Home-Other-Home	7.3	1.2	0.0	0.0
Two Stops (Subtotal)	12.1	2.0	27.3	2.5
Home-Work Related-Non home-Home	1.1	0.2	0.0	0.0
Home-Eat Meal-Non home-Home	2.1	0.3	5.5	0.5
Home-Shop-Non home-Home	2.5	0.4	3.6	0.3
Home-Personal Bsns-Non home-Home	1.7	0.3	0.0	0.0
Home-Soc Recn-Non home-Home	3.7	0.6	10.9	1.0
Home-Childcare-Non home-Home	0.0	0.0	1.8	0.2
Other	1.1	0.2	5.5	0.5
Three Stops	10.6	1.8	9.1	0.8
Four Stops	4.1	0.7	7.3	0.7
Five or more Stops	2.3	0.4	7.3	0.7
	100	100	100	100

*Valid includes sample of individuals who made at least one stop after returning home from work

In comparing the distributions between areas, it is to be noted that only 10 percent of Miami commuters pursue a post-return home activity pattern. Therefore the “valid” sample size, i.e., the sample of commuters who undertake a post-return home activity pattern, is quite small for the Miami area. Comparisons and interpretations should be done with caution in light of this small sample size.

First, it is found that the percent of commuters who undertake activities in the post-return home period is considerably larger in San Francisco Bay Area than in Miami (17 percent to 10 percent). So, immediately one can see that whereas Miami commuters showed a greater propensity to undertake activities on the way home from work (from Table 8), Bay Area commuters show a greater propensity than Miami commuters to pursue activities in the post-return home period.

Among those who pursue activities in the post-return home period, it is found that a much larger percent of the Bay Area commuters tend to perform one-stop chains than in Miami. While 71 percent of valid commuters in the Bay Area performed one-stop tours, the corresponding percent in the Miami area is only 49 percent. On the other hand, Miami shows a larger percentage of valid commuters performing two stop chains (27 percent vs. 12 percent). So, it appears that, conditional upon Miami commuters leaving home to undertake an activity in the post-return home period, they are more likely (than San Francisco commuters) to chain together multiple activities in the chain.

Looking at the one-stop sequences in more detail shows that the dominating activities undertaken in these tours are social recreation, shopping, and eat-meal for both Miami and San Francisco Bay Area commuters. Unlike Miami commuters, Bay Area commuters show larger percentages participating in work-related activities and other errands. If one were to look only at the one stop sequences, it would appear that the percent undertaking social recreation in the Bay Area is larger than in Miami (23 percent vs. 16 percent). However, after examining two-stop sequencing patterns, one can see that this is not necessarily true. The percent of valid commuters in the Miami sample who undertake social recreation in a two-stop sequence is nearly 11 percent (home→ social recreation → non-home → home). The corresponding percent for the Bay Area sample is only 3.7 percent. So, in fact, of the commuters who have undertaken activities in the post-return home period, the total percent who have pursued social recreation in either a one-stop or a two-stop sequence is virtually identical between the two areas (approximately 27 percent). Similar tendencies can be found in the context of eat meal, shop, and personal business activities because the total percentages of valid commuters who pursue one of these activities in either a one-stop or two-stop sequence are virtually identical between the two samples.

The analysis in this section has shed considerable light on the activity engagement patterns of individuals within various temporal periods with specific emphasis on the sequencing of activities. Unfortunately, the analysis within this chapter was partially hindered by the rather limited sample size in the Miami commuter sample that did not allow detailed examination of sequences in multi-stop chains and by demographic segment.

CONCLUSIONS

This chapter has presented comparisons of activity sequencing and stop placement patterns between commuter samples drawn from the Miami and San Francisco Bay Areas. In general, the comparisons show that activity sequencing and placement patterns vary between areas to different degrees depending on the temporal slice of the day being examined. In order of increasing level of differences observed, the temporal slices of the day may be arranged as follows:

1. At-work period: Least difference between areas
2. Before-work period: More difference between areas
3. After-work period: Most difference between areas

Overall, it was observed that activity sequencing and placement patterns are most similar during the at-work period when commuters are presumably constrained by work schedules. In both commuter samples, sequences involving eat-meal (at work) had a dominating presence. Some differences were found in the before-work period especially with respect to the specific activities undertaken during that period. Whereas Miami commuters were heavily oriented towards serve child activities and other errands, Bay Area commuters were distributed more uniformly across a range of activities including personal business, shopping, eat-meal, social recreation, and work-related.

The greatest differences were found in the nature of activity placement and sequencing in the after-work period. This period was broken up into two slices to distinguish between stops undertaken on the way home from work and those undertaken in separate chains after the return home from work. The major difference between the two commuter samples is that

Miami commuters are much more prone to pursuing activities on the way home from work, whereas Bay Area commuters are much more prone (in comparison to Miami commuters) to pursue activities in separate chains in the post-return home period. In San Francisco, about 23 percent of the commuters undertook stops on the way home from work and a similar percentage (about 17 percent) pursued activities (outside home) in the post-return home period. In Miami, the corresponding percentages are 54 percent and 10 percent respectively. The differences are striking and very consistent with earlier findings reported by Jou and Mahmassani (1996).

The differences between the samples may at least partially be explained by differences in income levels, household structure, and commute mode choice. First, Bay Area commuters showed higher income levels. This may contribute to their greater propensity to engage in shopping and social recreation activities at the end of the work day when compared with Miami commuters. Miami commuters were drawn from larger households that have children and this explains their greater participation in serve child activities and other errands. Also, the commute mode split showed that Miami included a much larger percent of automobile users. The flexibility afforded by the automobile may partially account for the greater propensity of Miami commuters to pursue activities on the way home as opposed to undertaking them in separate chains after the return home. Bay Area commuters who use transit or non-motorized modes may have had to return home before they could pursue other activities. These hypotheses need to be tested in future efforts by examining differences in activity sequencing patterns across household lifecycle groups, income groups, and commute mode choice groups.

In previous chapters, Gangrade, et. al. (2000) and Pendyala, et. al. (2000) found that overall time allocation patterns across activities and distributions of various temporal extremities (prism vertices) are very similar across these two commuter samples. The examination conducted in this chapter of activity stop placement and sequencing patterns within the various temporal periods shows that similarities do exist, but mostly in the at-work period. Even if daily time allocation patterns are very similar, the activity sequencing patterns (particularly in the after-work period) are very different. Models of activity sequencing and stop organization behavior should reflect these differences and incorporate the factors that contribute to these differences for activity based models to be applicable in multiple spatial contexts.

Future research efforts should focus on determining and isolating the contribution of various factors in explaining differences in activity sequencing and stop placement behavior. Figure 1 shows a framework wherein the differences between geographical contexts can be attributed to various factors including socio-economic and demographic characteristics, transportation system characteristics (transportation supply and level-of-service variables), and land use and accessibility variables. In addition, an unexplained component will also exist. A portion of the unexplained differences may be attributable to deterministic but unobserved factors and the remainder to random unobserved factors. Carefully constructed experiments that collect detailed data on the various influencing factors can prove useful in accomplishing such research.

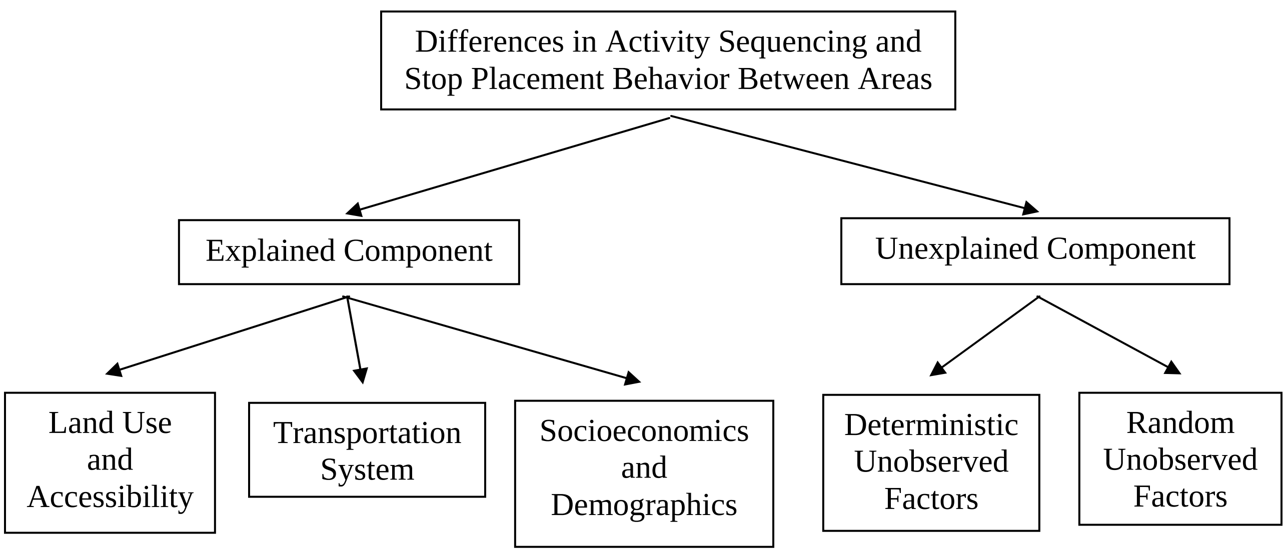

FIGURE 1 Framework for Analyzing Differences in Activity Patterns Between Geographic Areas

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GENERATION OF SYNTHETIC DAILY ACTIVITY-TRAVEL PATTERNS
CHAPTER III

SUMMARY

Microsimulation approaches to travel demand forecasting are gaining increasing attention due to their ability to replicate the multitude of factors underlying individual travel behavior. The implementation of microsimulation approaches usually entails the generation of synthetic households and their associated activity-travel patterns to achieve forecasts with desired levels of accuracy. This chapter develops a sequential approach to generate synthetic daily individual activity-travel patterns. The sequential approach decomposes the entire daily activity-travel pattern into various components, namely, activity type, activity duration, activity location, work location, and mode choice and transition. The sequential modeling approach offers practicality, provides a sound behavioral basis, and accurately represents individual's activity-travel patterns. In the proposed system, each component may be estimated as a multinomial logit model. Models are specified to reflect potential associations between individual activity-travel choices and such factors as time-of-day, socio-economic characteristics, and history dependence. As an example, the chapter furnishes results for estimated and validated activity type choice models. Validation results show that the predicted pattern of activity choices conforms with observed choices by time of day. Thus the chapter shows that realistic daily activity-travel patterns, which are requisites for microsimulation approaches, can be generated for synthetic households in a practical manner.

INTRODUCTION

Microsimulation of the behavior of a household or an individual is drawing attention as a new approach to travel demand forecasting (*1*). Microsimulation can replicate the behavior of complex systems or processes, and is therefore suited for the representation of travel behavior, which is a complex behavior. The factors that make travel behavior complex include: the multitude of contributing factors and decision rules involved; constraints that govern the behavior; inter-personal interactions; multiple planning horizons; and complexity of activity-travel decision making as a scheduling problem (*2*). Microsimulation is an effective approach to such a complex phenomenon which facilitates its practical, yet realistic, representation.

Achieving desired levels of accuracy in the outcome of travel demand forecasts produced by microsimulation of household behavior may require a large sample of households. This may happen when: high levels of spatial or temporal resolution are required of the outcome; sample households do not have a desirable geographical distribution; demand by small population segments is desired; or a high level of accuracy is desired. In such instances, the number of households available in the data set at hand may not be sufficiently large. As a result, the generation of synthetic households may be required. When the microsimulation expects daily travel patterns of household members as input data, the generation of synthetic daily travel patterns will be required.

An approach to the problem of synthetic travel pattern generation is presented in this chapter. The proposed synthetic travel pattern generator has a sequential structure and can be decomposed into components to which certain aspects of observed activity-travel behavior correspond, thus establishing a link between mathematical models and observational data. The model components are each relatively simple and are estimated using commonly adopted estimation methods and existing data sets.

The problem of synthetic travel pattern generation is presented formally in the second section. Accumulated knowledge on the characteristics of daily travel patterns is reviewed in the third section. Following this, a discussion of several modeling issues is presented in the fourth section. The fifth section presents aspects of travel behavior incorporated into the model system. The formulation of the model components constitutes the sixth section, while estimation and validation results are furnished in the seventh section. Conclusions are drawn in the final section.

PROBLEM DESCRIPTION

Consider a household member, i, whose daily activity-travel pattern can be characterized as

$$(\mathbf{X}_i,\mathbf{T}_i,\mathbf{L}_i) = (X_{i0}, X_{i1}, \ldots, X_{in}; T_{i0}, T_{i1}, \ldots, T_{in}; L_{i0}, L_{i1}, \ldots, L_{in}) \qquad (1)$$

where

X_{ij} = the type of the j-th activity pursued by individual i,

T_{ij} = the duration of the j-th activity pursued by individual i,

L_{ij} = the location of the j-th activity pursued by individual i (if the activity is travel, then L_{ij} refers to the destination of trip j; in this case $L_{ij} = L_{i,j+1}$),

n = the number of activities involved in individual i's daily activity-travel pattern,

and (X_{i0},T_{i0},L_{i0}) is the initial condition. Note that travel is included here as one of the activity types. For simplicity, travel mode, which may be stored in another vector, say $\mathbf{M_i}$, is not included in the discussion here. The mode choice component is discussed in a subsequent section of this chapter.

The development of a synthetic daily activity-travel pattern implies generating vectors $\mathbf{X}_i$, $\mathbf{T}_i$, and $\mathbf{L}_i$ given:

- attributes of individual i
- attributes of the household to which i belongs
- residence and work location of i
- demographic and socio-economic characteristics of the region
- land use characteristics of the region, and
- transportation network and travel time characteristics of the region.

Since it is most likely that synthetic activity-travel patterns will be generated for synthetic individuals and households, the first three items will comprise synthetic data. Generating synthetic individuals and households is, however, beyond the scope of this chapter (for discussions on the generation of synthetic households, see *3*); it is assumed here that all personal and household attributes, as well as work location, are known for i. The latter three items will consist of projected values in cases where synthetic activity-travel patterns are generated for forecasting.

ACCUMULATED KNOWLEDGE

The following discussions offer a brief summary of what is known about n, which is also a variable to be determined, and each of the three vectors, $\mathbf{X}_i$, $\mathbf{T}_i$, and $\mathbf{L}_i$. It is possible that additional information is available from the literature on time use. This literature is not well known in the transportation field, and needs to be explored further in the future.

Number of Activities Per Day: n

The total number of activity episodes captured in time use surveys tends to be 20 to 25 per person per day, including trips. In the transportation field, the average number of trips is between 3 to 5 per person per day. It is known that the number of trips captured varies greatly depending on the survey methodology. It is well established that total trip generation is associated with demographic and socio-economic attributes of the traveler.

Activity Type: X_i

There are certain regularities in the sequence with which individuals engage in different types of activities. For example, one may anticipate that the sequence of activities performed before leaving home for work or after coming back home from work, is fairly uniform across individuals. The literature in time use analysis needs to be explored to determine tendencies for activity sequences involving both in-home and out-of-home activities (*4*).

Kitamura (*5*) examined the sequence of trip purposes using standard trip diary data from Detroit. The trip purpose was used to identify the primary out-of-home activity type at each destination location. The analysis examined how out-of-home activities were sequenced in a home-based trip chain, i.e., the home-to-home series of trips which involves one or more stops. The results indicated that activities of more mandatory nature tend to be pursued first in a trip chain. The sequencing tendencies indicated the following hierarchy:

- work and school, work-related
- chauffeuring
- personal business (e.g., banking, dental and medical)
- shopping, and
- social and recreational

The presence of the same sequencing hierarchy was later found for activities throughout the day (*6*, *7*). Another important tendency is that activities pursued in the same trip chain tend to be similar (*5*).

Activity Duration: T_i

Several studies have investigated the duration of activity engagement. In a semi-markov process model of trip chaining, Lerman (*8*) used gamma distributions to represent the duration of sojourns at destination locations. Survival models have recently been applied to the time dimension in activity-travel patterns (*9*, *10*, *11*). These studies are typically based on the simplifying assumption that the durations of successive activities are independent.

Activity duration has been examined from the viewpoint of resource allocation. A theoretical model can be found in Kitamura, et al. (*12*) where the duration of an activity episode was analytically derived while assuming that the total daily activity pattern is optimized and that each activity episode has a logarithmic utility function. The model was estimated using a time use data set from the United States. Although the model is based on the assumption that daily time use is optimized as a whole, the resulting model applies to individual activity episodes. Golob and McNally (*13*) examined the allocation of time to different activity types using a structural equations model system. This approach facilitates the inference of causal relationships among activities of different types.

Critical in the analysis of activity duration is the correlation across the duration of respective activity episodes. As the total amount of time available is fixed at 24 hours a day, negative associations can be expected. In addition, the duration of each episode is also a function of n, the total number of episodes. The inter-relationships among duration of different types of activities and the number of activities, n, merit further exploration.

Activity Location: L_i

Non-home activity locations have traditionally been estimated using the gravity model of spatial interaction. The multinomial logit model of destination choice can be viewed as a special case of the gravity model family. In principle, these models depict that, *ceteris paribus*, more intense interaction exists between a pair of locations that are closer to each other, and the intensity of the interaction is positively related to the attraction level of the destination and the number of trips initiated at the origin.

One important issue is the characterization of location/destination choice for non-home-based trips, i.e., trips whose origin and destination are both non-home. For home-based destination choice underlying a simple trip chain involving only one stop (i.e., home-activity-home), the only spatial element to be considered is the separation between the destination and the home base. This does not hold true in the case of non-home-based choice. For example consider the choice of a shopping location on the way home from work; in this case, both the home location and the deviation from the regular commute route would be important considerations. Kitamura and Kermanshah (*7*) constructed a non-home-based destination choice model which included both the usual origin-to-destination travel time, t_{ij}, and the destination-to-home travel time, t_{ih}, in a multinomial logit choice model. Their estimation results clearly indicated that t_{ij} and t_{ih} are equally important for non-home-based destination choice. This finding is readily applicable to the generation of synthetic activity-travel patterns.

Travel Mode: M_i

There are numerous studies on travel mode choice. Most studies, however, are seriously limited because they are trip-based, i.e., they analyze each trip separately in isolation from other trips. Consider the choice of commuting by car because a car is needed for work. Then this mode choice behavior cannot be explained by solely examining the home-to-work commute trip and comparing the attributes of the travel modes available for that trip.

One of the critical requirements in synthetic pattern generation is to observe the constraints imposed on the transition between travel modes. For example, transition from public transit to driving alone is usually not possible unless the transition takes place at the home or work base where a private car is placed or at a special facility such as a park-and-ride lot. For a trip chain that originates and terminates at the home base, the sequence of travel modes tends to be governed by the boundary condition that the mode of the first trip from home is identical to that of the last trip to home. These regularities and tendencies serve as a set of constraints in the generation of activity-travel patterns.

MODELING CONSIDERATIONS

There are two broad classes of approaches to the generation of synthetic activity-travel patterns: sequential (incremental) approaches vs. simultaneous (holistic) approaches. The former adopt rules in order to generate, one by one, the activity that will immediately follow, given the history of activity generation so far. The latter approaches, on the other hand, deploy behavioral paradigms that are each concerned with the entire daily activity-travel pattern.

One paradigm for the simultaneous approaches is that an individual with given attributes has a probability vector that depicts the likelihoods with which he or she will exhibit respective activity-travel patterns. A study by Pas (*14*) is readily applicable to operationalize this paradigm. Another paradigm is utility maximization where an individual chooses that activity-travel pattern, from among a set of all feasible patterns, which offers the maximum utility. Studies based on this assumption include Adler and Ben-Akiva (*15*), Recker, et al. (*16*), and Recker (*17*). The two paradigms can be integrated to produce probabilities for alternative daily activity-travel patterns.

The simultaneous approaches have theoretical elegance. They can be expected to be more sensitive to parameters describing the travel environment than sequential approaches. In addition, simultaneous approaches can better reflect individuals' travel planning effort. Despite the advantages offered by simultaneous modeling approaches, a sequential approach is proposed in this study. There are three major reasons.

- *Practicality*: One important advantage of sequential approaches is the ease of implementation they offer. When viewed as an optimization problem, daily activity-travel behavior is very complex (*2*). Exact formulation of this behavior produces an overwhelmingly complex mathematical problem. The size of the problem at each step is much smaller in sequential approaches because a daily pattern is synthesized incrementally.
- *Behavioral Basis*: Sequential approaches do not lack a behavioral basis. For example, when proposing the paradigm of satisficing, Simon (*18*) noted that a person is not capable of enumerating all possible alternatives or discerning minute differences among them. Furthermore, a person often will not have complete information associated with all alternatives. As such, even though certain travel choices may be considered simultaneous, it may be argued that people sequentially process "information elements" in order to reduce the size and dimensionality of the problem.
- *Contexts of Synthetic Activity-Travel Pattern Generation*: Synthetic activity-travel patterns are usually generated to represent baseline travel characteristics of the population under prevailing conditions. In this context, sequential model systems offer policy sensitivities that are consistent with the objectives of synthetic pattern generation.

The sequential approach adopted in this chapter is based on the identity that, given n, the X-T-L triple can be expressed as:

$$\begin{aligned}
\Pr[X_i, T_i, L_i] &= \Pr[X_{i1}, X_{i2}, \ldots, X_{in}; T_{i1}, T_{i2}, \ldots, T_{in}; L_{i1}, L_{i2}, \ldots, L_{in}] \\
&= \Pr[X_{in}, T_{in}, L_{in} | X_{i1}, X_{i2}, \ldots, X_{i,n-1}; T_{i1}, T_{i2}, \ldots, T_{i,n-1}; L_{i1}, L_{i2}, \ldots, L_{i,n-1}] \\
&\times \Pr[X_{i,n-1}, T_{i,n-1}, L_{i,n-1} | X_{i1}, X_{i2}, \ldots, X_{i,n-2}; T_{i1}, T_{i2}, \ldots, T_{i,n-2}; L_{i1}, L_{i2}, \ldots, L_{i,n-2}] \\
&\times \ldots \\
&\times \Pr[X_{i1}, T_{i1}, L_{i1}] \qquad (2)
\end{aligned}$$

Each probability on the right-hand side can be formulated as a model for activity type, location and duration, given the past history of activity and travel. In adopting the sequential approach, the joint probability of an X-T-L triple needs to be decomposed into sequential elements. The following decompositions are possible:

$$
\begin{aligned}
&\Pr[X_{ij}, T_{ij}, L_{ij} | \tilde{X}_{i,j\text{-}1}, \tilde{T}_{i,j\text{-}1}, \tilde{L}_{i,j\text{-}1}] \\
&\quad = \Pr[L_{ij} | X_{ij}, T_{ij}, \tilde{X}_{i,j\text{-}1}, \tilde{T}_{i,j\text{-}1}, \tilde{L}_{i,j\text{-}1}] \Pr[T_{ij} | X_{ij}, \tilde{X}_{i,j\text{-}1}, \tilde{T}_{i,j\text{-}1}, \tilde{L}_{i,j\text{-}1}] \Pr[X_{ij} | \tilde{X}_{i,j\text{-}1}, \tilde{T}_{i,j\text{-}1}, \tilde{L}_{i,j\text{-}1}] \\
&\quad = \Pr[T_{ij} | X_{ij}, L_{ij}, \tilde{X}_{i,j\text{-}1}, \tilde{T}_{i,j\text{-}1}, \tilde{L}_{i,j\text{-}1}] \Pr[X_{ij} | L_{ij}, \tilde{X}_{i,j\text{-}1}, \tilde{T}_{i,j\text{-}1}, \tilde{L}_{i,j\text{-}1}] \Pr[L_{ij} | \tilde{X}_{i,j\text{-}1}, \tilde{T}_{i,j\text{-}1}, \tilde{L}_{i,j\text{-}1}] \\
&\quad = \ldots
\end{aligned}
\tag{3}
$$

etc., where $\tilde{X}_{i,j\text{-}1} = (X_{i0}, X_{i1}, \ldots, X_{i,j\text{-}1})'$, etc.

Since all permutations of X_{ij}, T_{ij} and L_{ij} lead to the same joint probability, the model's replication capability should not depend on which permutation is adopted. Therefore that permutation which can be theoretically supported and/or which offers most modeling flexibility and sensitivity can be selected.

EXPLORATION OF POTENTIAL ASSOCIATIONS

As noted previously, knowledge has been accumulated on characteristics of activity-travel behavior. A few salient aspects of activity-travel behavior that merit inclusion in a synthetic generator are outlined in this section.

- *History Dependence*: History dependence has been found to be prevalent in studies of activity type choice (*5*, *19*) and location choice (*20*, *21*, *22*, *23*, *24*). While it is also likely that history dependence is prevalent for activity duration choice, the knowledge of the history dependence in activity duration appears to be extremely limited.
- *Time-of-Day Dependence*: Activity engagement is strongly dependent on the time of day. Tabulations of time use data (e.g., *25*) show surprising homogeneity in activity engagement across individuals. This is partly institutional (e.g., work and school) and partly physiological (e.g., meals, sleeping). The time-of-day dependence of activity engagement can be represented by formulating engagement probabilities as time-dependent functions (*6*).
- *Spatial and Temporal Constraints*: Different activities have different levels of constraints in terms of (i) engagement, (ii) duration, (iii) location, and (iv) timing. Higher levels of engagement and duration constraints are typically associated with work and school (mandatory) activities. It may be assumed that more flexible activities are organized

around these constrained activities. Some types of activities may have tight constraints when they are pursued with prior commitment, e.g., a medical appointment. In general, constraints associated with activity engagement vary significantly depending on institutional and situational factors (e.g., store hours), prior arrangement and commitment, as well as the type of activity. An issue in this effort is whether constraints associated with each activity should be explicitly considered and modeled, or treated as random elements. Considering data availability, only the latter approach is feasible. However, constraints on regular events such as work and school merit explicit consideration.

- *Planned vs. Unplanned Activities*: Some activities are routine, some are planned ahead, yet some are unplanned and are pursued in response to unanticipated events. It is desirable that the degree of planning be represented when synthesizing travel patterns as it allows the analysis of transportation policy impacts on an individual's travel plans. In the context of synthetic pattern generation, however, representing the level of planning in activity engagement is of lesser importance, given the constraints associated with activities are well understood. Also, data availability is an issue. Based on these considerations, the model system in this study does not explicitly incorporate the degree of planning.
- *Travel Time Budget*: History dependence in L_i as well as in T_i would arise if a traveler allocates a certain amount of time for traveling. This leads to the notion of travel time budgets (e.g., *26*). There have been disputes on whether individuals have a fixed time budget that is invariant across individuals. However, more recent results offer evidence that when the duration of a trip is reduced, then a portion of the time saving tends to be used to travel more (*13*, *27*).
- *Prism Constraints*: The spatial expanse that is accessible to an individual for activity engagement is determined by the speed of movement and the amount of time available. Hagerstrand (*28*) defined this expanse in the time-space dimension as the time-space "prism." The prism contains all possible locations where activities can be engaged, and defines the amount of time available for activities at each location within it. Kondo and Kitamura (*29*) adopted the prism concept in the analysis of trip chaining behavior. Beckmann, et al. (*26*) used the concept to define accessibility measures. The prism concept is important because it defines the state space for the evolution of location choice.
- *Trade-off between Activity Duration and Travel Time*: The trade-off between the duration of activity and the time spent to reach the activity location is also important. One may choose

to visit a nearby opportunity and spend more time on the activity there, or visit a farther, but better opportunity and spend less time there. This consideration is adopted by Kitamura, et al. (*12*) in the formulation of time-utility functions. The model in this study accounts for this by making the probability of L_{ij} conditional on T_{ij}.

- *Modal Continuity, Permissible Transitions and Time-of-Day Dependence*: Despite the voluminous studies on travel mode choice, little is known on history dependence and time-of-day dependence of travel mode choice. Modal continuity and modal transition have rarely been addressed in the literature (a rare example can be found in *23*). In general, the travel modes used by an individual in a series of trips tend to be governed by the constraints surrounding modal transitions. In addition, as both transit and highway levels of service vary along the time of day, it is likely that mode choice is time-of-day dependent.
- *Relationships among Travel Choices*: It is now widely recognized that various dimensions of travel behavior are related to one another. For example, activity type choice influences destination choice as a traveler would choose a destination that fulfills the specific activity need. Similarly, inter-relationships exist between destination choice and mode choice, activity type choice and departure time choice, and departure time choice and activity duration. The sequential model system developed in this study explicitly incorporates inter-dependencies among travel choice dimensions in synthesizing activity-travel patterns.

MODEL FORMULATION

For X_{ij} which is not travel, the following decomposition of the X-T-L triple may be adopted:

$$\Pr[X_{ij}, T_{ij}, L_{ij} | \bar{X}_{i,j-1}, \bar{T}_{i,j-1}, \bar{L}_{i,j-1}]$$

$$= \Pr[L_{ij} | X_{ij}, T_{ij}, \bar{X}_{i,j-1}, \bar{T}_{i,j-1}, \bar{L}_{i,j-1}] \Pr[T_{ij} | X_{ij}, \bar{X}_{i,j-1}, \bar{T}_{i,j-1}, \bar{L}_{i,j-1}] \Pr[X_{ij} | \bar{X}_{i,j-1}, \bar{T}_{i,j-1}, \bar{L}_{i,j-1}] \quad (4)$$

In this formulation, an activity type is selected first; given the type, its duration is determined; and finally, a location is chosen given the type and duration. Each of these decision elements is assumed to be dependent on the past history of behavior. This formulation is based on the view that activity engagement is the most fundamental decision that drives duration and location choice. While this may not hold true under all conditions, it may be regarded a typical activity engagement decision process.

When X_{ij} is travel, the following decomposition would be more appropriate:

$$\Pr[X_{ij}, T_{ij}, L_{ij} | \bar{X}_{i,j-1}, \bar{T}_{i,j-1}, \bar{L}_{i,j-1}]$$

$$= \Pr[T_{ij}|X_{ij}, L_{ij}, \vec{X}_{i,j-1}, \vec{T}_{i,j-1}, \vec{L}_{i,j-1}]\Pr[L_{ij}|X_{ij}, \vec{X}_{i,j-1}, \vec{T}_{i,j-1}, \vec{L}_{i,j-1}]\Pr[X_{ij}|\vec{X}_{i,j-1}, \vec{T}_{i,j-1}, \vec{L}_{i,j-1}] \quad (4')$$

Namely, the destination, L_{ij}, is determined before travel time, T_{ij}. This reflects the view that travel time can not be determined before destination and mode are determined.

Overview of the Synthetic Travel Pattern Generator

The components of the synthetic travel pattern generator are:

- activity-type choice models
  - home-based and non-home-based
  - workers and non-workers
- activity duration models
  - workers and non-workers
  - by activity type
- activity location choice models
  - home-based vs. non-home-based
  - workers and non-workers
  - by activity type
- mode choice and mode transition models
  - home-based and non-home-based
- initial departure timing models
  - workers and non-workers
- initial location models
  - workers and non-workers

where "worker" refers to an individual who is employed, either full-time or part-time, or a student. It is possible for a part-time workers' daily activity-travel pattern to not include a commute trip. At this stage, model components have been developed for weekdays only. The activity types used in the models are: work, work-related, school, return to work, social/recreation, shopping, personal business, eat out, home (transient), and home (absorbing). The remainder of this section describes each model component.

Activity-Type Choice Models

Activity-type choice models are concerned with $\Pr[X_{ij}|\vec{X}_{i,j-1},\vec{T}_{i,j-1},\vec{L}_{i,j-1}]$. These models probabilistically determine the next activity type to be engaged. Two types of models, home-based models and non-home-based models, are developed. The former is for an out-of-home activity that follows an in-home sojourn, while the latter is for an activity, whether in-home or out-of-home, that follows an out-of-home sojourn. While the latter includes "in-home activity" as an alternative in the choice set, the former excludes it. It is to be noted that the home-based vs. non-home-based distinction does not refer to the location where the choice is made. Both types of models are developed for workers and non-workers separately. The history dependence of activity type transition is represented by formulating the probability of an activity type as a function of the series of activities so far engaged, $\vec{X}_{i,j-1}$, the time that has been allocated to them, $\vec{T}_{i,j-1}$, and the current location, $L_{i,j-1}$.

Activity Duration Models

Consider an activity type, a. Given X_{ij} = a, T_{ij} will have a probability distribution function whose parameters are functions of t, $\vec{X}_{i,j-1}$, $\vec{T}_{i,j-1}$, $L_{i,j-1}$, and $\vec{Z}_i$ as follows:

$$\Pr[T_{ij} \le q|X_{ij} = a, \vec{X}_{i,j-1}, \vec{T}_{i,j-1}, \vec{L}_{i,j-1}, \vec{Z}_i] = G_a(q: \vec{X}_{i,j-1}, \vec{T}_{i,j-1}, L_{i,j-1}, \vec{Z}_i),\ \ q \ge 0,\ a = 1, 2,\ ...,\ k \qquad (5)$$

where

t = time of day when the (j-1)th activity ended

$\vec{Z}_i$ = vector of person attributes and other explanatory variables.

G_a is a distribution function. Two sets of activity duration models are developed; one for workers and the other for non-workers. The same activity classification scheme as in the activity-type choice models is adopted and models are developed for all activity types except absorbing home (person returns home for the day).

Some distribution functions may be preferred over others for activity duration. For example, let an activity comprise n task elements, and let task completion times be identically and independently distributed (i.i.d.) with a negative exponential distribution for all task elements. Then the distribution of the duration of this activity is a type-n Erlang distribution. Other distributions, including negative exponential, Weibull, and log-normal distributions, have geneses that offer interpretations suitable for activity duration. The Weibull distribution is used in this modeling effort considering its goodness-of-fit and intuitively appealing interpretation in the context of activity duration modeling.

Activity Location Choice Models

The problem here is to determine the probability that the location of the j-th activity is g, given the type and duration of the activity, the completion time of the (j-1)th activity, t, $\tilde{X}_{i,j-1}$, $\tilde{T}_{i,j-1}$ and $\tilde{L}_{i,j-1}$. The models are formulated for all activity types, except in-home activity.

Home-Based Models

The home-based location choice models take on a form that is similar to conventional destination choice models:

$$
\begin{aligned}
&\Pr[L_{ij} = g | h_i, X_{ij}, T_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}, \tilde{Z}_i, \tilde{A}, \tilde{S}] \\
&\quad = \Pr[L_{ij} = g | t, h_i, X_{ij} = a, T_{ij} = q, \tilde{Z}_i, \tilde{A}, \tilde{S}] \\
&\quad = H_a(g : t, h_i, q, \tilde{Z}_i, \tilde{A}, \tilde{S}) \qquad (6)
\end{aligned}
$$

where h_i denotes the residence zone, $\tilde{A}$ is a vector of attractiveness measures of alternative locations, and $\tilde{S}$ is a matrix of origin-destination travel times. Note the assumption that the location choice is conditionally independent of $\tilde{X}_{i,j-1}$, $\tilde{T}_{i,j-1}$ and $\tilde{L}_{i,j-2}$, given t, h_i (=$L_{i,j-1}$), X_{ij} (=a), and T_{ij} (=q).

Non-Home-Based Models

As will be discussed later, a travel mode is assigned in the procedure prior to the selection of destination location for a trip whose origin is not the home base. Let M_{ij} be the mode of the trip made to the j-th activity location. With the assumption that destination choice is conditionally independent of $\tilde{M}_{i,j-1}$ as well as $\tilde{X}_{i,j-1}$, $\tilde{T}_{i,j-1}$ and $\tilde{L}_{i,j-2}$, given t, h_i, $L_{i,j-1}$ (=f), X_{ij} (=a), T_{ij} (=q), and M_{ij} (=r),

$$
\begin{aligned}
&\Pr[L_{ij} = g | h_i, X_{ij}, T_{ij}, M_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}, \tilde{M}_{i,j-1} \tilde{Z}_i, \tilde{A}, \tilde{S}] \\
&\quad = \Pr[L_{ij} = g | t, h_i, X_{ij} = a, T_{ij} = q, L_{i,j-1} = f, M_{i,j-1} = r, \tilde{Z}_i, \tilde{A}, \tilde{S}] \\
&\quad = Q_a(g : t, h_i, q, f, r, \tilde{Z}_i, \tilde{A}, \tilde{S}) \qquad (7)
\end{aligned}
$$

Mode Choice and Mode Transition Models

A travel mode is assigned to each trip using the following procedure:

- the travel mode for the first trip in each home-based trip chain is determined (home-based models), and
- a mode transition matrix is developed and applied to determine subsequent travel modes on a trip-by-trip basis (non-home-based models).

The model system incorporates a dummy variable that indicates whether a private car is parked at the work place, which makes the probability very high that a car will be used for a trip originating from the work place. Models are developed for workers and non-workers separately. Travel modes are grouped into: auto driver, auto passenger, public transit, and bicycle and walk.

Home-Based Models

The home-based models incorporate accessibility indices for the residence zone and, for workers, accessibility indices for the work zone. Accessibility indices by mode are defined as the "log-sum" variables of the utility functions of the destination choice models. Highway and transit travel times and distances to destination zones are also incorporated. Also included in the models are descriptors of the destination zone (e.g., percent retail) and the time of day when the trip starts. The models take on the form:

$$\Pr[M_{ij} = r | h_i, X_{ij}, T_{ij}, L_{ij}, \tilde{X}_{i,j\text{-}1}, \tilde{T}_{i,j\text{-}1}, \tilde{L}_{i,j\text{-}1}, \tilde{M}_{i,j\text{-}1} \tilde{Z}_i, \tilde{A}, \tilde{S}]$$

$$= \Pr[M_{ij} = r | t, h_i, X_{ij} = a, T_{ij} = q, L_{ij} = f, \tilde{H}_{i,j\text{-}1}, \tilde{Z}_i, \tilde{A}, \tilde{S}] \quad (8)$$

where $\tilde{H}_{i,j\text{-}1}$ is defined as $\tilde{H}_{i,j\text{-}1} = (H_{i1,j\text{-}1}, H_{i2,j\text{-}1}, \ldots, H_{im,j\text{-}1})'$, m being the number of modes and

$$H_{i\,r,\,j-1} = 1, \text{ if } \tilde{H}_{i,j\text{-}1} \text{ contains mode r, for } r = 1,2,\ldots,m;$$

$$H_{ir,j-1} = 0, \text{ otherwise.}$$

Non-Home-Based Models

The non-home-based models are transition models which determine the probability that a certain travel mode will be used for a trip given the mode of the previous trip. Additional explanatory variables include descriptors of the destination zone, car-parked-at-work dummy (for workers) and the time of day. The non-home-based mode choice models are trip-end models that are applied before destination location is determined. They can be summarized as follows:

$$\begin{aligned}
&\Pr[M_{ij} = r | h_i, X_{ij}, T_{ij}, X_{i,j-1}, T_{i,j-1}, L_{i,j-1}, M_{i,j-1}, Z_i, A, S] \\
&\quad = \Pr[M_{ij} = r | t, h_i, w_{i,j-1}, X_{ij} = a, T_{ij} = q, M_{i,j-1} = u, H_{i,j-1}, Z_i, A, S]
\end{aligned} \tag{9}$$

where $w_{i,j-1}$ is the car-parked-at-work dummy. As noted earlier, non-home-based mode choice models are transition models, and replicate modal continuity conditions in the data set.

Initial Departure Timing Models

These models may be viewed as the duration models for the first activity of the day starting at say, 3:00 a.m., which is typically an in-home activity (most probably, sleeping). In this study, models are estimated for workers and non-workers separately, and applied in synthetic pattern generation to those sample individuals who are at home at 3:00 a.m.

Initial Activity Type/Location Models

These models determine the type and zonal location of the first activity. As noted earlier, this is usually an in-home activity and the location is the residence zone. Data sets thus do not typically offer rich information (in terms of variation across individuals) for these models. As a result, they tend to be simple frequency models without many explanatory variables.

Work Location Models

These models are equivalent of home-based work trip distribution models. The probability that a worker commutes to a certain zone is formulated as a function of network auto travel times, zonal attributes, and person and household attributes. The models are formulated as multinomial logit models.

SAMPLE ESTIMATION RESULTS

This section provides sample results of the estimation of activity type choice models and activity duration models for the following:

- Work activity for workers
- Social Recreation activity for workers and non-workers

For purposes of brevity, the presentation of results in this chapter has been limited to two modules of the generator and two activity types. This section is intended to provide a representative indication of the performance of the model for mandatory (work) and discretionary (social recreation) activities and for workers and non-workers, thus covering a variety of behavioral conditions. The 1991 travel diary data set of the Southern California Association of Governments is used for model estimation and validation purposes. The data set provides a total of 136,640 trip records for 32,515 individuals. As such, it provides rich information with a sufficient sample size in each population segment considered in this effort. Sample estimation results for each of the two modules are summarized in the subsections that follow.

Activity Type Models

The data set was randomly divided into two subsets; one subset was used for estimation purposes and the other for validation purposes. Multinomial logit models of activity type choice were estimated using standard maximum likelihood methods. Estimation and validation results are presented in Tables 1 and 2 respectively.

Table 1 presents estimation results for six activity type choice models. They are:

- Home-based and non-home-based models for workers
- Return to work
- Social-recreation
- Home-based and non-home-based models for non-workers
    - Social-recreation

Models estimated for workers set work as the reference alternative (utility is set to zero), while models for non-workers set shopping as the reference alternative. Explanatory variables include socio-economic characteristics of the person, dummy variables of time-of-day, and lagged dependent variables of history dependence. Those time periods which are not represented in the model are used as reference periods.

TABLE 1
Sample Estimation Results for Activity Type Choice Models

HB for Workers/Students		**HB for Non-workers/Non-students**		**NHB for Workers/Students**		**NHB for Non-workers/non-students**	
Return to Work		*Return to Work*		*Return to Work*		*Return to Work*	
Variables	Estimates	Not Applicable		Variables	Estimates	Not Applicable	
Constant	-0.32 (-1.2)			Constant	-1.56 (-2.4)		
D(3-6:30am)	-0.82 (-0.6)			D(7:30-8:30am)	1.05 (1.5)		
D(6:30-7:30am)	-2.01 (-1.7)			D(8:30-9:30am)	1.67 (2.4)		
D(7:30-8:30am)	-1.35 (-1.6)			D(9:30-10:30am)	2.94 (4.4)		
D(8:30-9:30am)	-0.88 (-1.2)			D(10:30am-12:30pm)	3.83 (5.9)		
D(9:30-11:30am)	0.87 (2.2)			D(12:30-2:30pm)	4.75 (7.3)		
D(11:30am-1:30pm)	2.52 (8.2)			D(2:30-4:30pm)	3.91 (6.0)		
D(1:30-3:30pm)	1.49 (4.9)			D(4:30-6:30pm)	1.91 (2.9)		
D(3:30-5:30pm)	-0.10 (-0.3)			D(6:30-8:30pm)	2.13 (3.0)		
D(5:30-7:30pm)	-0.78 (-2.5)			D(8:30-10:30pm)	3.19 (3.6)		
				D(10:30pm-3am)	1.37 (1.5)		
Social/Recreation		*Social/Recreation*		*Social/Recreation*		*Social/Recreation*	
Variables	Estimates	Variables	Estimates	Variables	Estimates	Variables	Estimates
Constant	1.22 (4.9)	Constant	-0.19 (-0.7)	Constant	-3.08 (-14.5)	Constants	0.75 (2.4)
D(3-6:30am)	-3.53 (-13.0)	D(3-6:30am)	1.46 (3.3)	D(7:30-8:30am)	-0.37 (-1.3)	D(3:00-8:30am)	-0.69 (-1.6)
D(6:30-7:30am)	-4.42 (-16.1)	D(6:30-8:30am)	0.92 (3.0)	D(8:30-9:30am)	0.85 (3.4)	D(8:30-10:30am)	-1.55 (-4.6)
D(7:30-8:30am)	-4.70 (-16.9)	D(8:30-10:30am)	0.03 (0.1)	D(9:30-10:30am)	1.87 (7.5)	D(10:30-12:30am)	-2.03 (-6.2)
D(8:30-9:30am)	-3.55 (-13.1)	D(10:30am-2:30pm)	-0.36 (-1.3)	D(10:30am-12:30pm)	2.81 (12.2)	D(12:30-2:30pm)	-1.70 (-5.2)
D(9:30-11:30am)	-2.30 (-8.8)	D(2:30-6:30pm)	-0.07 (-0.2)	D(12:30-2:30pm)	3.03 (13.1)	D(2:30-4:30pm)	-1.78 (-5.4)
D(11:30am-1:30pm)	-1.46 (-5.5)	D(6:30-7:30pm)	0.88 (2.9)	D(2:30-4:30pm)	4.30 (18.5)	D(4:30-6:30pm)	-1.30 (-3.8)
D(1:30-3:30pm)	-0.99 (-3.7)	D(7:30-8:30pm)	0.86 (2.7)	D(4:30-6:30pm)	4.19 (16.9)	D(6:30-8:30pm)	-0.55 (-1.6)
D(3:30-5:30pm)	0.20 (0.8)	D(mid to old couples)	0.39 (5.0)	D(6:30-8:30pm)	5.50 (16.6)		
D(5:30-7:30pm)	0.07 (0.3)			D(8:30-10:30pm)	6.33 (10.2)		
D(7:30-9:30pm)	1.29 (5.7)			D(10:30pm-3am)	4.70 (8.4)		
D(history)	-0.80 (-10.2)			D(history)	-0.11 (-2.8)		
Summary Statistics	*N=20,928*	*Summary Statistics*	*N=6,108*	*Summary Statistics*	*N=52,478*	*Summary Statistics*	*N=11,929*
Final Likelihood	-28232.33	Final Likelihood	-8507.53	Final Likelihood	-90093.69	Final Likelihood	-19052.58
Initial Likelihood	-43518.55	Initial Likelihood	-9830.45	Initial Likelihood	-124685.22	Initial Likelihood	-23212.76
Likelihood w. Const	-38135.64	Likelihood w. Const	-9302.57	Likelihood w. Const	-102731.17	Likelihood w. Const	-20806.40
1-L(F)/L(0)	0.35	1-L(F)/L(0)	0.13	1-L(F)/L(0)	0.28	1-L(F)/L(0)	0.18
1-L(F)/L(C)	0.26	1-L(F)/L(C)	0.09	1-L(F)/L(C)	0.12	1-L(F)/L(C)	0.08

Note: Values in the parentheses are t-ratios. D refers to dummy variable, coded as 1 or 0; brief descriptions in the parentheses identify the condition(s) for which the dummy variable is equal to 1.

TABLE 2
Validation Results for Home-based Activity Type for Workers/Students

Time Period	*Workers: HB Return to Work* Actual	Expected	χ^2	*Workers: NHB Return to Work* Actual	Expected	χ^2	*Workers: HB Social Recn* Actual	Expected	χ^2	*Workers: NHB Social Recn* Actual	Expected	χ^2
3:00 am - 5:59 am	0	0	0.00	0	0	0.38	24	31	1.56	0	1	0.81
6:00 am - 7:59 am	1	1	0.00	1	1	0.03	95	101	0.31	3	6	1.76
8:00 am - 9:59 am	7	6	0.26	18	14	1.72	114	122	0.58	29	22	2.28
10:00 am - 11:59 am	14	21	2.13	58	57	0.02	100	100	0.00	42	48	0.63
12 noon - 1:59 pm	149	141	0.41	298	274	2.14	110	108	0.05	73	69	0.17
2:00 pm - 3:59 pm	68	68	0.00	120	109	1.23	163	179	1.39	118	124	0.33
4:00 pm - 5:59 pm	28	25	0.39	31	39	1.59	352	383	2.57	150	154	0.11
6:00 pm - 7:59 pm	18	36	8.91	6	12	3.19	531	555	1.01	149	126	4.10
8:00 pm - 9:59 pm	7	10	1.01	3	6	1.19	152	149	0.07	53	55	0.09
10:00 pm - 2:59 am	10	5	5.56	2	2	0.00	23	33	2.86	27	24	0.30

Time Period	*Non-Workers: HB Social Recn* Actual	Expected	χ^2	*Non-Workers: NHB Social Recn*[a] Actual	Expected	χ^2
3:00 am - 6:59 am	19	20	0.07			
7:00 am - 8:59 am	72	72	0.00	14	16	0.21
9:00 am - 10:59 am	101	105	0.13	51	45	0.89
11:00 am - 12:59 pm	65	67	0.06	52	58	0.58
1:00 pm - 2:59 pm	36	63	11.52	58	58	0.01
3:00 pm - 4:59 pm	56	59	0.17	48	57	1.40
5:00 pm - 6:59 pm	71	59	2.24	41	36	0.76
7:00 pm - 2:59 am	73	66	0.68	29	40	2.79

Sample Sizes Used for Model Validation

Model Type	*N*
HB for Workers	14,494
HB for Non-Workers	2,384
NHB for Workers	11,120
NHB for Non-Workers	4,608

[a] The first time period for this model is 3:00 am to 8:59 am.

The models clearly show the time-of-day dependence of activity type choice. For example, in the home-based model for workers, the "return to work" activity peaks around 11:30 a.m. to 1:00 p.m.; this may be explained by workers having lunch and then returning to work. Social/recreation activities peak between 7:30 p.m. and 9:30 p.m. as evidenced by the larger coefficients associated with dummy variables representing evening hours. During the early morning, coefficients for social recreation are less than those for work indicating that the work activity peaks during that period.

Socio-economic variables also play important roles in determining activity type choice. The work and social recreation activity models presented in this chapter do not include socio-economic variables as they were found to be statistically insignificant at the 0.05 level. However, other activity types including personal business, shopping, eat out, and school (not shown in this chapter) were significantly influenced by socio-economic characteristics.

History dependence is represented by a lagged dummy variable, which takes on a value of 1 if the activity is performed earlier in the day and 0 otherwise. History dependence effects are found to be statistically insignificant for the return to work, but are found to be significant in explaining workers' social-recreation activity engagement. The coefficients have negative signs indicating that if a social-recreation activity was pursued previously in the day, then there is a reduced likelihood of repeating the activity. History dependence was also found to be significant for other activity types, notably shopping and personal business (not presented in this chapter).

Table 2 presents validation results for the six models for which estimation results were presented in Table 1. The validation results are presented by time of day over a 24 hour period for return to work and social recreation activities. For each time period, the actual frequency of each activity type and the expected frequency (calculated as the product of mean probability and total frequency) are provided. χ^2 statistics are then calculated for each cell. In this table, if the χ^2 statistic is less than the critical value at n-1 degrees of freedom (where n is the number of time periods), the predicted frequency distribution is not significantly different from the actual frequency distribution. The χ^2 statistic associated with each cell also indicates the activity that contributes most to differences between the predicted and observed distributions.

Table 2 shows that when the model is applied to the validation set, the overall activity pattern by time-of-day is captured successfully. An examination of the χ^2 statistics indicates that, without exception, the actual and the expected frequency distributions are not significantly different for all of the six models presented. It is noteworthy that similar results were obtained for other activity types also (tables not shown).

Activity Duration Models

Table 3 presents estimation results for a few activity duration models. These models are estimated assuming that the duration of an activity episode is described by the Weibull distribution.

The Weibull distribution is often used to model the failure time distribution of manufactured components. Analogously, it may be used to model the distribution of the length (duration) of activity episodes. The Weibull density function is convenient in that it provides a wide variety of density curves to model real life failure time distributions. In addition, unlike the Gamma distribution, the Weibull distribution has a closed-form expression for its cumulative distribution function.

In all of the three models presented in the table, the model coefficients have the expected sign. History dependence is a significant factor influencing the length of an activity episode. For example, as the cumulative past time spent at work increases, the length of a "return to work" activity episode decreases. Similarly, as time spent at work or school increases, the duration of social-recreation activity episodes decreases.

Time-of-day is also found to be a significant factor explaining activity duration. Social-recreation activities are shorter in the morning and longer in the evening for workers. The reverse is true for non-workers who may often pursue social-recreation opportunities in the morning. Return to work activity durations are longest in the morning and late evening, but shorter during mid-afternoon. Finally, socio-economic variables such as gender, employment status, age, and household structure are found to influence activity durations.

Validation of the activity duration model (results not presented in the interest of brevity) may be done in a manner similar to that for activity type choice models. The observed and predicted frequency distributions of activity durations by activity type may be compared using χ^2 test-statistics to determine whether the activity duration models are statistically replicating observed activity sojourn patterns.

TABLE 3
Sample Estimation Results for Activity Duration Models (Weibull Distribution)

Full- or Part-time Workers		**Full- or Part-time Workers**		**Non-Workers/Non-Students**	
Return to work		*Social Recreation*		*Social Recreation*	
Variables	Estimates	Variables	Estimates	Variables	Estimates
Constant	1.29 (44.32)	Constant	0.890 (20.71)	Constant	0.804 (37.48)
D(Male)	0.027 (1.58)	D(Male)	0.076 (3.14)	D(Male)	0.131 (4.38)
D(Full-time Employ)	0.117 (5.07)	D(Full-time Employ)	0.048 (1.75)	History School	-0.0091 (-1.61)
History Work	-0.017 (-3.55)	Age	-0.0036 (-3.88)	History Social/Recn	-0.022 (-2.15)
History Return Work	-0.138 (-12.8)	History Work	-0.017 (-4.69)	D(7:00-9:00 am)	0.281 (5.42)
D(7:00-9:00am)	0.382 (5.16)	History Social/Recn	0.0065 (0.59)	D(9pm-12Midnight)	0.099 (1.08)
D(1:00-4:00pm)	-0.057 (-3.22)	D(Family;Child 5-15 yr)	-0.108 (-3.11)		
D(7:00-9:00pm)	0.248 (3.67)	D(Couple; Wife <35 yr)	-0.166 (-3.26)		
		D(5:00-7:00am)	-0.271 (-3.89)		
		D(7:00-9:00am)	-0.091 (-1.51)		
		D(7:00-9:00pm)	0.029 (0.956)		
		D(9pm-12midnight)	0.106 (2.03)		
γ	1.84 (79.37)	γ	1.15 (97.99)	γ	1.11(84.47)
Summary Statistics	*N=4,070*	*Summary Statistics*	*N=5,369*	*Summary Statistics*	*N=4,171*
Final Likelihood	-4295.327	Final Likelihood	-8997.566	Final Likelihood	-7172.690
Initial Likelihood	-6748.779	Initial Likelihood	-9330.422	Initial Likelihood	-7288.913

Note: 1. Values in the parentheses are t-ratios. D refers to dummy variable, coded as 1 or 0; brief descriptions in the parentheses identify the condition(s) for which the dummy variable is equal to 1.

2. History variables refer to the cumulative past time spent on a certain activity from the beginning of the day to the current activity.

CONCLUSIONS

An analytical framework has been proposed in this chapter for the development of a procedure for generation of synthetic activity-travel patterns. As more refined travel demand forecasting and policy analysis are demanded in the current transportation planning contexts, it is becoming inevitable that a new generation of travel demand models be adopted to satisfy planning needs. Microsimulation of travel behavior is emerging as a promising approach. Many issues, including the generation of synthetic activity-travel patterns, need to be resolved before its practical adaptation; yet only limited knowledge has been accumulated on these issues. In this study, attempts have been made to include a broad range of analytical issues and develop a rationale for the proposed approach. It is hoped that the chapter has aided in paving the way for the development of a synthetic activity-travel pattern generator and toward the formulation of the next generation of travel demand models.

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MICROSIMULATION OF DAILY ACTIVITY-TRAVEL PATTERNS

CHAPTER IV

SUMMARY

The development and validation results of the microsimulator for the generation of daily activity-travel patterns are presented in this chapter. The simulator assumes a sequential, history- and time-of-day dependent structure. Its components are developed based on a decomposition of a daily activity-travel pattern into components to which certain aspects of observed activity-travel behavior correspond, thus establishing a link between mathematical models and observational data. Each of the model components is relatively simple and is estimated using commonly adopted estimation methods and existing data sets. A computer code has been developed and daily travel patterns have been generated by Monte Carlo simulation. Study results show that individuals' daily travel patterns can be synthesized in a practical manner by micro-simulation. Results of validation analyses suggest that properly representing rigidities in daily schedules is important in simulating daily travel patterns.

1. INTRODUCTION

Urban passenger travel demand has traditionally been forecast based on deterministic models that pertain to four aspects of daily travel: the number of trips, the origin and destination of each trip, the mode of travel, and the route of travel. Conventional four-step procedures which predict these four aspects by sequentially placed four model components, have been critiqued in the past from various viewpoints. For example, Dickey notes that "[the traditional four-step travel-demand estimation process] is cumbersome, expensive, and requires a large amount of data. The generation of trips is independent of the transportation supply characteristics and possible technological improvements, and the models are generally site-specific—that is, they are not transferable from one urban area to another" (Dickey, 1983, p. 227). When discrete choice models were being introduced into the transportation planning field, it was argued that the aggregate models are not data efficient, susceptible of biases due to ecological correlations, not transferable due to the use of zone systems, too rigidly structured and as a result not policy sensitive, and not supported by behavioral theories (e.g., Domencich & McFadden, 1975; Spear, 1977; Tye et al., 1982). Oppenheim (1995) notes that "the conventional approach is not based on any single unifying rationale that would explain or legitimize all aspects of demand jointly ..." and that the sequential model structure is incapable of properly representing the effects of congestion without feedback loops, which are computationally inefficient and "may or may not converge to a stable distribution."

The following two assumptions have played critical roles in the development of the four-step procedures: 1) each trip can be analyzed independently of the other trips made by the same individual, and 2) the time-of-day dimension can be ignored in the analysis. As a result of these assumptions, it was possible to develop practical demand forecasting procedures within the limited computational and data-handling capabilities of the 50s and 60s. The ability of the four-step procedure in replicating and forecasting daily travel patterns, however, is limited as a result. For example, trip chaining is not at all represented in the trip-based four step procedures. As a consequence, modal shift may be erroneously forecast by the four step procedure (Kitamura, 1997). Although "Dissatisfaction with trip-based forecasting tools and attempts to move practice toward activity-based approaches predate the milestone legislation of the 1990s in the U.S." (Goulias, 1997), practical methods of demand forecasting and policy analysis have been predominantly trip-based.

On the second assumption, it is curious why the time dimension was entirely omitted in the four-step procedures when the main preoccupation of urban transportation planning—congestion—has to do with the concentration of demand in space and time. The lack of a time axis in the analytical framework implies a lack of coherent procedures to predict travel demand by time of day. For example, peak spreading cannot be dealt with without devising a procedure, outside the framework of the four-step procedures, to assign trips to different periods of the day. Furthermore, recent emphases on environmental impacts of urban transportation have intensified the needs to introduce the time dimension into travel demand forecasting procedures. Weiner (1993) lists as emissions modeling requirements the following six items: 1) VMT by hour of the day by grid square, 2) average speeds by hour by grid location, 3) vehicle mix by hour of the day by grid square, 4) proportion of cold starts by hour of the day, 5) seasonal variation in VMT, vehicle mix, etc., and 6) annual growth in VMT. These requirements call for methodologies by which:

- trip starting time and ending time can be determined in a logically coherent manner;
- elapsed time between successive two trips by the same vehicle can be estimated such that whether the latter trip involves a cold start can be determined;
- vehicle type is explicitly treated; and
- day-to-day variations and seasonal variations in travel demand are appropriately captured.

It would be obvious that the introduction of the time dimension is critical to address the first two issues (Kitamura, 1997).

In sum, with the recent emphases on the environment and resource consumption, travel demand management (TDM), distribution of costs and benefits, and other social issues, current urban transportation planning contexts demand refined tools for forecasting and policy analysis. Spatial and temporal characteristics of travel demand need be more precisely and accurately represented. The conventional four-step procedures are unlikely to be able to satisfy the current requirements.

Many alternative approaches have been proposed in which attempts were made to treat daily travel behavior in its entirety (e.g., Adler & Ben-Akiva, 1979; Bhat & Koppelman, 1994; Pas, 1983; Recker, 1995; Recker et al., 1986). Two major approaches taken in these studies are: application of discrete choice models, and application of mathematical programming concepts. Treating daily travel behavior within the framework of discrete choice analysis may not be effective because, with the spatial and temporal dimensions, the choice set becomes astronomically large if one wishes to gain adequate levels of precision in forecasts. Treating the decision process underlying daily behavior as a mathematical programming problem, on the other hand, is not tractable for two reasons. Firstly, the decision process deals with an extremely complex problem to formulate and to find a solution for, leading to prohibitive computational requirements. Secondly, it is unlikely that human decision making can be adequately formulated as mathematical optimization problems.

The approach taken in this study is the micro-simulation of individual daily activity-travel behavior. It has been noted earlier (Kitamura, Chen et al., 1997) that

> "Micro-simulation of the behavior of a household or an individual is drawing attention as a new approach to travel demand forecasting (Miller, 1996). Micro-simulation can replicate the behavior of complex systems or processes, and is therefore suited for the representation of travel behavior, which is a complex behavior. The factors that make travel behavior complex include: the multitude of contributing factors and decision rules involved; constraints that govern the behavior; inter-personal interactions; multiple planning horizons; and complexity of activity-travel decision making as a scheduling problem (Pas, 1990). Micro-simulation is an effective approach to such a complex phenomenon which facilitates its practical, yet realistic, representation."

A sequential, simulation approach to the generation of daily activity-travel patterns is presented in this chapter. In this approach, a daily activity-travel pattern is decomposed into components to which certain aspects of observed activity-travel behavior correspond, thus establishing a link between mathematical models and observational data. Each of the model components is relatively simple and is estimated using commonly adopted estimation methods and existing data sets. A computer code has been developed and daily travel patterns have been generated by Monte Carlo simulation.

The development of the model system and initial results of model validation are presented in this chapter. The objectives of this chapter are two-fold. Firstly, it aims at demonstrating that individuals' daily travel patterns can be synthesized in a practical manner by Monte Carlo simulation. Secondly it attempts to examine discrepancies between observed and simulated travel patterns and show that properly representing rigidities in daily schedules is important in simulating daily travel patterns. The latter point is an inference obtained from the results of the validation analyses so far conducted. The simulator is still under development and the intent of this chapter is to report on the structure of the simulator and on behavioral insights so far obtained from the ongoing development effort.

Representation of daily activity-travel patterns is first discussed and the structure of the sequential model system is presented formally in Section 2. The respective model components are described in Section 3. Section 4 reports on the results of initial validation studies of the model system, using the 1991 household survey results provided by the Southern California Association of Governments (SCAG). Section 5 is a brief conclusion.

2. REPRESENTATION OF DAILY ACTIVITY-TRAVEL PATTERNS

The daily activity-travel pattern of an individual, i, is composed of a series of activities and trips. Let

$$(\mathbf{X}_i, \mathbf{T}_i, \mathbf{L}_i, \mathbf{M}_i) = (X_{i0}, X_{i1}, \ldots, X_{in}; T_{i0}, T_{i1}, \ldots, T_{in}; L_{i0}, L_{i1}, \ldots, L_{in}; M_{i0}, M_{i1}, \ldots, M_{in}) \quad (1)$$

represent individual i's daily pattern, where

X_{ij} = the type of the j-th activity (or a bundle of activities) pursued by individual i (excluding travel),
T_{ij} = the duration of the j-th activity pursued by individual i,
L_{ij} = the location of the j-th activity pursued by individual i,
M_{ij} = the mode of travel used to reach the j-th activity location, and
n = the number of activities involved in individual i's daily activity-travel pattern,

and (X_{i0}, T_{i0}, L_{i0}, M_{i0}) is the initial condition. The X_{ij}'s are defined here to collectively refer to the bundle of activities pursued at a location. Consequently there is a trip between every pair of successive activities, and $L_{ij} \neq L_{i,j+1}$ for j = 0, 1, ..., n - 1. This definition is introduced purely because of the presentational simplicity it offers, and the modeling framework described in this chapter is in principle applicable with a more activity-based definition of the X_{ij}'s where they refer to respective episodes of activity engagement irrespective of their locations.

An individual's activity-travel pattern varies from day to day. It is viewed in this study that this variation is random, and each possible pattern occurs with a certain probability. The approach taken in this study is to establish these probabilities and generate ($\mathbf{X}_i$, $\mathbf{T}_i$, $\mathbf{L}_i$, $\mathbf{M}_i$) according to the probabilities through Monte Carlo simulation. Now, consider the following identity:

$$\begin{aligned}
&\Pr[\mathbf{X}_i, \mathbf{T}_i, \mathbf{L}_i, \mathbf{M}_i] \\
&\quad = \Pr[X_{i0}, X_{i1}, \ldots, X_{in}; T_{i0}, T_{i1}, \ldots, T_{in}; L_{i0}, L_{i1}, \ldots, L_{in}; M_{i0}, M_{i1}, \ldots, M_{in}] \\
&\quad = \Pr[X_{in}, T_{in}, L_{in}, M_{in} | X_{i0}, X_{i1}, \ldots, X_{i,n-1}; T_{i0}, T_{i1}, \ldots, T_{i,n-1}; L_{i0}, L_{i1}, \ldots, L_{i,n-1}; M_{i0}, M_{i1}, \ldots, M_{i,n-1}] \\
&\quad\quad \times \Pr[X_{i,n-1}, T_{i,n-1}, L_{i,n-1}, M_{i,n-1} | X_{i0}, X_{i1}, \ldots, X_{i,n-2}; T_{i0}, T_{i1}, \ldots, T_{i,n-2}; L_{i0}, L_{i1}, \ldots, L_{i,n-2}; M_{i0}, M_{i1}, \\
&\quad\quad \ldots, M_{i,n-2}] \times \ldots \times \Pr[X_{i0}, T_{i0}, L_{i0}, M_{i0}] \qquad (2)
\end{aligned}$$

Namely, the simultaneous probability associated with $(\mathbf{X}_i, \mathbf{T}_i, \mathbf{L}_i, \mathbf{M}_i) = (X_{i0}, X_{i1}, \ldots, X_{in}; T_{i0}, T_{i1}, \ldots, T_{in}; L_{i0}, L_{i1}, \ldots, L_{in}; M_{i0}, M_{i1}, \ldots, M_{in})$ can be expressed as a product of a series of conditional probabilities,

$$\Pr[X_{ij}, T_{ij}, L_{ij}, M_{ij} | X_{i0}, X_{i1}, \ldots, X_{i,j-1}; T_{i0}, T_{i1}, \ldots, T_{i,j-1}; L_{i0}, L_{i1}, \ldots, L_{i,j-1}; M_{i0}, M_{i1}, \ldots, M_{i,j-1}], \quad j = 1, 2, \ldots, n. \qquad (3)$$

In this conditional probability, the attributes of the next activity are dependent on the past history of activity engagement and travel (types of activities engaged, $X_{i0}, X_{i1}, \ldots, X_{i,j-1}$; their durations, $T_{i0}, T_{i1}, \ldots, T_{i,j-1}$; and locations, $L_{i0}, L_{i1}, \ldots, L_{i,j-1}$). Note that the T_{ij}'s collectively define the clock time when the j-th activity starts as

$$t_0 + T_{i0} + d(L_{i0}, L_{i1}, M_{i1}) + T_{i1} + d(L_{i1}, L_{i2}, M_{i2}) + T_{i2} + \ldots + d(L_{i,j-2}, L_{i,j-1}, M_{i,j-1}) + T_{i,j-1}, \qquad (4)$$

where $d(p, q, m)$ is the travel time from p to q by mode m and t_0 is the clock time at the beginning of the study period. The attributes of the next activity are therefore time-of-day dependent. Note that travel time is assumed in this study to be static and determinable given the origin, destination and mode used.

For notational simplicity, let $\mathbf{H}_{ij}$ represent the portion of the daily pattern up to the j-th activity, namely:

$$\mathbf{H}_{ij} = (X_{i0}, X_{i1}, \ldots, X_{ij}; T_{i0}, T_{i1}, \ldots, T_{ij}; L_{i0}, L_{i1}, \ldots, L_{ij}; M_{i0}, M_{i1}, \ldots, M_{ij}) \qquad (5)$$

Then one can further decompose $\Pr[X_{ij}, T_{ij}, L_{ij}, M_{ij} | \mathbf{H}_{i,j-1}]$ as

$$\Pr[X_{ij}, T_{ij}, L_{ij}, M_{ij} | \mathbf{H}_{i,j-1}]$$
$$= \Pr[X_{ij} | \mathbf{H}_{i,j-1}] \times \Pr[T_{ij} | X_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[L_{ij} | X_{ij}, T_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[M_{ij} | X_{ij}, T_{ij}, L_{ij}, \mathbf{H}_{i,j-1}]$$
$$= \Pr[L_{ij} | \mathbf{H}_{i,j-1}] \times \Pr[X_{ij} | L_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[T_{ij} | L_{ij}, X_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[M_{ij} | X_{ij}, T_{ij}, L_{ij}, \mathbf{H}_{i,j-1}]$$
$$= \Pr[T_{ij} | \mathbf{H}_{i,j-1}] \times \Pr[L_{ij} | T_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[M_{ij} | T_{ij}, L_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[X_{ij} | T_{ij}, L_{ij}, M_{ij}, \mathbf{H}_{i,j-1}]$$
$$= \ldots \text{ etc.} \tag{6}$$

With these alternative decompositions, the probability of a daily pattern, $\Pr[\mathbf{X}_i, \mathbf{T}_i, \mathbf{L}_i, \mathbf{M}_i]$, can be expressed as a series of conditional probabilities that correspond to traditional travel choice models such as mode choice and destination choice models. The following decomposition schemes are used in the Synthetic Travel Pattern Generator (STPG) developed in this study:

If $L_{i,j-1}$ = home base:

$$\Pr[X_{ij}, T_{ij}, L_{ij}, M_{ij} | \mathbf{H}_{i,j-1}]$$
$$= \Pr[X_{ij} | \mathbf{H}_{i,j-1}] \times \Pr[T_{ij} | X_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[L_{ij} | X_{ij}, T_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[M_{ij} | X_{ij}, T_{ij}, L_{ij}, \mathbf{H}_{i,j-1}] \tag{7a}$$

If $L_{i,j-1} \neq$ home base:

$$\Pr[X_{ij}, T_{ij}, L_{ij}, M_{ij} | \mathbf{H}_{i,j-1}]$$
$$= \Pr[X_{ij} | \mathbf{H}_{i,j-1}] \times \Pr[T_{ij} | X_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[M_{ij} | X_{ij}, T_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[L_{ij} | X_{ij}, T_{ij}, M_{ij}, \mathbf{H}_{i,j-1}] \tag{7b}$$

The attributes of j-th activity are thus determined by probabilistic models representing

- activity type choice,
- activity duration choice,
- activity location (destination) choice, and
- travel mode choice.

The decomposition scheme takes on the form of a trip-interchange model in the first case where the location of the preceding activity ($L_{i,j-1}$) is the home base, while it assumes the form of a trip-end model when $L_{i,j-1}$ is not the home base. This reflects the consideration that the choice of mode for a trip which starts from a non-home origin is strongly conditioned by the mode taken for the preceding trip; it is therefore likely that the destination of the trip is conditioned on the mode used.

The model components of the STPG system developed in this study have a number of unique features which are discussed in the next section. Additional discussions on the model system, modeling issues, and sample estimation results of the activity choice models and activity duration models can be found in Kitamura, Chen et al. (1997). The properties of the destination choice models adopted in the system are discussed in detail in Kitamura, Chen et al. (1998). The mode choice component is one of the focuses of the next section.

3. MODEL COMPONENTS

The above four groups of models are specified for different segments of individuals and trips as defined in Table 1. A "home-based" model in this study refers to a model that is concerned with a trip originating from the home base (e.g., a home-based mode choice model) or one concerned with an activity whose location is reached from the home base (a home-based activity type choice model, or a home-based activity location choice model). A "non-home-based" model, on the other hand, refers to a model that deals with a trip originating from a non-home location or an activity which is reached from a non-home location. A non-home-based model in this study is thus not necessarily concerned with non-home-based trips as traditionally defined.

Table 1
Segmentation of Major Model Components

Model Group	Segmentation Base		
	Employment[1]	Base[2]	Activity Type[3]
Activity Type Choice	×	×	
Activity Duration	×		×
Activity Location Choice	×	×	×
Mode Choice		×	

[1]Worker vs. Non-worker
[2]Home-based vs. Non-home-based
[3]Defined when the respective models are discussed in text.

In addition, the following model components are included in the STPG:

- work/school location models,
- initial departure timing models, and
- initial location models.

The first group of models determines the work or school location for each individual who is employed or a student. The models are formulated as multinomial logit models which can be considered to belong to the family of production-constrained gravity models. The initial departure timing models are simple probability distribution models for T_{i0}. The timing of the first trip of the day is determined by these models in the STPG. The initial location models are also simple probabilistic models that depict the location of each individual at t_0. In this study, a 24-hour period from 3:00 AM to 2:59 AM of the following day, is set as the study period. Therefore 3:00 AM is adopted as t_0, at which time 98% of the individuals in the sample used for model estimation were at the home base.

In the rest of this section, the activity type choice models, duration models, destination choice models and mode choice models are discussed. The following notation will be used in the discussion in addition to the set of variables that have been defined so far:

t_{ij} = the time of day when the j-th activity of individual i is completed,
$\mathbf{Z}_i$ = a vector of variables representing attributes of individual i and those of the household to which individual i belongs,
h_i = the residence location of individual i,
w_i = the work or school location of individual i,
SD = a vector of variables representing demographic and socio-economic characteristics of the study area,
LU = a vector of variables representing land use characteristics of the study area, and
TR = a vector of variables representing transportation network and travel time characteristics of the study area.

The model components have been estimated using the results of the 1991 home interview travel survey conducted by SCAG, along with accompanying land use and network data defined for 1,527 traffic analysis zones (TAZs).[1] Because of the size of the data set, some models have been estimated using sub-samples of randomly selected individuals or trips from the original survey sample.

3.1. ACTIVITY TYPE CHOICE MODELS

These models determine probabilistically the type of the next activity in the STPG. Table 2 presents the activity types that are used to define the choice sets of the four model components in the system. Because a standard trip record file maintained by a metropolitan planning organization (MPO) is used in the estimation of the model components of this study, these activity types are defined in terms of trip purpose categories. Non-work activities are classified into: school, social/recreational, shopping, personal business, eat out, and other (the "other" category includes primarily "serve passenger" purposes). The choice set of the home-based model for non-workers may contain these activity types.

Three additional activity types are introduced into the home-based model for workers, which are: work, work-related, and return to work location. Two "home" states are introduced into the non-home-based models. The first of the two, "home - transient," refers to in-home activities pursued in a temporary stay at the home base; it represents the case where the individual returns home temporarily to leave home again within the study period. The other, "home - absorbing," implies a final return to the home base for the study period.

Choice sets formulated in STPG simulation runs are subject to various constraints and do not necessarily contain all the activity types shown in Table 1. For the home-based model for workers, the constraints include: 1) "return to work" can be included only after "work" has been chosen; and 2) "work" cannot be included once "work" has been chosen. For the non-home-

[1] Estimation of the types of models involved in the synthetic activity generator presents a range of problems due to (i) potential serial correlation in the error terms, and (ii) inclusion of lagged dependent variables. Although serial correlation alone does not impair consistency in the case of linear models, it does lead to inconsistency in the case of the non-linear models adopted here (see Kitamura, 1995 and Kitamura and Bunch, 1990, for further discussion). These problems are ignored in the estimation of this study.

based model for workers, the constraints include, in addition to 1) and 2) above, 3) "return-to-office" and "work" are not included if the previous activity is "work" or "return-to-office."

The activity type choice models in STPG can be described as follows:

$$\Pr[X_{ij} = a|\mathbf{H}_{i,j-1}] = F(a: t_{i,j-1}, L_{i,j-1}, \mathbf{D}_{i,j-1}, \mathbf{Z}_i, \Psi_{ij}), \quad \forall a \in \psi_{ij} \tag{8}$$

where

$\mathbf{D}_{i,j-1}$ = a vector of variables representing the history of activity engagement by individual i up to the (j - 1)th activity, and

Ψ_{ij} = the set of activity types available for the j-th activity.

The variable, $L_{i,j-1}$, serves as a home vs. non-home indicator in the models developed in this study. All activity type choice models are formulated as multinomial logit models.

Table 2
Choice Sets of Activity Type Choice Models

Home-Based Models		Non-Home-Based Models	
Workers	Non-Workers	Workers	Non-Workers
Work Work-related Return to work School Social/recreational Shopping Personal business Eat out Other	School Social/recreational Shopping Personal business Eat out Other	Home - transient Home - absorbing Work Work-related Return to work School Social/recreational Shopping Personal business Eat out Other	Home - transient Home - absorbing School Social/recreational Shopping Personal business Eat out Other

Estimation results indicate that the time of day variable, $t_{i,j-1}$, is the predominant factor that influences activity types. Simple representations of activity history are adopted in these models, with $\mathbf{D}_{i,j-1}$ specified as dummy variables that indicate whether activities of respective types have been engaged. Indications have been obtained that personal business is positively history dependent, i.e., the probability of engaging in a personal business activity is larger if the same type of activity has been engaged in the past. Shopping and social/recreational have been found to be negatively history dependent. For details, see Kitamura and Chen (1996).

3.2. ACTIVITY DURATION MODELS

The activity duration models take on the form,

$$\Pr[T_{ij} \leq s | X_{ij} = a, \mathbf{H}_{i,j-1}, \mathbf{Z}_i] = G(s: a, t_{i,j-1}, \mathbf{D}_{i,j-1}, \mathbf{Z}_i), \ \ s > 0. \tag{9}$$

Weibull distribution models of the following form are exclusively used in this study for all activity types:

$$P_T(t) = \frac{\gamma}{\alpha_i}\left(\frac{t}{\alpha_i}\right)^{\gamma-1} \exp\left[-\left(\frac{t}{\alpha_i}\right)^{\gamma}\right], \quad t > 0 \tag{10a}$$

$$\alpha_i = \exp(\theta' X_i) \tag{10b}$$

where $P_T(t)$ represents a cumulative distribution, θ is a vector of coefficients, X_i is a vector of explanatory variables (i.e., $t_{i,j-1}$, $\mathbf{D}_{i,j-1}$, and $\mathbf{Z}_i$), and γ is a "shape" parameter. If γ takes on a value of 1, the distribution reduces to a negative exponential distribution. The mean and variance of the distribution are given respectively as

$$E[T] = \alpha_i \Gamma\left(1 + \gamma^{-1}\right) = \exp(\beta' X_i)\Gamma\left(1 + \gamma^{-1}\right) \tag{11a}$$

$$\mathrm{Var}(T) = \exp(2\beta' X_i)\{\Gamma(1 + 2\gamma^{-1}) - \Gamma^2(1 + \gamma^{-1})\}\,. \tag{11b}$$

Note that the mean and variance are assumed to be different from observation to observation according to the value of X_i.

Two sets of activity duration models are developed for workers and non-workers separately. The same sets of activity types as in Table 2 are adopted for both workers and non-workers, except for that no models are developed for "home - absorbing." As explanatory variables, selected demographic, socio-economic variables, dummy representing the time of day ($t_{i,j-1}$) and cumulative amounts of time spent on types of activities in the past ($D_{i,j-1}$). For estimation results, see Kitamura & Chen (1996).

3.3. ACTIVITY LOCATION (DESTINATION) CHOICE MODELS

An activity-location (or destination) choice model predicts the probability that a particular location will be chosen from among the universe of alternative locations. The home-based model is formulated as follows in this study:

$$\begin{aligned} \Pr[L_{ij} = \omega | X_{ij} = a,\ T_{ij} = s,\ \mathbf{H}_{i,j-1},\ \mathbf{Z}_i,\ \mathbf{SD},\ \mathbf{LU},\ \mathbf{TR},\ \Omega] \\ = D(\omega\text{: } a,\ s,\ t_{i,j-1},\ L_{i,j-1},\ \mathbf{Z}_i,\ \mathbf{SD},\ \mathbf{LU},\ \mathbf{TR},\ \Omega),\ \ ^{\forall}\omega \in \Omega \end{aligned} \qquad (12)$$

where Ω is the set of all possible destination locations. The non-home-based model can be summarized as

$$\begin{aligned} \Pr[L_{ij} = \omega | X_{ij} = a,\ T_{ij} = s,\ M_{ij} = m,\ \mathbf{H}_{i,j-1},\ \mathbf{Z}_i,\ \mathbf{SD},\ \mathbf{LU},\ \mathbf{TR},\ \Omega] \\ = D(\omega\text{: } a,\ s,\ m,\ t_{i,j-1},\ L_{i,j-1},\ h_i,\ \mathbf{Z}_i,\ \mathbf{SD},\ \mathbf{LU},\ \mathbf{TR},\ \Omega),\ \ ^{\forall}\omega \in \Omega. \end{aligned} \qquad (13)$$

The destination choice models are formulated in this study as multinomial logit models by activity type and by trip origin (home base vs. others). Activity types are aggregated here into five types: work-related, social/ recreation or shopping, eat meal, personal business, and others. Note that work and school destinations are determined by the work and school location models in the STPG; no destination choice models are therefore applied to work, school, and return-to-office trips in the model system.

All person and household attributes (elements of $\mathbf{Z}_i$) are multiplied by the zone-to-zone travel time. This represents the assumption that the effect of spatial separation varies across individuals of different attributes. Estimation results support this assumption. Zonal attraction measures such as retail employment, as well as inter-zonal travel time, show highly significant effects that can be theoretically supported.

The destination choice models are developed in the study in part to test the following hypotheses:

1. time-of-day affects destination choice behavior;
2. the duration of stay at the destination affects destination choice, and
3. home location affects non-home-based destination choice.

The statistical results offer strong evidence in support of the hypotheses. The results indicate that the distance to a destination tends to be shorter in later parts of the day; individuals tend to travel farther for activities that take longer, and tend to find closer destinations for shorter activities; and the destination-to-home travel time is as significant and have roughly as much effect on non-home-based destination choice as the origin-to-destination travel time. The last finding confirms the earlier results by Kitamura & Kermanshah (1984). For further discussion, see Kitamura, Chen et al. (1998).

3.4. MODE TRANSITION MODELS

As noted earlier, the STPG adopts the trip-interchange scheme for home-based destination and mode choice, while the trip-end scheme is adopted for non-home-based mode and destination choice. The SCAG model choice models are adopted for home-based trips in the current version of STPG (see *SCAG Regional Mode Choice Model Development Project,* Final Report, October 28, 1996). The discussion here therefore focuses on the non-home-based mode choice models of the STPG, which comprise a series of mode transition matrices.

The current version of non-home-based mode choice models can be summarized as:

$$\begin{aligned} &\Pr[M_{ij} = m|\, X_{ij} = a,\, T_{ij} = s,\, \mathbf{H}_{i,j-1},\, \mathbf{Z}_i,\, \mathbf{TR},\, \Theta_{ij}] \\ &\quad = \Pr[M_{ij} = m|M_{i,j-1} = m',\, t_{i,j-1},\, L_{i,j-1},\, C_{i,j-1},\, O_i,\, \Theta_{ij}] \\ &\quad = Q(m{:}\ m',\, t_{i,j-1},\, L_{i,j-1},\, C_{i,j-1},\, O_i,\, \Theta_{ij}) \qquad (14) \end{aligned}$$

where

Θ_{ij}=the set of travel modes available to reach the j-th activity site,

$C_{i,j-1}$ = the location of individual i's personal vehicle at the time of the j-th activity, and

O_i = the employment status of individual i.

In the non-home-based mode choice models of this study, $L_{i,j-1}$ is treated as a binary indicator of whether it is the work/school base of individual i; $C_{i,j-1}$ that of whether individual i's personal vehicle is parked at the work/school base; and O_i that of whether individual i is employed or a student.

The focus of the approach here is on modal transition.[2] The models are not differentiated by trip purpose, nor are any indicators of levels of service included. The approach emphasizes the availability of a personal vehicle and the likelihood of leaving a personal vehicle behind. The latter is assumed to be high when the individual is at the work/school base. This approach was adopted primarily because the STPG was originally conceived as a tool to generate synthetic travel patterns for synthetic households and thereby create a database of household, person and trip attributes that are comparable to those in travel survey data bases that that are typically maintained by MPOs. If the STPG is to be applied as a tool for forecasting or policy analysis, then the non-home-based mode choice models may be modified for increased policy sensitivity.

Modal transition probability matrices are presented for workers and non-workers in Table 3. The table is based on a tabulation of the primary mode of each trip, and does not represent the linkages of travel modes within a trip (e.g., walk to a bus stop, bus to a rail station, rail to downtown, walk to the office). The matrix for workers exhibits clearly that modal transition tends to be homogeneous with transitions within the same mode predominating. In fact nearly 84% (54,835) of the observed 65,407 transitions involve one mode, most notably from auto driver to auto driver (59.4% of total).

Although observed frequencies are not presented in the table, transitions are in fact relatively symmetric. For example, there are 906 transitions observed from auto driver to bike/walk, versus 901 from bike/walk to auto driver; 318 from auto passenger to public transit, versus 302 from public transit to auto passenger. One notable exception is the transition between auto driver and auto passenger: 2,384 transitions observed from auto driver to auto passenger,

[2] Mode here refers to the primary mode of a trip. The analysis uses a "linked" trip file where segments of different travel modes within a multi-mode trip are combined into one trip (thus the trip purpose, "change mode," is eliminated) with a primary mode identified.

versus 4,063 from auto passenger to auto driver. More detailed analysis is required to determine what has caused this asymmetry.

The diagonal elements of the transition probability matrix for non-workers are smaller than those of the matrix for workers. Yet in fact about the same percentage (84.0%) of the 17,579 transitions are within the same mode. Auto driver is a more dominant travel mode for non-workers than for workers, at least in this data set from the Los Angeles metropolitan area. There are only 177 transitions (1.01% of the total) in the data file that do not involve auto driver. Interestingly the non-workers' matrix shows an opposite asymmetry in the transition between auto driver and auto passenger: 1,073 transitions from auto driver to auto passenger, versus 688 from auto passenger to auto driver.

Although the tables here are not differentiated by base and parking location, the simulation of activity-travel patterns by the STPG accounts for whether the transition is taking place at the work/school base, and whether the personal vehicle has been parked at the work/school base. This is believed to have given additional realism to the simulation of non-home-based mode choice.

Table 3
Non-Home-Based Modal Transition Matrices

Workers

	"To" Mode				Total	
"From" Mode	Driver	Passenger	Transit	Walk/Bike	P	N
Auto Driver	0.921	0.057	0.001	0.021	1.000	42,197
Auto Passenger	0.250	0.687	0.020	0.043	1.000	16,278
Public Transit	0.024	0.176	0.702	0.098	1.000	1,720
Walk/Bike	0.173	0.122	0.024	0.681	1.000	5,212
Total	0.671	0.222	0.026	0.081	1.000	65,407

Non-Workers

	"To" Mode				Total	
"From" Mode	Driver	Passenger	Transit	Walk/Bike	P	N
Auto Driver	0.903	0.066	0.001	0.030	1.000	16,207
Auto Passenger	0.881	0.101	0.005	0.013	1.000	781
Public Transit	0.705	0.045	0.250	-	1.000	44
Walk/Bike	0.870	0.049	0.002	0.079	1.000	547
Total	0.901	0.067	0.001	0.031	1.000	17,579

-: No observation

4. VALIDATION STUDY

The STPG is currently under development and its components are undergoing the process of continuous validation and improvement. Presented in this section are results of validation studies that were performed in phases using different samples. First, results of a validation study of the activity type choice models are presented. Results of a study based on simulation runs of the entire STPG system are then presented.

4.1. ACTIVITY GENERATION

Because of the large sample size of the SCAG data set used in the study, it was possible to split the original sample into two sub-samples of approximately equal size and use one for model estimation and the other for validation. In the validation study, the 24-hour study period was divided into 7 to 10 periods, depending on the sample size and temporal distribution of activity starting times. For each period, the choice probability of the activity type chosen by each individual in the validation data set was computed using the applicable model, with the coefficient estimates obtained from the estimation data set and an explanatory variable vector derived from the validation data set. The predicted choice probabilities were aggregated and treated as the expected frequencies of activity types, and were compared with the observed frequencies of activity types in the validation data set.

Table 4 presents a summary of validation results by time periods for the four activity-type choice models. As a goodness-of-fit measure, a chi-square statistic is shown for each time period. Considering that the chi-square statistics are often based on very large samples, the results suggest that overall the models are performing well, especially those for non-workers. Notable, however, is the significant chi-square values found for the workers' models in most of the time periods after 12:00 noon. In the case of the home-based model for workers, for example, work and school activities are often under- or over-estimated, especially between 2:00 PM and 7:59 PM. Presumably these discrepancies are caused by the fact that the STPG incorporates no mechanism to represent fixities in individuals' daily activity-travel patterns, such as work and school schedules.

The results nonetheless indicate that the activity choice models developed in the study, especially those for non-workers, well capture salient characteristics of activity engagement over the 24-hours period. Such systematic discrepancies as noted above at the same time warrant critical examination of the modeling approach taken here. As noted above, it would be productive to examine alternative model structures where fixities in activity schedules can be represented. It is also worthy to note that the models are formulated as history dependent models, but do not necessarily take on the form of Markovian models of activity type transition as was often done in the past (e.g., Hanson & Marble, 1971; Horton & Shuldiner, 1967; Kitamura, 1983; Kondo, 1974; Nystuen, 1967; Sasaki, 1972). This may be an effective approach to accounting for such typical activity sequences as work → eat meal → return to work → home. It may also be effective in representing the tendencies in activity sequencing that activities of more mandatory nature tend to be pursued first (Kitamura, 1983).

Table 4
Validation Results: Activity Choice Model

Workers

Period	Home-Based		Non-Home-Based	
	χ^2	N	χ^2	N
3:00 - 5:59 AM	16.31*	442	-	26
6:00 - 7:59 AM	7.21	4023	9.59	302
8:00 - 9:59 AM	11.54	3950	11.56	609
10:00 - 11:59 AM	14.53	966	4.93	848
12:00 - 1:59 PM	18.69*	868	27.25**	1580
2:00 - 3:59 PM	34.71**	993	24.72**	2108
4:00 - 5:59 PM	29.43**	1198	22.72**	2526
6:00 - 7:59 PM	49.59**	1545	19.76*	1706
8:00 - 9:59 PM	15.87*	410	16.75*	863
10:00 PM - 2:59 AM	13.20	99	7.62	552

All χ^2 statistics have 8 degrees of freedom.
*: Significant at α = 0.05
**: Significant at α = 0.01

Non-Workers

Home-Based			Non-Home-Based		
Period	χ^2	N	Period	χ^2	N
3:00 - 6:59 AM	3.44	65	3:00 - 8:59 AM	10.36	240
7:00 - 8:59 AM	4.76	373	9:00 - 10:59 AM	15.42*	596
9:00 - 10:59 AM	9.28	548	11:00 AM - 12:59 PM	12.15	963
11:00 AM - 12:59 PM	7.62	383	1:00 - 2:59 PM	3.23	845
1:00 - 2:59 PM	16.47*	368	3:00 - 4:59 PM	11.67	933
3:00 - 4:59 PM	3.91	274	5:00 - 6:59 PM	11.30	490
5:00 - 6:59 PM	8.98	221	7:00 PM - 2:59 AM	14.83*	541
7:00 PM - 2:59 AM	3.16	152			

All χ^2 statistics have 6 degrees of freedom.
*: Significant at $\alpha = 0.05$
**: Significant at $\alpha = 0.01$

Another factor that deserves attention is constraints on activity and travel. The modeling approach of this study does not account for space-time constraints that govern individuals' movement. A micro-simulation model system that explicitly incorporates Hägerstrand's prism constraints (Hägerstrand, 1970) has been developed (Kitamura & Fujii, 1997) and applied to evaluate the effectiveness of alternative TDM measures in regional CO_2 emissions reduction (Kitamura, Fujii, et al., 1998). Incorporation of indicators of constraints and accessibility is one of the directions for the future extension of the STPG system.

4.2. SYSTEM VALIDATION

The STPG system as a whole, with all its components incorporated, is tested by comparing observed daily travel patterns and simulated patterns. In this validation study a sample of 3,500 individuals was randomly drawn from the SCAG data base.[3] Based on the demographic and socio-economic characteristics of each of the 3,500 individuals and land use and network data supplied by SCAG, the STPG system was deployed to simulate daily activity-travel patterns for the 3,500 individuals. The predicted activity-travel patterns were then compared to the observed activity patterns. This comparison was carried out with respect to various aspects of activity-travel patterns. Note that the simulation here represents no policy scenarios.

[3] These 3,500 individuals are not expected to constitute a hold-out sample as each sample individual may have been in the estimation samples for some modules of the STPG.

Activity-travel patterns are simulated by the STPG as follows. First, data on the attributes of the individual and household (including the residence zone) are input. Given this information, a work (or school) zone is selected for a worker (or a student) using the work (or school) location model by Monte Carlo simulation. An initial location of the individual at t_0 and an initial departure time (= $t_0 + T_{i0}$) are then simulated. Following this, (X_{ij}, T_{ij}, L_{ij}, M_{ij}) are generated activity by activity using the model components described in Section 3. The simulation process ends for the individual when "home - absorbing" is selected by the activity type choice model, or when $t \geq 27$ (= 3:00 AM of the following day).

Table 5 compares the number of trips between the SCAG sample and STPG simulation. The STPG over-predicts the number of trips by 19.0%; the number of trips per person in the SCAG sample is 4.40, while the simulated number is 5.23. The table also indicates that the STPG under-estimates the number of home-originated trips by 13.5%, and over-estimates non-home-originated trips by 44%. The primary reason for this discrepancy is suspected to be the aforementioned absence of a mechanism in the STPG to represent fixities in individuals' daily activity-travel patterns.

Table 5
Number of Trips: Observed vs. Simulated

	SCAG Observed	STPG Simulated
Number of Trips	15,384	18,303
Home-Originated	6,738	5,831
Non-Home-Originated	8,646	12,472
Trips per Person	4.40	5.23

Table 6 presents the distribution of trip purposes. A comparison of the observed and simulated frequencies indicates that the over-prediction of the total trip frequency in the STPG simulation is due to the over-prediction of work, other, and home trips. Work-related, shopping and social/recreation trips are also over-predicted, while school trips are under-predicted in the simulation. In terms of relative frequency, work, other, and work-related trips are over-represented in the STPG simulation.

Table 6
Distribution of Trip Purposes: Observed vs. Simulated

A. All Individuals

	SCAG Observed		STPG Simulated	
	Frequency	%	Frequency	%
Home	5,353	34.8	5,879	32.1
Work[1]	2,268	14.7	3,318	18.1
Work-Related	426	2.8	649	3.6
School	845	5.5	606	3.3
Shopping	1,363	8.9	1,589	8.7
Social/Recreation	1,356	8.8	1,612	8.8
Eat Meals	907	5.9	902	4.9
Personal Business	1,698	11.0	1,670	9.1
Other	1,168	7.6	2,078	11.4
Total	15,384	100.0	18,303	100.0

[1] Includes "return to work.:
The chi-square statistic associated with the table is 168.2
with 8 degrees of freedom.

B. By Employment Status

	Workers				Non-Workers			
	SCAG Observed		STPG Simulated		SCAG Observed		STPG Simulated	
	Frequency	%	Frequency	%	Frequency	%	Frequency	%
Home	4,244	34.8	4,548	30.9	1,109	34.8	1,331	37.2
Work[1]	2,231	18.3	3,318	22.6	37	1.2	0	0
Work-Related	396	3.2	649	4.4	30	0.9	0	0
School	808	6.6	606	4.1	37	1.2	0	0
Shopping	841	6.9	1,018	6.9	522	16.4	571	16.0
Social/Recreation	992	8.2	1,109	7.5	364	11.5	503	14.1
Eat Meals	735	6.0	698	4.7	172	5.4	204	5.7
Personal Business	1,115	9.1	1,307	8.9	583	18.3	363	10.2
Other	833	6.8	1,474	10.0	335	10.5	604	16.9
Total	12,195	100.0	14,727	100.0	3,189	100.0	3,576	100.0

As noted earlier, work activities tend to be governed by rigid schedules, which is not represented in the current version of STPG. It is plausible that, because of this, the simulation tended to generate trips for workers which would be in reality impossible due to work schedules. The single most important source of the problem, then, would be the use of a statistical distribution model for work durations and the assumption implied by it that the work duration is a random variable.

The distribution of trip purposes by employment, shown in the second part of Table 6, is consistent with this conjecture. The total number of trips is over-predicted for workers by over 20% (12,195 trips observed vs. 14,727 simulated). The relative frequency of home trips is under-predicted, while those of work and work-related are over-represented for workers. As a result, the simulation generated more complex travel patterns with multi-stop trip chains for workers.

The distribution of the number of trips per person by employment is shown in Table 7.

Table 7
Distribution of Number of Trips Per Person: Observed vs. Simulated

	SCAG Observed		STPG Simulated	
	Frequency	%	Frequency	%
Workers				
1	25	0.9	0	0.0
2	898	31.7	416	14.7
3	321	11.3	327	11.5
4	557	19.6	488	17.2
5	305	10.8	462	16.3
6	233	8.2	394	13.9
7	174	6.1	300	10.6
8	117	4.1	187	6.6
9	88	3.1	127	4.5
10	54	1.9	59	2.1
>10	65	2.3	77	2.7
Total	2837	100.0	2837	100.0
Non-Workers				
1	4	0.6	2	0.3
2	168	25.3	123	18.6
3	69	10.4	59	8.9
4	120	18.1	106	16.0
5	74	11.2	89	13.4
6	71	10.7	77	11.6
7	37	5.6	74	11.2
8	52	7.8	49	7.4
9	30	4.5	27	4.1
10	17	2.6	20	3.0
>10	21	3.2	37	5.6
Total	663	100.0	663	100.0

The simulation captures overall tendencies in the observed data; both have a mode of two trips per day, for both workers and non-workers. As suggested above, the simulation in fact has produced more workers with 5 or more trips per day, and less with exactly two trips. Workers have been simulated to have more complex daily travel patterns. The distribution of the number of trips is better represented for non-workers.

Observed and simulated trip length distributions are compared in Fig. 1 through Fig. 4. Fig. 1 and Fig. 2 are for home-based trips (whose one end is the home base, as traditionally defined) for workers and non-workers respectively; Fig. 3 and Fig. 4 are for non-home-based trips (neither of whose ends involves the home base) for workers and non-workers respectively. Although the STPG simulation captures the overall tendencies in trip length distribution, there are noticeable discrepancies. Rather surprisingly, the observed distribution for home-based trips for workers from the sub-sample of the SCAG data set has a mode in the shortest range of 1 to 10 min. The simulated distribution appears more plausible with a mode in the 11-to-20-min. range. Except for non-home-based trips for non-workers, discrepancies between the observed and simulated distributions are most noticeable in the ranges from 1 to 10 min. and 31 to 40 min. For non-home-based trips for non-workers, the discrepancy appears to occur in the range from 21 to 40 min.

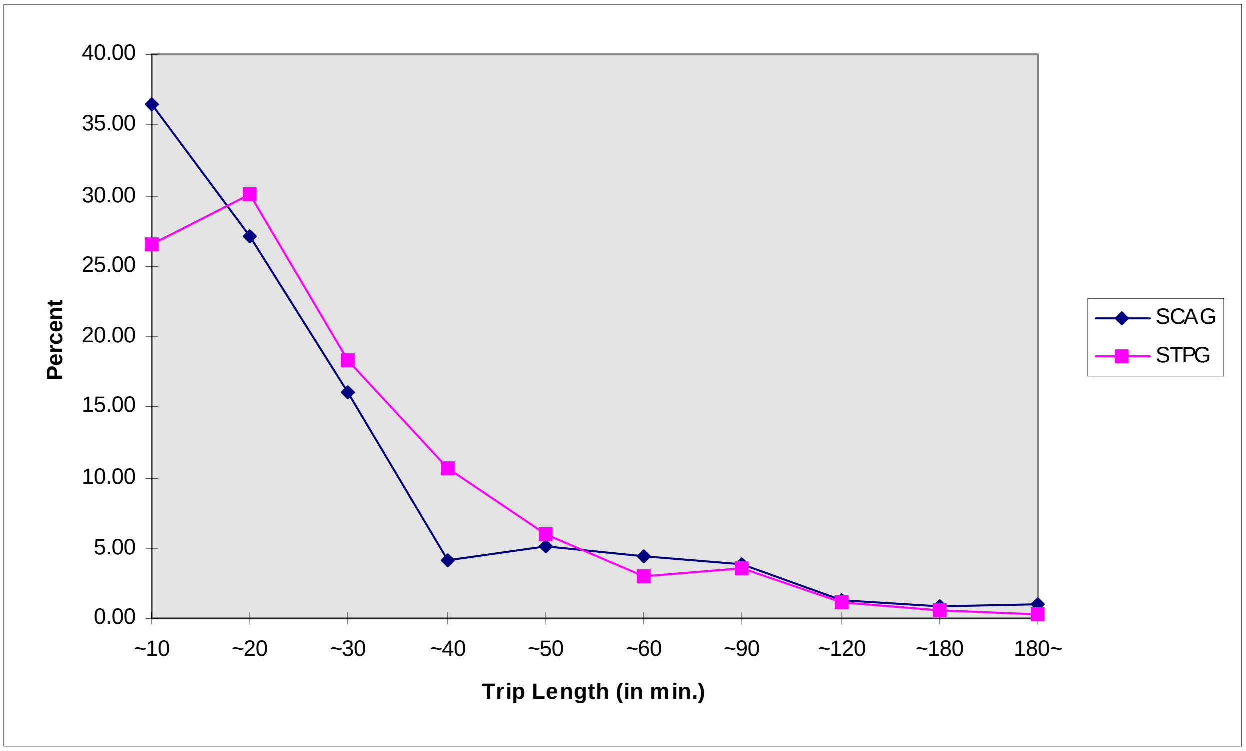

Figure 1. Distribution of Home-Based Trip Length for Workers

The observed trip length distributions of non-home-based trips are roughly exponential with a mode in the shortest 1-to-10 min. range. The simulation approximates the observation well for both workers and non-workers, except for that the observed distributions have thicker tails.

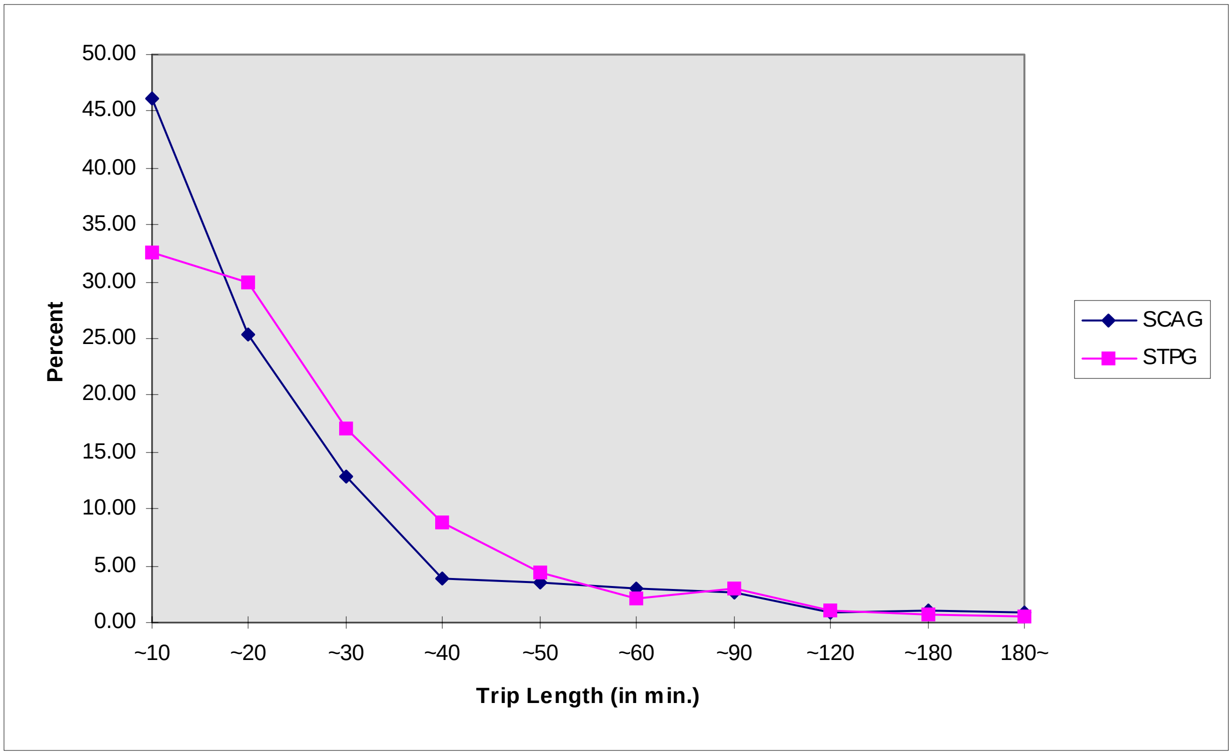

Figure 2. Distribution of Home-Based Trip Length for Non-workers

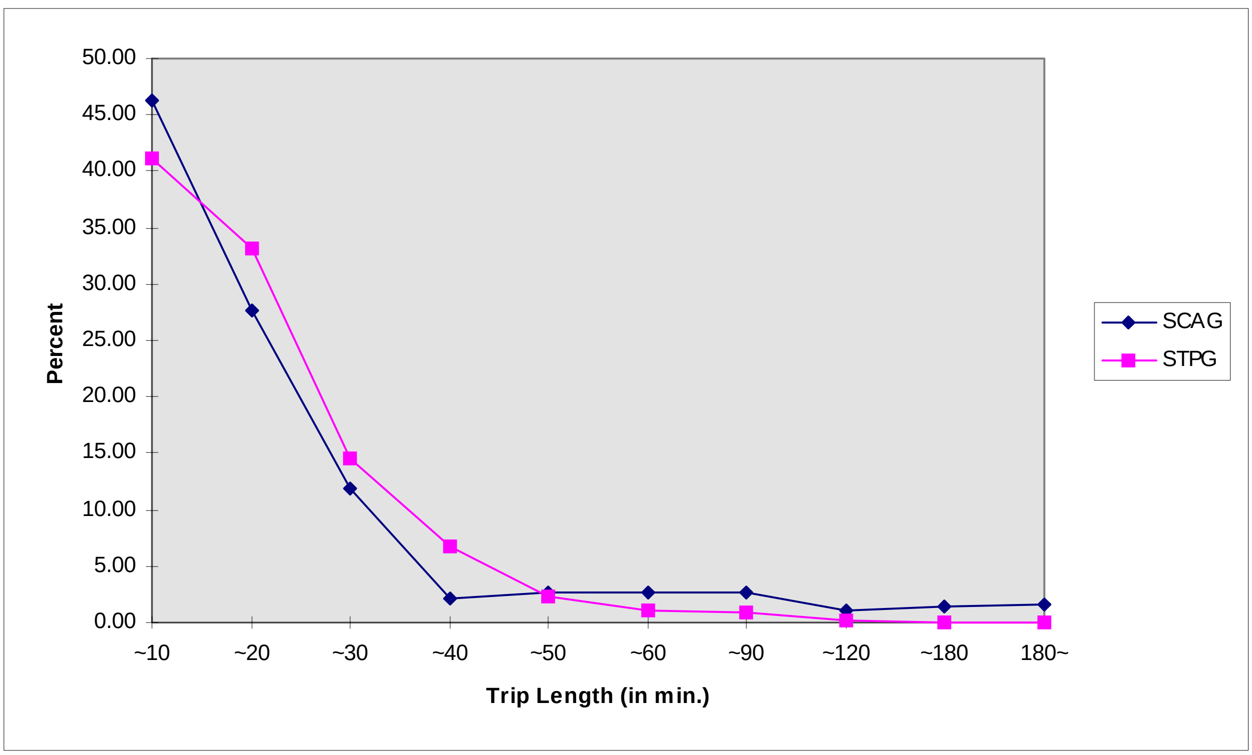

Figure 3. Distribution of Non-Home-Based Trip Length for Workers

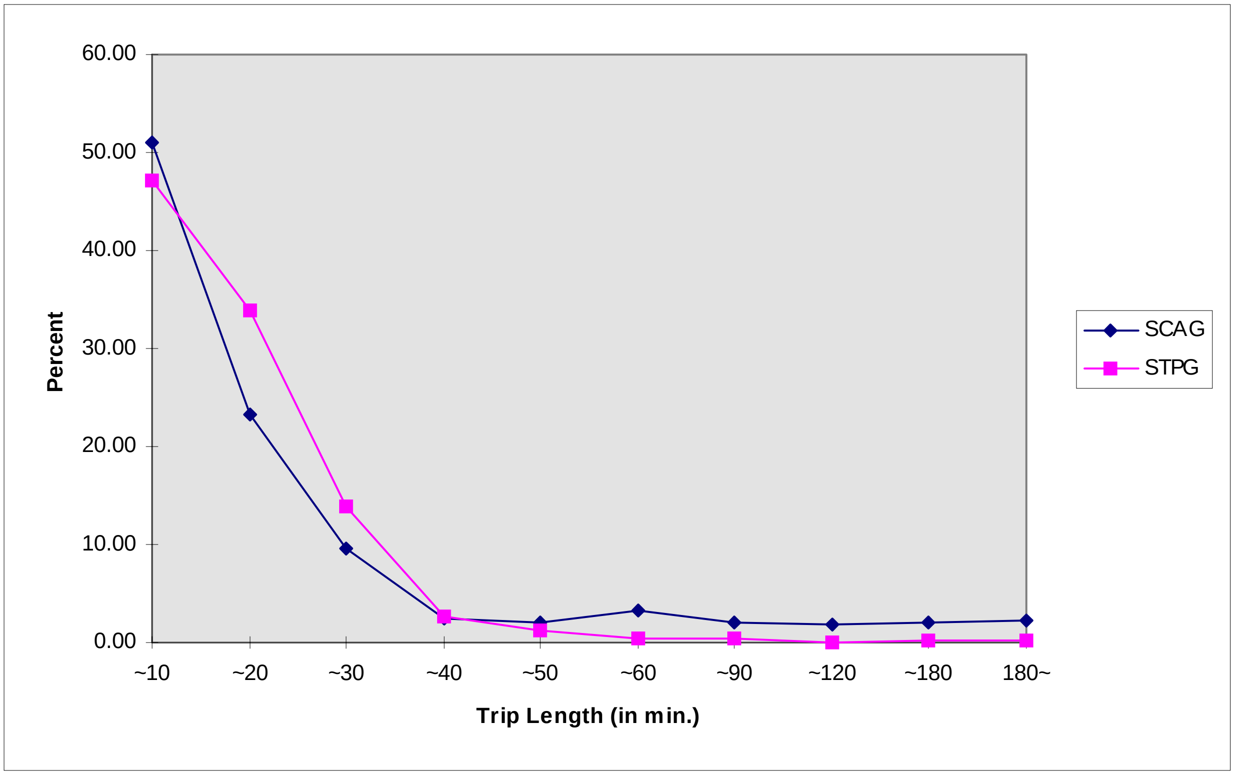

Figure 4. Distribution of Non-Home-Based Trip Length for Non-workers

The distribution of travel modes is compared in Table 8. Comparisons are made for home-originated trips vs. non-home-originated trips and for workers vs. non-workers. It is shown that the simulation produced better results for auto-driver and auto-passenger than for public transit and walk/bike; likewise results are better for workers than for non-workers and results for non-home-originated trips are better than those for home-originated trips. Discrepancies are relatively small in terms of percentage figures. Due to the large sample size, however, the differences are statistically very significant.

In the STPG results, both auto driver and auto passenger are over-represented, while public transit and walk/bike are substantially under-represented. These tendencies are more pronounced for home-originated trips, whose modal split is simulated using the trip-interchange model developed by SCAG. The mode transition matrices for non-home-originated trips are producing better results.

5. CONCLUSION

This chapter has presented an analytical framework for the generation of synthetic activity-travel patterns and demonstrated that daily travel patterns can be created in a practical manner through micro-simulation. The model system proposed in the study performs, in the nomenclature of the conventional demand forecasting analysis, trip generation, trip distribution, and mode choice; namely all of the steps in the four-step procedures except network assignment. Furthermore, unlike the four-step procedures, the proposed system does this for the entire daily travel pattern of an individual and along the time-of-day axis. The system can be a very powerful tool for demand forecasting and policy analysis as well as the generation of synthetic travel pattern data.

Table 8
Distribution of Travel Modes: Observed vs. Simulated

	SCAG Observed		STPG Simulated	
All Trips	Frequency	%	Frequency	%
Auto Driver	9,794	63.7	12,383	67.7
Auto Passenger	3,733	24.3	5,021	27.4
Public Transit	406	2.6	246	1.3
Walk/Bike	1,437	9.4	653	3.6
Total	15,370	100.0	18,303	100.0
Home-Originated Trips				
Auto Driver	3,848	57.2	3,759	64.4
Auto Passenger	1,796	26.7	1,916	32.9
Public Transit	223	3.3	50	0.9
Walk/Bike	865	12.8	106	1.8
Total	6,732	100.0	5,831	100.0
Non-Home-Originated Trips				
Auto Driver	5,946	68.9	8,624	69.1
Auto Passenger	1,937	22.4	3,105	24.9
Public Transit	183	2.1	196	1.6
Walk/Bike	572	6.6	547	4.4
Total	8,638	100.0	12,472	100.0
For Workers				
Auto Driver	7,729	63.4	9,759	66.3
Auto Passenger	2,956	24.2	4,121	28.0
Public Transit	353	2.9	228	1.5
Walk/Bike	1,147	9.4	619	4.2
Total	12,185	100.0	14,727	100.0

For Non-workers				
Auto Driver	2,065	64.8	2,624	73.4
Auto Passenger	777	24.2	900	25.2
Public Transit	53	1.7	18	0.5
Walk/Bike	290	9.1	34	1.0
Total	3,185	100.0	3,576	100.0

Excludes 14 observations in the SCAG sample with unknown travel mode. The chi-square statistic associated with the table for all trips is 574.0 with 3 degrees of freedom.

The model system, however, can be further enhanced as there are several research issues to be resolved and model components to be expanded and refined. Issues that have been identified for further investigation include:

- incorporation of fixities in work/school schedules,
- coherent treatment of the work/school base in a series of destination choices,
- integration of mode and destination choices in a series of home-based and non-home-based trips,
- representation of space-time constraints in the activity type, duration and destination choice components,
- representation of pertinent coupling constraints, e.g., a private vehicle must be brought back to the home base, and
- incorporation of accessibility and other measures for increased policy sensitivity.

Some of the weaknesses of the current STPG stems from its history dependent structure. Although this may be resolved by making the model system future dependent, models with future dependencies possess their own difficulties. A promising approach is to establish prisms for each worker first then apply a two-tier model structure in which activity engagement is first determined for all the prisms, then activities and trips are generated as described here within each prism.

There is no question that the model system can be improved further. Yet the results obtained so far are extremely encouraging and support the proposed approach as a promising path toward the development of a next generation of transportation planning tools.

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STOCHASTIC FRONTIER MODELS OF PRISM VERTICES
CHAPTER V

SUMMARY

A methodology to estimate the location and size of space-time prisms that govern individuals' activity and travel is presented in this chapter. Because the vertices of a prism are unobservable, stochastic frontier models are formulated to locate prism vertices along the time axis using observable explanatory variables such as commute characteristics and personal and household attributes. The location of a prism vertex is estimated by the models in a coherent manner, with a mean difference of 1.46 hours between the observed trip ending time and the expected location of the terminal vertex for workers' evening prisms. The estimation results also aid in enhancing our understanding of prism constraints by offering relationships between vertex locations and commute characteristics, personal attributes and area characteristics.

1. INTRODUCTION

That individuals' behavior in time and space is subject to a variety of constraints, has been one of the tenets of activity-based approaches to travel behavior (see, e.g., Pas, 1997; for activity-based approaches, see Damm 1983; Jones et al., 1983; Kitamura, 1988; Jones et al., 1990; Axhausen & Gärling, 1992; Gärling et al., 1994; Ettema, 1996; and Kurani and Kitamura, 1996). Hägerstrand (1970) proposed the notion of space-time "prism" to represent the effects of constraints and define the region that an individual can occupy in space and time. Hägerstrand also classified constraints, some of which define prisms, into three categories: capability constraints, coupling constraints and authority constraints. The prism concept has since been adopted in many studies of travel behavior (e.g., Lenthorp, 1976; Kitamura, et al., 1981; Damm, 1982; Kondo & Kitamura, 1987; Nishii & Kondo, 1992).

The prism concept is useful in both analyzing and predicting travel behavior. If travel behavior is examined without taking into account those constraints that govern it, then serious errors would result. A typical example would be to model travel mode choice without examining vehicle availability (which is a type of coupling constraint or authority constraint). On the other hand, it can be anticipated that the fit of a model or its predictive ability would improve by explicitly incorporating such constraints. In fact Fujii et al. (1997) report that their destination-mode choice model, which incorporates prism constraints and coupling constraints for private travel modes, exhibits a very good fit.

The prism concept is also used to form a platform for activity engagement analysis. Damm (1982) views activity engagement decision as a choice of prisms in which activities are to be engaged. A recent micro-simulation model called PCATS (Kitamura & Fujii, 1998) simulates individuals' activity and travel along a continuous time axis within a set of prisms defined for each individual. The concept of prism is an extremely useful one, both as a conceptual framework and as a construct for the analysis and prediction of travel behavior. The prism itself, however, is difficult to observe, not to mention to predict.

This study is an attempt to define the beginning and ending point (called a "vertex" in this study) of Hägerstrand's prism. While a trip is observable and is by definition always contained in a prism, the prism itself can rarely be defined based on observed information. Although the vertices of a prism is often determined by coupling constraints (e.g., one must be at a certain place by certain time), such constraints are often unobserved, or not well defined. For example, consider a commuter who must report at work by 9:00 A.M. In this case a prism has one of the vertices located at the workplace at 9:00 A.M. in the space-time coordinates. The other vertex, which designates the beginning point of the prism, is not defined, except that it is located at the home base somewhere prior to 9:00 A.M along the time axis.

To apply models of travel behavior that incorporate space-time constraints, it is desired that the location in time and space of prism vertices be estimated such that these models can be applied in more general contexts. In this study, an attempt is made to develop models to locate prism vertices along the time axis. The models are formulated as stochastic frontier models, which are used to estimate the location of an unobservable frontier (or, an upper or lower bound) based on the measurement of an observable variable that is governed by the frontier. In this study, the location on the time axis of a prism vertex is the unobservable frontier, and the starting or ending time of a trip is the observable quantity governed by the frontier.

The stochastic frontier model is described in Section 2. Section 3 describes the data set used in the empirical analysis of this study and presents distributions of selected variables that describe work schedules, which often define prism vertices. Results of model estimation are presented in Section 4. Section 5 is a brief summary and conclusions.

2. STOCHASTIC FRONTIER MODELS

By definition, a trip in a prism always starts at or after the origin vertex of the prism, and ends at or before its terminal vertex. While the beginning and ending times of a trip are almost always available from travel survey data, the origin and terminal vertices of a prism are normally unobserved. Although sometimes it is possible to infer the location along a time axis of a prism vertex, this is rather an exception than a norm. A modeling approach, therefore, is adopted in this study to estimate the location of prism vertices using observed variables.

Adopted in the modeling approach are the inequalities,

$$\begin{aligned} &\text{at origin vertex:} && \tau_o \le t_o \\ &\text{at terminal vertex:} && t_t \le \tau_t \end{aligned} \tag{1}$$

where τ_o is the location along a time axis of the origin vertex of a prism, τ_t the location of the terminal vertex, t_o the beginning time of a trip in the prism, t_t the ending time of the trip. It is assumed that τ_o and τ_t are unobserved. From the inequalities,

$$t_o = \tau_o + u_o, \quad t_t = \tau_t - u_t, \tag{2}$$

where u_o and u_t are non-negative random variables.

A possible model that applies to these relationships is the stochastic frontier model (Aigner et al., 1977), whose general form can be presented as

$$Y_i = \beta' X_i + \varepsilon_i = \beta' X_i + v_i - u_i \tag{3}$$

where i denotes the observation, Y_i is the observed dependent variable (in this case a trip beginning or ending time), β a vector of coefficients, X_i a vector of explanatory variables, v_i and u_i the random error terms, $-\infty < v_i < \infty$, and $u_i \geq 0$.

In the context of this study, $\beta' X_i + v_i$ can be viewed as the location of the terminal vertex of a prism with the random element, v_i. The observed trip ending time (Y_i in the above notation) will not exceed $\beta' X_i + v_i$ because u_i is non-negative. A model for an origin vertex can be formulated similarly as $Y_i = \beta' X_i + v_i + u_i$.

In the econometric literature on stochastic frontier models, v_i is typically assumed to be normal, and a truncated (half) normal distribution is often used for u_i. In this case, Aigner et al. (1977) give the distribution of ε_i as (subscript i is suppressed below)

$$h(\varepsilon) = \frac{2}{\sqrt{2\pi}\sigma}\{1 - \Phi(\varepsilon\lambda / \sigma)\} \exp\left[-\frac{\varepsilon^2}{2\sigma^2}\right], \quad -\infty < \varepsilon < \infty \qquad (4)$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u / \sigma_v$, v ~ $N(0, \sigma_v^2)$, and u has the density function,

$$g(u) = \frac{2}{\sqrt{2\pi}\sigma_u} \exp\left[-\frac{u^2}{2\sigma_u^2}\right], \quad u \geq 0. \qquad (5)$$

The likelihood function is said to be not entirely well behaved for models with this error density function. Waldman (1982) provides the result that if the third moment of the model's residuals is positive, then "the least squares slope estimates and $\bar{\lambda} = 0$ represent a local maximum of the likelihood."

This formulation is adopted in this study with: an observed trip starting or ending time as Y_i; and selected attributes of the individual and household, and commute characteristics as X_i. Because of the way the model is constructed, the inequalities of Eq. (1) are always satisfied. Yet, there remains the question of whether $\beta' X_i + v_i$ in fact represents the prism constraint in the strict sense of Hägerstrand. One could argue that $\beta' X_i + v_i$ may represent a threshold which an individual subjectively holds as the earliest possible starting time or the latest possible ending time for a trip, but may not coincide with actual constraints that are governing. For example, a commuter may believe that he cannot possibly leave home before 6:30 A.M. in the morning, thus the origin vertex of his prism before the work starting time is located, at least in his mind, at 6:30 A.M. But it is not likely that this is an objectively defined constraint. In fact the same commute may leave home before 6:00 A.M. for a business trip.

Models of prism vertices are estimated in this study with empirical data without any information on the individual's beliefs or perceptions of prism constraints. Yet, observed travel behavior is governed by subjective beliefs and perceptions, e.g., "I must return home by midnight" or "I cannot possibly leave home before 6:30 A.M." Thus some ambiguity is unavoidable about the nature of $\beta' X_i + v_i$; it is unlikely that it represents a prism vertex in the strict sense of Hägerstrand. It is yet reasonable to assume that $\beta' X_i + v_i$ is nonetheless a useful measure for the practical purpose of determining the earliest possible departure time or latest possible arrival time for a trip.

Some of the previous studies of daily activity evolved around the fact that workers' daily activities are regulated by their work schedules (e.g., Damm, 1982). It has been commonly assumed that the work starting time defines the terminal vertex of a worker's morning prism before work, and work ending time defines the origin vertex of his evening prism after work. The prism during the lunch break is determined by the beginning time and the ending time of the break.

Work schedules that define these prism vertices are determined primarily by institutional factors, and personal or household attributes are expected to have relatively small effects. There is therefore little room to apply such a model as described above to prism vertices that are defined by a work schedule. In fact stochastic frontier models are developed in this study for the origin vertex of workers' morning prisms, the terminal vertex of workers' evening prisms, and the terminal vertex of non-workers' day prisms. For those prism vertices that are defined by work schedules, different approaches (e.g., using observed frequency distributions of work starting or ending times by industry and occupation) may be more effective. As a precursor of such modeling efforts, distributions of work starting times, work ending times, and other aspects of work schedules are tabulated in the next section using the sample of individuals used in the model development of this study.

3. SAMPLE OF THE EMPIRICAL ANALYSIS

The stochastic frontier model presented in the previous section is applied to data obtained from a household travel survey conducted in the Kyoto-Osaka-Kobe metropolitan area in 1990. The survey, which was the most recent large-scale survey in the area, targeted 15.7 million residents of at least 5 years old who inhabited in the study area at the time of the survey. Approximately 2.4% of them, or 380,000 inhabitants, were surveyed and usual demographic, socio-economic, and trip information was collected from them. The sample used in the analysis of this study comprises those individuals who resided in the City of Kyoto and reported at least one trip. A total of 21,578 individuals fall in this category, representing 9,589 households.

Table 1 presents the distribution of age, sex, and employment status in the study sample. Discrepancies are noticeable particularly for employment status. Presumably this is due to the fact that sampling in the survey was household-based, while the table is an unweighted tabulation of individuals. Thus students (including grade-school to high-school students), who tend to be in larger households, are over-represented in the table, and retirees, who tend to live alone or in small households, are under-represented. The sample, however, is a random sample and these discrepancies should not have any adverse effects on the quality of the models estimated in this study.

Table 1. Distributions of Age, Sex and Employment Status in the Study Sample and the Census Data

Variable	Category	Sample	Census
Age	(mean)	35.8	37.8
Sex	male	50.1%	48.5%
	female	49.9%	51.5%
Employment status	Worker	51.5%	59.9%
	Student	27.9%	11.9%
	Homemaker	14.8%	18.0%
	Non-worker/Retiree	5.7%	10.2%
N		21,578	1,222,665

Figure 1 shows the distribution of home-to-work commute trip ending times and work-to-home commute trip starting times. Since the travel survey results offer no information on work schedules *per se*, they have to be inferred from trip starting or ending times. The ending time of a home-to-work commute trip can be interpreted to approximate the work starting time, thus the terminal vertex of the commuter's morning prism before work. Likewise, the starting time of a work-to-home commute trip may represent the work ending time and the origin vertex of the evening prism after work.

Figure 1-a indicates that, although home-to-work commute trip ending times are distributed almost throughout the day, there is a sharp concentration in the period between 8:00 A.M. and 8:59 A.M. In fact approximately 53.9% of the sample commuters have trip ending times in this one-hour period. Compared to this, the distribution of work-to-home trip starting times (Figure 1-b) is more spread, with a peak in the period between 5:30 P.M. and 7:59 P.M. The less concentrated distribution of evening commute starting times is perhaps a reflection of Japanese work styles that are quite different from those in North America or Europe.

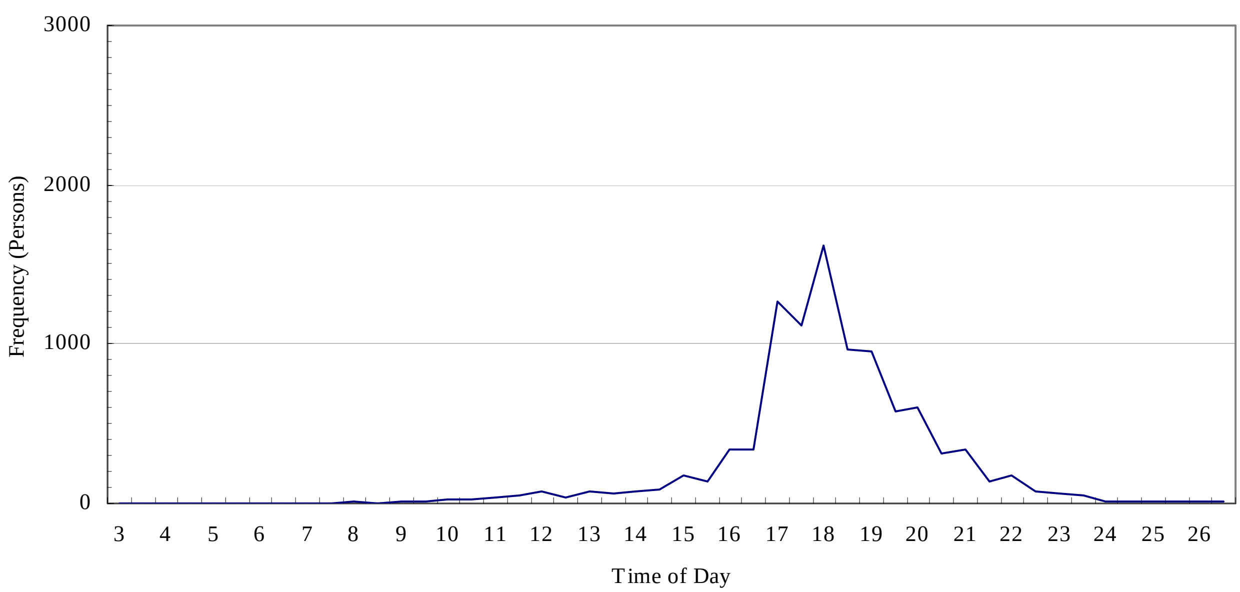

Figure 1-a. Sample Distribution of Home-to-Work Commute Trip Ending Times

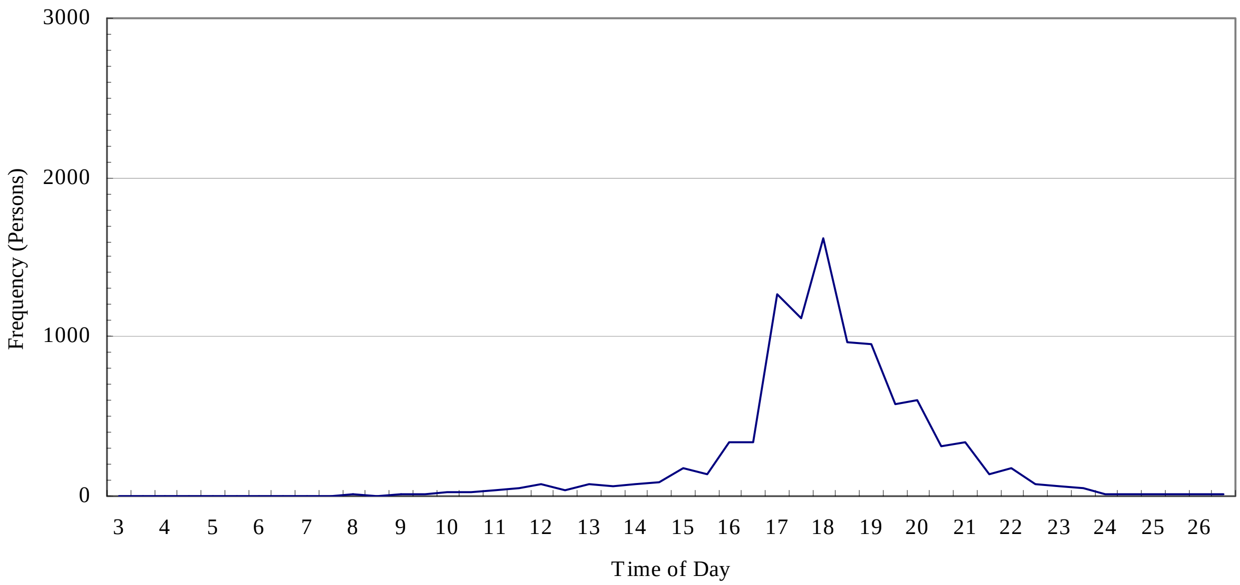

Figure 1-b. Sample Distribution of Work-to-Home Commute Trip Starting Times

Figure 2 presents distributions concerning lunch breaks based on a sample of 755 workers who made trips during their breaks. The beginning time of a trip from the workplace for non-work purposes is regarded as the beginning time of the break, and the ending time of the trip back to the workplace is regarded as the ending time of the break. Figure 2-a presents the distribution of lunch break starting times thus defined. A sharp peak can be found between 12:15 P.M. and 12:29 P.M.

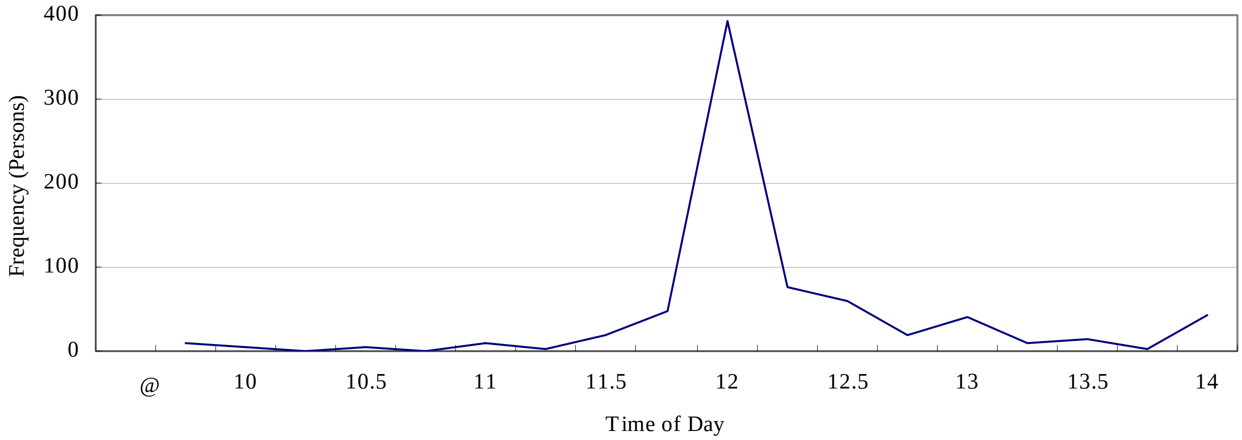

Figure 2-a. Sample Distribution of Lunch Break Starting Times

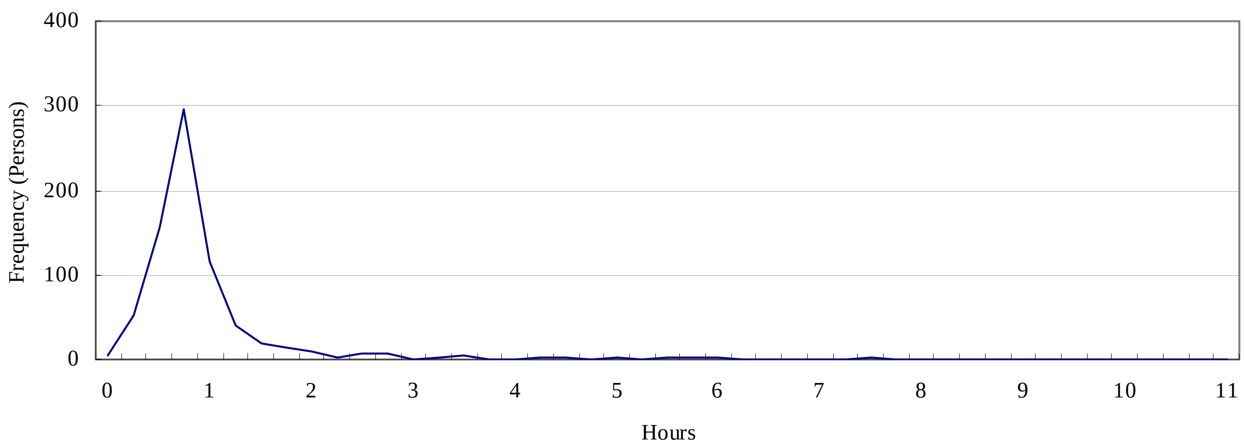

Figure 2-b. Sample Distribution of Lunch Break Lengths

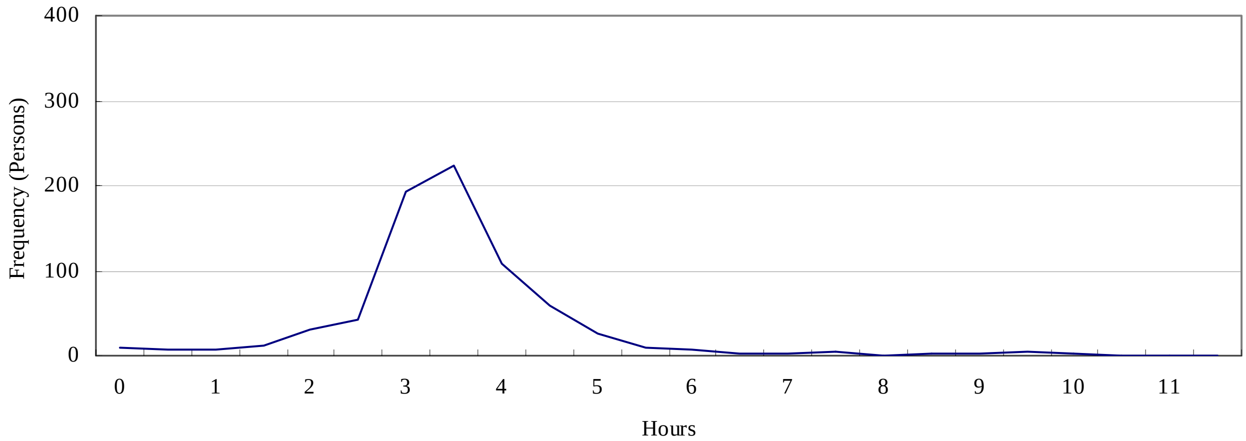

Figure 2-c. Sample Distribution of the Elapsed Time since the Work Starting Time till the Lunch Break

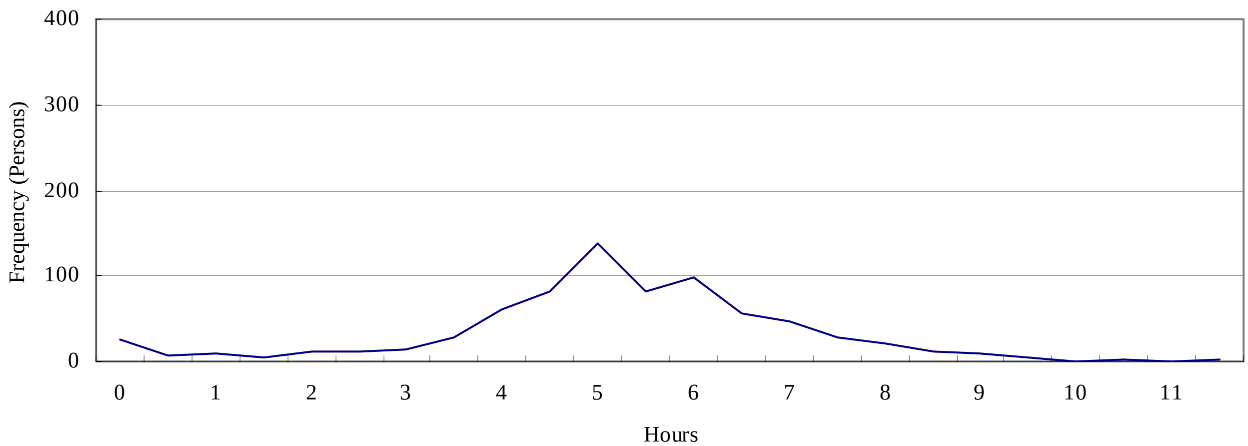

Figure 2-d. Sample Distribution of the Elapsed Time from the End of the Lunch Break till the Work Ending Time

The length of a lunch break is defined here as the difference between the starting time of a trip out of the workplace and the ending time of the subsequent trip back to the workplace. The sample distribution of lunch break lengths (Figure 2-b) has a mode in the 45 minutes to 59 minutes range, with 32.5% of the sample exceeding 1 hour.

The distribution of the elapsed time since the work starting time till the lunch break is shown in Figure 2-c. With a mean of 3.74 hours, most observations fall in the range of 3 to 4 hours. Figure 2-d presents the distribution of the elapsed time from the end of the lunch break till the work ending time. This distribution is more spread and has a larger mean of 5.40 hours.

This exploratory analysis of the sample individuals from the City of Kyoto has indicated the presence of regularities in work schedules. Yet, it makes it evident that not every worker has work hours of, say, 8:00 A.M. to 12:00 noon and 1:00 P.M. to 5:00 P.M. More elaborate analyses of work schedules will be needed in the future to develop models of work schedules, which will be capable of defining key prism vertices for workers. Results of such analyses will complement the stochastic frontier models of this study, to form a model system of prism vertices for workers.

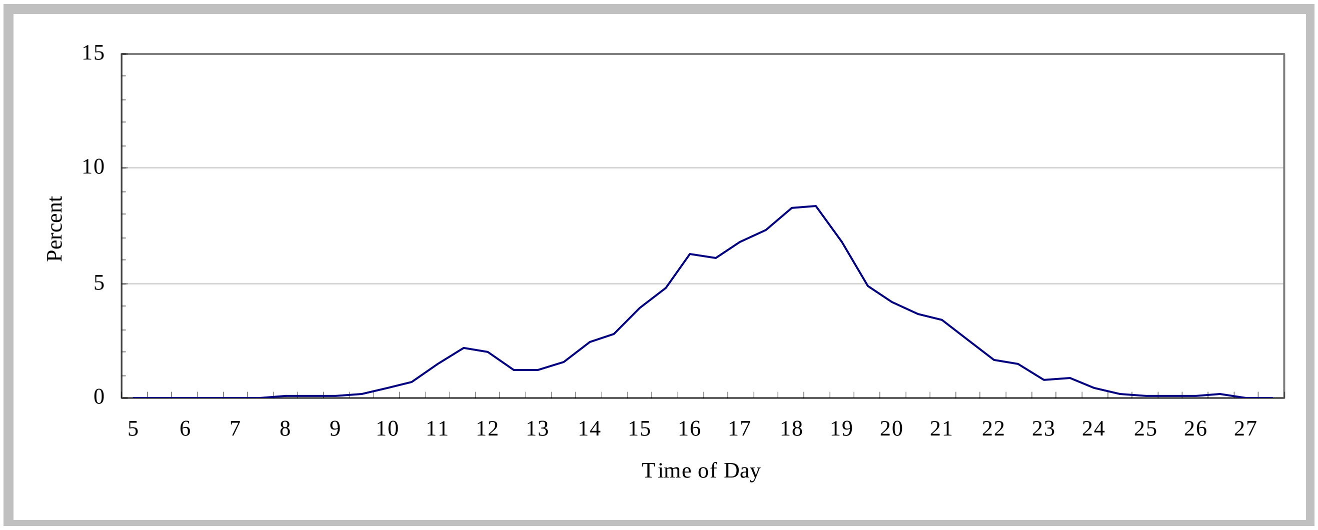

Figure 3-a. Sample Distribution of the Ending Time of the Last to-Home Trip of the Day for the Entire Sample

The distribution of the ending time of the last to-home trip of the day is shown in Figure 3 for the entire study sample (3-a), for workers (3-b), students (3-c) and other individuals (3-d), respectively. The workers' distribution is most concentrated with a mode in the period between 6:30 P.M. and 6:59 P.M., and a mean ending time of 6:54 P.M. Students' mean is earlier than this at 5:05 P.M. The distribution for "other" individuals is bimodal, with a morning peak between 11:30 A.M. and 11:59 A.M., and an afternoon peak between 4:00 P.M. and 4:29 P.M.

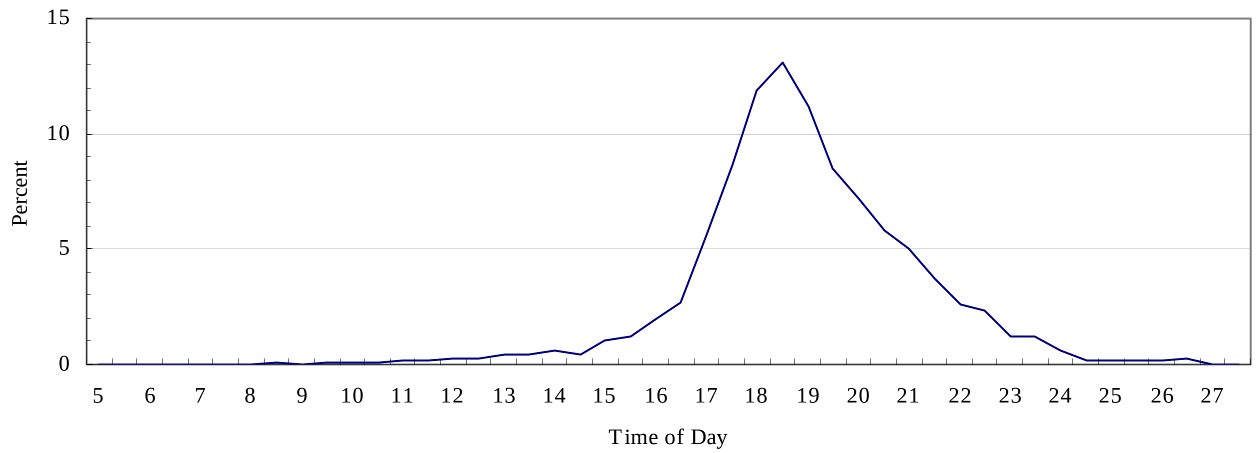

Figure 3-b. Sample Distribution of the Ending Time of the Last to-Home Trip of the Day for Workers

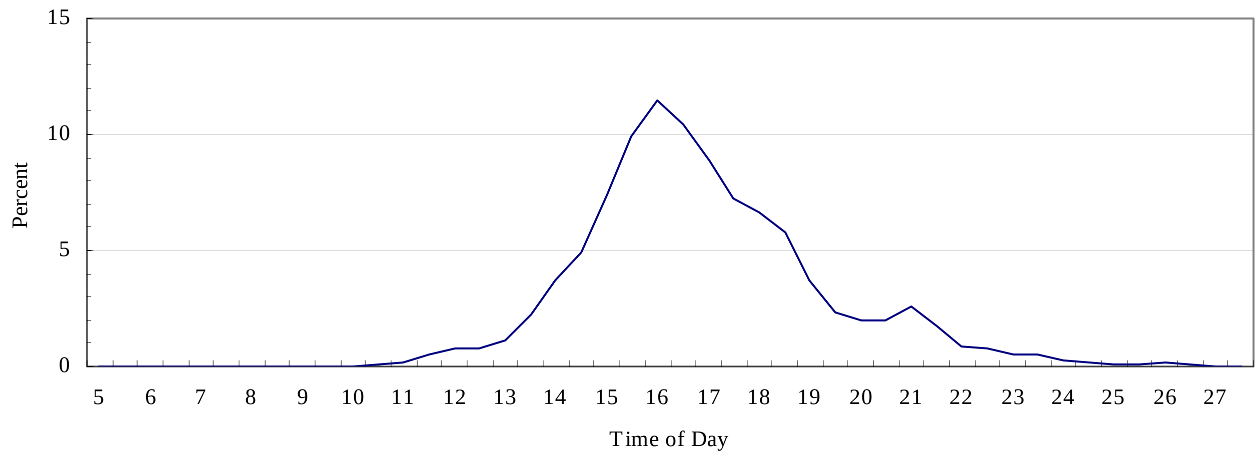

Figure 3-c. Sample Distribution of the Ending Time of the Last to-Home Trip of the Day for Students

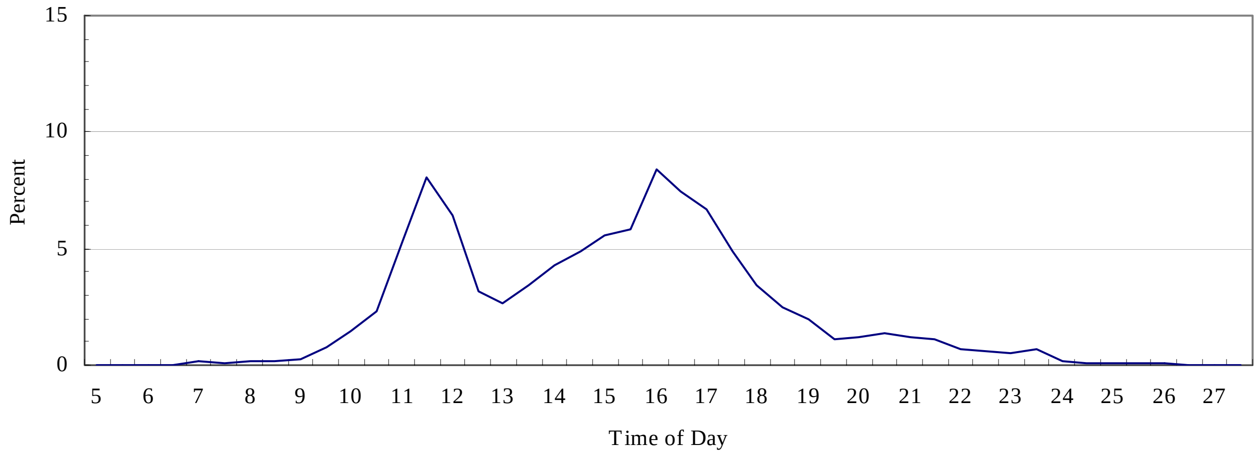

Figure 3-d. Sample Distribution of the Ending Time of the Last to-Home Trip of the Day for Other Individuals

4. MODEL ESTIMATION RESULTS

The sample described in the previous section is used to estimate stochastic frontier models of prism vertices. Models for the following prism vertices are presented in this chapter:

Origin vertex of the worker's morning prism,
Terminal vertex of the worker's evening prism,
Origin vertex of the homemaker's day prism, and
Origin vertex of the non-worker/retiree's day prism.

The explanatory variables that appear in the models are defined in Table 2. No models of the terminal vertex of the homemaker's or non-worker's day prism were successfully estimated.

The dependent variables of the models presented in this chapter are defined with the time of day expressed in minutes, with 12:00 A.M. (midnight) being 0; so 6:00 A.M. is expressed in the model as 360, and 6:00 P.M. as 1080. All models assume that v_i has a normal distribution and u_i has a half-normal distribution. The expected value of u_i is evaluated as

$$E[u_i] = \left(\frac{2}{\pi}\right)^{1/2} \tilde{\sigma}_u \qquad (6)$$

where $\tilde{\sigma}_u$ is an estimate of σ_u.

The model for the terminal vertex of the worker's evening prism is presented in Table 3. The mean of the dependent variable is 1133.9, which corresponds to 6:54 P.M. The model includes as its explanatory variables commute characteristics, personal attributes and indicators of life-cycle stage. The likelihood-ratio chi-square statistic indicates the model as a whole is highly significant.

The most significant explanatory variable is *No Commute*, a 0-1 dummy indicator for not commuting on the survey day. The coefficient estimate of this variable indicates that a worker's terminal vertex will be located about 96 minutes earlier in the day in the case he does not commute to work. The result suggests that a worker has different mind-sets about the time by which he believes he must return home between those days when he commutes to work and days when he does not. Also interesting is the coefficient estimate of *Commute Time* (in hours), whose value (52.4 minutes) implies that the terminal vertex of a worker's evening prism is pushed back in time almost as much as his commute duration.

The estimation results show expected tendencies that a female member of a household with children (*Female in a Family with Children*) tends to have a terminal vertex that is about 100 minutes (= 11.67 - (-89.45)) earlier than that of her male counterpart (*Male in a Family with Children*); a female in a couple also tends to have a vertex earlier than her male counterpart (see the coefficient estimates for *Female in a Couple*, *Male in a Younger Couple* and *Male in an Older Couple*); and the terminal vertices of younger singles tend to be located later, both for males and females, but more so for males (see *Single Male-Younger* and *Single Female-Younger*). Workers engaged in the primary industry have vertices on average about 70 minutes earlier than their counterparts in the other industries (*Primary Industry*).

Table 2. Definition of Explanatory Variables

Variable	Definition
Commute Time	One-way commute time on survey day, in hours
Public Transit	1 if commuted by public transit on survey day; 0 otherwise
No Commute	1 if did not commute on survey day; 0 otherwise
Age	Age in years
ln(Age)	Natural log of age in years
Male	1 if male; 0 otherwise
Driver's License	1 if holds driver's license; 0 otherwise
Household Head	1 if household head; 0 otherwise
Primary Industry	1 if engaged in primary industry; 0 otherwise
No. of Workers	Number of workers in household
No. of Children	Number of members age 6 - 10 in household
No. of Old Members	Number of members age 65 and over in household
No. of Cars	Number of cars available to household
Single Person	1 if single person; 0 otherwise
Single-Younger	1 if single person, age less than 40; 0 otherwise
Single-Older	1 if single person, age 40 and over; 0 otherwise
Single Male-Younger	1 if single male, age less than 40; 0 otherwise
Single Male-Older	1 if single male, age 40 and over; 0 otherwise
Single Female-Younger	1 if single female, age less than 40; 0 otherwise
Single Female-Older	1 if single female, age 40 and over; 0 otherwise
Male in a Younger Couple	1 if male in couple, age less than 40; 0 otherwise
Male in an Older Couple	1 if male in couple, age 40 and over; 0 otherwise
Female in a Couple	1 if female in couple; 0 otherwise
Male in a Family with Children	1 if male in family with members age 6 - 10; 0 otherwise
Female in a Family with Children	1 if female in family with members age 6 - 10; 0 otherwise
Male in a Family with Old Members	1 if male in family with members age 65 and over; 0 otherwise
Female in a Family with Old Members	1 if female in family with members age 65 and over; 0 otherwise
Female, Other	1 if female that does not belong to any of the above categories; 0 otherwise
Population Density	Inhabitants per 100 square-meter in residence area
Service Establishment Density	Number of service establishments per 0.01 km^2 in residence area

Table 3. Stochastic Frontier Model of Workers' Evening Prism, Terminal Vertex

Variable	Coef.	t
Constant	1211.24	186.71
Commute Time	52.38	11.17
Public Transit	25.08	6.43
No Commute	-96.05	-24.79
Driver's License	25.02	7.70
Household Head	-15.89	-4.01
Primary Industry	-70.09	-6.17
No. of Cars	-4.46	-2.69
Single Male-Younger*	30.36	5.48
Single Male-Older	-20.57	-3.86
Single Female-Younger	9.16	1.40
Single Female-Older	-33.83	-5.24
Male in a Younger Couple	26.67	4.08
Male in an Older Couple	-18.71	-2.43
Female in a Couple	-67.29	-9.39
Male in a Family with Children	11.67	2.37
Female in a Family with Children	-89.45	-11.34
Male in a Family with Old Members	-32.20	-6.75
Female in a Family with Old Members	-34.23	-5.60
Female, Other	-48.64	-10.38
Service Establishment Density	1.28	1.49
R^2, Adjusted R^2	0.176, 0.174	
L(0), L(β)	-68894.0, -67811.1	
χ^2 (df)	2165.9 (21)	
Var(v), E[u], Var(u)	12930, 45.28, 4523.2	
N	10,762	

*The basis of the twelve life-cycle indicators (*Single Male, Older* through *Female, Other*) is a male from a household of three or more members, with no members between 6 to 10 years old or over 65 years old.

The expected value of u_i is evaluated at 45.3 minutes; a worker returns home on average about 45 minutes before the terminal vertex of his evening prism. The expected location of a vertex can be evaluated as $\vec{\beta}' X_i$, where $\vec{\beta}$ is the estimated coefficient vector. The distributions of expected vertex locations and the distribution of trip ending times are compared in Figure 4a and the distribution of differences between expected vertex locations and trip ending times is shown in Figure 4b. Figure 4a shows that trip ending times are distributed with a mode in the interval between 6:30 P.M. and 6:59 P.M., while expected terminal vertices have a mode in the interval between 8:00 P.M. and 8:29 P.M., and have a more concentrated distributions than trip ending times. Since v_i has an estimated variance of 12930, the vertex itself (i.e., $\vec{\beta}' X_i + v_i \; \beta' X_i + v_i$) would show more widespread distribution. The difference between the expected vertex location and the trip ending time (i.e., $\vec{\beta}' X_i - Y_i \; \beta' X_i - Y_i$) has a mean of 87.8 and a mode in the range from 2.0 to 2.5 hours (Figure 4.b). The results suggest that the model is producing expected terminal vertex locations that appear realistic relative to trip ending times. Approximately 20.3% of the sample have negative differences, which is simply due to large values of v_i.

Table 4. Stochastic Frontier Model of Workers' Morning Prism, Origin Vertex

Variable	Coef.	t
Constant	436.91	144.64
Commute Time	-34.09	-10.41
No Commute	108.42	46.92
Male	-30.98	-15.51
Driver's License	-9.57	-4.42
Primary Industry	-31.11	-4.38
No. of Cars	3.33	3.09
Single-Younger	7.13	2.15
Single-Older	-4.72	-1.81
Service Establishment Density	1.91	3.47
R^2, Adjusted R^2	0.235, 0.234	
L(0), L(β)	-67025.5, -64334.8	
χ^2 (df)	5381.4(10)	
Var(v), E[u], Var(u)	2651.25, 57.56, 7309.38	
N	10,762	

Tables 4 through 6 present the models of the origin vertex, estimated for workers' morning prisms, homemakers' day prisms, and non-workers/retirees' day prisms, respectively. The models are "cost frontier" model and is formulated as $\beta' X_i + v_i + u_i$. The non-workers' models have poorer fit than the workers' models shown in Tables 3 and 4, and contain fewer explanatory variables.

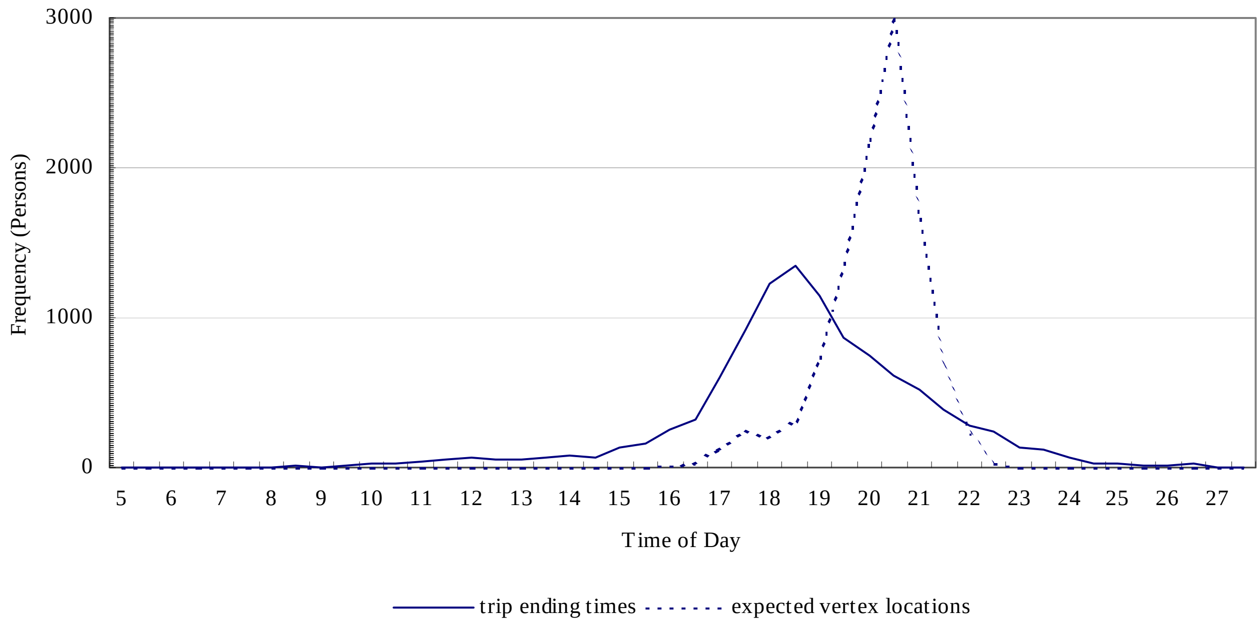

Figure 4-a. Distributions of Expected Vertex Locations and Trip Ending Times

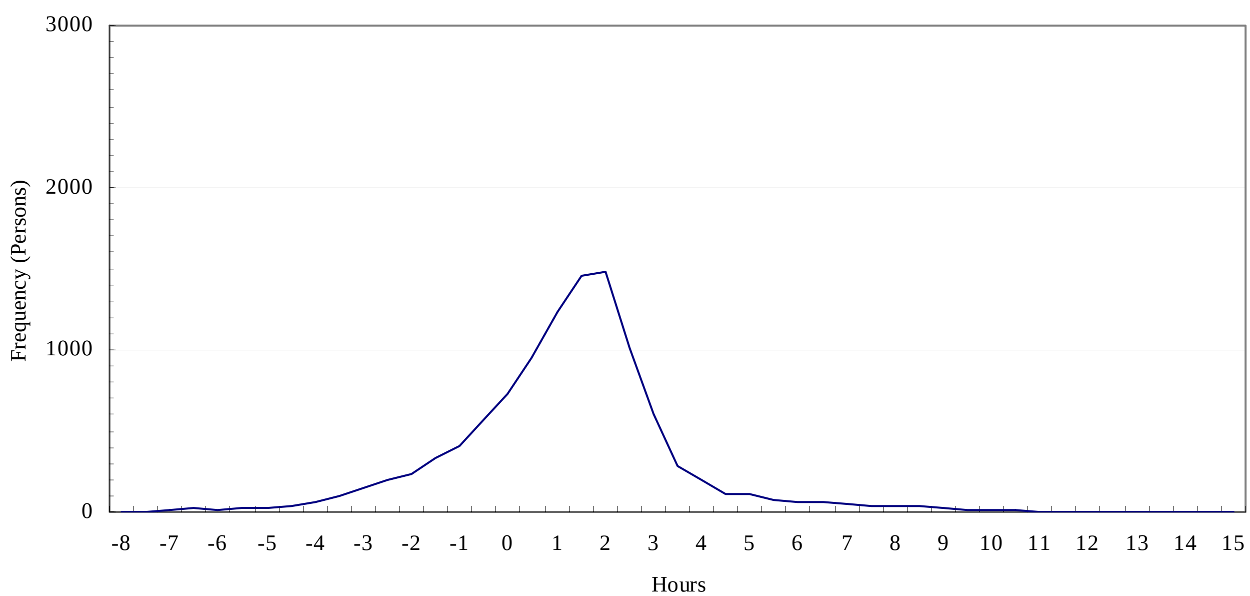

Figure 4-b. Distribution of the Differences between Expected Vertex Locations and Trip Ending Times

Comparing the workers' models in Tables 3 and 4 to each other offers interesting asymmetries. The coefficient estimates of *Commute Time* are 52.38 for the evening prism (Table 3) and -34.09 for the morning prism. As noted earlier, the terminal vertex location is moved back in time almost as much as the commute duration for the evening prism. The origin vertex of the morning prism, on the other hand, is advanced along the time axis only by 34 minutes for 1 hour of commute. The morning vertex location seems to be less elastic with respect to commute duration. Likewise, the coefficient estimates of *Primary Industry* is -70.09 for the evening prism and -31.11 for the morning prism. Again, the morning vertex location appears to be less elastic with respect to engagement in the primary industry. With -96.05 for the evening prism and 108.42 for the morning prism, on the other hand, the estimated coefficients of *No Commute* are almost symmetric. Workers appear to conceive contracted prisms on non-working days with the morning vertex and the evening vertex moved closer to each other about the same amount, slightly more for the morning vertex.

Table 5. Stochastic Frontier Model of Homemakers' Day Prism, Origin Vertex

Variable	Coef.	t
Constant	559.18	45.51
Age	-0.51	-2.33
Driver's License	-18.20	-3.37
No. of Workers	7.30	2.34
No. of Children	-31.45	-7.22
No. of Old Members	-11.87	-2.48
Population Density	14.61	1.97
Service Establishment Density	-6.63	-3.03
R^2, Adjusted R^2	0.021, 0.019	
L(0), L(β)	-20342.2, -20094.0	
χ^2 (df)	496.5(8)	
Var(v), E[u], Var(u)	3752.6, 87.5, 16899.8	
N	3,171	

The model for homemakers show that the origin vertex tends to be located earlier when there are more children or more older members in the household; a driver's license holder tends to have a vertex earlier; and an older homemaker tends to have an earlier vertex. The last tendency can also be found in the model for non-workers/retirees. This model shows male non-workers/retirees tend to have a vertex earlier, and single non-workers/retirees have it later in time.

Table 6. Stochastic Frontier Model of Non-workers/Retirees' Day Prism, Origin Vertex

Variable	Coef.	t
Constant	703.90	15.83
ln(Age)	-60.50	-5.95
Male	-29.21	-3.65
Single Person	34.81	3.63
Population Density	26.85	3.12
No. of Workers	8.02	1.49
R^2, Adjusted R^2	0.066, 0.062	
L(0), L(β)	-7750.3, 7636.7	
χ^2 (df)	227.2 (6)	
Var(v), E[u], Var(u)	4292.4, 93.5, 19286.1	
N	1,193	

5. CONCLUSIONS

This study represents an initial effort to develop a methodology to estimate the location and size of space-time prisms that govern individuals' activity and travel. Because the vertices of a prism are unobservable, stochastic frontier models are developed to locate prism vertices along the time axis using observable explanatory variables such as commute characteristics and personal and household attributes. The results obtained in this study are encouraging in that the location of a prism vertex is estimated by the model in a coherent manner, with a mean difference of 1.46 hours between the observed trip ending time and the expected location of the terminal vertex for workers' evening prisms. The estimation results also aided in enhancing our understanding of prism constraints by offering relationships between vertex locations and commute characteristics, personal attributes and area characteristics. It is hoped that the study results will serve as a basis for the development of models of travel behavior under space-time constraints.

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FORMULATION OF TIME SPACE PRISMS TO MODEL CONSTRAINTS ON PERSONAL ACTIVITY-TRAVEL PATTERNS
CHAPTER VI

SUMMARY

The notion of time-space prisms has often been used in the context of describing activity-travel patterns of individuals. This chapter presents a methodology for estimating the temporal vertices of time-space prisms using the stochastic frontier modeling technique. Observed trip starting and ending times are used as dependent variables and socio-economic characteristics and commute characteristics serve as independent variables. The models are found to offer plausible results indicating that temporal vertices of time-space prisms, though unobservable, can be estimated based on temporal characteristics of observed activity-travel patterns. Comparisons of stochastic frontier models of prism vertices and the distributions of prism vertices are presented using two activity data sets collected in the United States – San Francisco and Miami. Differences and similarities in temporal vertex locations are highlighted in the chapter.

1. INTRODUCTION

The notion of time-space prisms was introduced by Hagerstrand (1970) in the early 1970s to describe the spatio-temporal constraints in which people make activity and travel decisions. Since then, many researchers in the travel behavior arena have addressed or utilized the concept of time-space prisms for modeling activity and travel engagement patterns of individuals (e.g., Pas 1997; for activity-based approaches, see Damm 1983; Jones et al. 1983; Kitamura 1988; Jones et al. 1990; Axhausen & Gärling 1992; Gärling et al. 1994; Ettema 1996; and Kurani and Kitamura 1996). More recently, the emergence of activity and time use based approaches to travel demand modeling has opened up new opportunities for more completely formulating human time-space prisms that constrain person travel behavior choices (e.g., Lenthorp 1976; Kitamura, et al. 1981; Damm 1982; Kondo and Kitamura 1987; Nishii and Kondo 1992). This is because there are now several activity based time use data sets that more fully capture the spatial and temporal characteristics of both in-home and out-of-home activity engagement patterns. These data sets have been collected only in the recent past in the context of the development of activity based travel demand models.

The representation of spatio-temporal constraints in the modeling of human activity and travel behavior is very important. In any given day, a person has only 24 hours available and much of that time may be spent on basic subsistence activities including sleeping, working (to earn a living), and personal/household care. The temporal aspects of these types of activities tend to be rigid and impose constraints on an individuals' potential activity-travel engagement pattern (Pendyala et. al. 1997). Similarly, in a spatial context, one can postulate that fixed home and work locations (coupled with various temporal constraints) limit the range of spatial choices for a person. Thus, it can be seen that time-space constraints play an important role in shaping people's activity-travel patterns.

The accurate and complete representation of time-space prisms has taken on added importance in the context of the emergence of microsimulation approaches to travel demand forecasting. Whereas in the traditional zone-based four-step travel demand modeling approaches, one did not focus on the individual traveler, microsimulation approaches attempt to simulate activity and travel patterns at the level of the individual traveler (Pendyala et. al. 1998). When dealing with individual travelers and their potential behavioral responses to evolving transportation policy scenarios, it is imperative that a mechanism by which individual time-space prisms can be accurately modeled be developed.

This chapter is aimed at developing a methodology by which temporal vertices of time-space prisms of individuals can be effectively represented in a comprehensive framework that encompasses both in-home and out-of-home activity engagement and time use. The approach adopted in the chapter would be to utilize recent activity and time use data to model temporal vertices of time-space prisms for each individual as a function of his or her socio-economic and demographic characteristics.

Thus, this study is an attempt to define the beginning and ending point (called a “vertex” in this study) of Hägerstrand’s prism. While a trip is observable and is by definition always contained in a prism, the prism itself can rarely be defined based on observed information. Although the vertices of a prism is often determined by coupling constraints (e.g., one must be at a certain place by certain time), such constraints are often unobserved, or not well defined. For example, consider a commuter who must report at work by 9:00 A.M. In this case a prism has one of the vertices located at the workplace at 9:00 A.M. in the space-time coordinates. The other vertex, which designates the beginning point of the prism, is not defined, except that it is located at the home base somewhere prior to 9:00 A.M along the time axis.

In this chapter, models are developed to locate prism vertices along the time axis. The models are formulated as stochastic frontier models, which are used to estimate the location of an unobservable frontier (or, an upper or lower bound) based on the measurement of an observable variable that is governed by the frontier. In this study, the location on the time axis of a prism vertex is the unobservable frontier, and the starting or ending time of a trip is the observable quantity governed by the frontier. In particular, the chapter focuses on three items of interest:

1. Formulation and estimation of time vertices using stochastic frontier models
2. Comparison of space-time prism vertices between geographic areas
3. Investigation of day-to-day variability in time vertices.

The remainder of this chapter is organized as follows. The stochastic frontier model is described in Section 2. Section 3 describes the surveys from which the data sets used in this study are derived. Section 4 describes the socio-economic and demographic characteristics of the samples used in this study. Results of model estimation and comparisons between the two areas are presented in Section 5.   Section 6 presents a detailed discussion comparing the model results between the two areas from which data sets have been derived for this study. Section 7 wraps up the chapter with conclusions.

2. STOCHASTIC FRONTIER MODELS

By definition, a trip in a prism always starts at or after the origin vertex of the prism, and ends at or before its terminal vertex. While the beginning and ending times of a trip are almost always available from travel survey data, the origin and terminal vertices of a prism are normally unobserved. Although sometimes it is possible to infer the location along a time axis of a prism vertex, this is rather an exception than a norm. A modeling approach, therefore, is adopted in this study to estimate the location of prism vertices using observed variables.

Adopted in the modeling approach are the inequalities,

at origin vertex: $\tau_o \leq t_o$

at terminal vertex: $t_t \leq \tau_t$ (1)

where τ_o is the location along a time axis of the origin vertex of a prism, τ_t the location of the terminal vertex, t_o the beginning time of a trip in the prism, t_t the ending time of the trip. It is assumed that τ_o and τ_t are unobserved. From the inequalities,

$$t_o = \tau_o + u_o, \quad t_t = \tau_t - u_t, \tag{2}$$

where u_o and u_t are non-negative random variables.

A possible model that applies to these relationships is the stochastic frontier model (Aigner et al. 1977), whose general form can be presented as

$$Y_i = \beta' X_i + \varepsilon_i = \beta' X_i + v_i - u_i \tag{3}$$

where i denotes the observation, Y_i is the observed dependent variable (in this case a trip beginning or ending time), β a vector of coefficients, X_i a vector of explanatory variables, v_i and u_i the random error terms, $-\infty < v_i < \infty$, and $u_i \geq 0$.

In the context of this study, $\beta' X_i + v_i$ can be viewed as the location of the terminal vertex of a prism with the random element, v_i. The observed trip ending time (Y_i in the above notation) will not exceed $\beta' X_i + v_i$ because u_i is non-negative. A model for an origin vertex can be formulated similarly as $Y_i = \beta' X_i + v_i + u_i$.

In the econometric literature on stochastic frontier models, v_i is typically assumed to be normal, and a truncated (half) normal distribution is often used for u_i. In this case, Aigner et al. (1977) give the distribution of ε_i as (subscript i is suppressed below)

$$h(\varepsilon) = \frac{2}{\sqrt{2\pi}\sigma}\{1 - \Phi(\varepsilon\lambda / \sigma)\} \exp\left[-\frac{\varepsilon^2}{2\sigma^2}\right], \quad -\infty < \varepsilon < \infty \tag{4}$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u / \sigma_v$, v $\sim N(0, \sigma_v^2)$, and u has the density function,

$$g(u) = \frac{2}{\sqrt{2\pi}\sigma_u} \exp\left[-\frac{u^2}{2\sigma_u^2}\right], \quad u \geq 0. \tag{5}$$

The likelihood function is said to be not entirely well behaved for models with this error density function. Waldman (1982) provides the result that if the third moment of the model's residuals is positive, then "the least squares slope estimates and $\hat{\lambda} = 0$ represent a local maximum of the likelihood."

This formulation is adopted in this study with: an observed trip starting or ending time as Y_i; and selected attributes of the individual and household, and commute characteristics as X_i. Because of the way the model is constructed, the inequalities of Eq. (1) are always satisfied. Yet, there remains the question of whether $\beta' X_i + v_i$ in fact represents the prism constraint in the strict sense of Hägerstrand. One could argue that $\beta' X_i + v_i$ may represent a threshold which an individual subjectively holds as the earliest possible starting time or the latest possible ending time for a trip, but may not coincide with actual constraints that are governing. For example, a commuter may believe that he cannot possibly leave home before 6:30 A.M. in the morning, thus the origin vertex of his prism before the work starting time is located, at least in his mind, at 6:30 A.M. But it is not likely that this is an objectively defined constraint. In fact the same commuter may leave home before 6:00 A.M. for a business trip.

Models of prism vertices are estimated in this study with empirical data without any information on the individual's beliefs or perceptions of prism constraints. Yet, observed travel behavior is governed by subjective beliefs and perceptions, e.g., "I must return home by midnight" or "I cannot possibly leave home before 6:30 A.M." Thus some ambiguity is unavoidable about the nature of $\beta' X_i + v_i$; it is unlikely that it represents a prism vertex in the strict sense of Hägerstrand. It is yet reasonable to assume that $\beta' X_i + v_i$ is nonetheless a useful measure for the practical purpose of determining the earliest possible departure time or latest possible arrival time for a trip.

Some of the previous studies of daily activity evolved around the fact that workers' daily activities are regulated by their work schedules (e.g., Damm 1982). It has been commonly assumed that the work starting time defines the terminal vertex of a worker's morning prism before work, and work ending time defines the origin vertex of his or her evening prism after work. The prism during the lunch break is determined by the beginning time and the ending time of the break.

Work schedules that define these prism vertices are determined primarily by institutional factors, and personal or household attributes are expected to have relatively small effects. There is therefore little room to apply such a model as described above to prism vertices that are defined by a work schedule. In fact stochastic frontier models are developed in this study for the origin vertex of workers' morning prisms and the terminal vertex of workers' evening prisms. For those prism vertices that are defined by work schedules, different approaches (e.g., using observed frequency distributions of work starting or ending times by industry and occupation) may be more effective. Distributions of work starting times, work ending times, and other aspects of work schedules are provided in Section 4 for samples of individuals used in the model development of this study.

3. OVERVIEW OF SURVEYS

The data sets used in this study are derived from recent activity-travel surveys conducted in the United States. This section provides a brief overview of the surveys from which the data sets have been derived.

3.1 San Francisco Bay Area Survey

A two-day activity based time use and travel survey was conducted in the nine counties of the San Francisco Bay Area in 1996. Detailed information on both in-home and out-of-home activities and trips undertaken by an individual was recorded. The survey also collected data on the usage of the Bay Bridge in connection with a peak-period toll study; however, variables in the data set related to this aspect of the study were not used in the context of this study. While information on all trips and trip segments (in the case of chained trips) was collected, in–home activity information was requested only for those activities that were longer than 30 minutes in duration. However, a few respondents provided detailed information on all in-home activities. Information on all out-of-home activities was collected irrespective of their duration.

The Computer Aided Telephone Interview (CATI) technique was used to conduct the survey. The survey elicited responses from 14,431 persons residing in 5,857 households in the Bay Area. They provided detailed household and person level socio-economic and demographic data. In general, the survey intended to collect detailed activity and trip information for all individuals residing in a household. 8,817 individuals residing in 3,919 households provided detailed activity and trip information over a 48-hour period. After extensive data checking, cleaning, and merging/organizing, the final data set obtained for use in this study included 7,982 persons residing in 3,827 households. Among the 7,982 persons, 4,331 were commuters and the remaining 3,651 persons were non-commuters. Full-time or part-time workers, irrespective of their school status and work location, were treated as commuters in this study. Individuals reporting activities performed out of the study area, or those who provided activity trip information for one day or less during the survey period were ignored for the purpose of this study.

3.2 Miami Survey

An activity-based travel behavior and time-use survey was conducted in the Miami-Dade County area of Florida in 1998. The survey collected detailed information on both in-home and out-of-home activities and on all travel associated with these activities. Unlike the San Francisco Bay Area survey, activity and travel behavior data was collected for only a one-day (24-hour) period in this survey. In addition, the sample consisted exclusively of commuters who were defined as individuals who commuted to a regular work or school location at least three days a week. Only one randomly selected commuter was chosen to participate from each household.

Similar to the Bay Area survey, the Miami survey was administered using the Computer Aided Telephone Interview (CATI) technique. Socioeconomic and demographic information about the household and about persons residing in the household was collected first. Information regarding the usual commute to and from work was collected from the randomly selected commuter. Activity and time use data was collected only from eligible commuter respondents. Unlike the Bay Area survey, the Miami survey did not have any duration threshold for reporting of activities. All activities, regardless of their length, were recorded in the data set. Similar to the Bay Area survey, the Miami survey included information on all trips including individual trip segments of chained trips.

Socio-economic and demographic data was collected for 2,539 persons residing in 1,040 households. As mentioned earlier, activity and trip data was collected only from commuters with the constraint that each commuter must be drawn from a different household. 803 commuters provided detailed information on their usual commute to and from work; of these, 640 commuters provided detailed activity and trip information for the 24-hour survey period. The analysis in this study was, however, performed only on a sample of 589 commuters as the remaining respondents included full time students with no work. Even though the omitted respondents were considered commuters from a survey standpoint, it was felt that they should not be included here for reasons of compatibility and comparability across the two surveys.

A final note is due here regarding the rather large difference in sample sizes between the two survey samples. In general, the magnitude of sample size difference seen here calls for the exercise of caution in performing and interpreting comparisons. However, it should be noted that the analysis and comparisons in this chapter are restricted to activity and travel phenomena of a frequent nature and done across the entire samples with no breakdown by socio-demographic segment. Within the context of these broad and controlled comparisons, it was felt that both survey samples offered robust statistical measures.

4. SAMPLE CHARACTERISTICS

This section provides a brief overview of the socio-economic and demographic characteristics of the two survey samples. A comparison of household characteristics is presented first followed by a comparison of person characteristics. At the person-level, comparisons are made exclusively between commuter samples.

As mentioned previously, the sample included 3,827 households from the Bay Area and 640 households from Miami. The average household size in the Bay Area is found to be 2.3 while that in Miami is substantially higher at 3.2 (Table 1). While the Bay Area survey average household size is quite comparable with census information, it was found that the Miami figure was substantially higher than the census figure. One possible reason for this is that the exclusive commuter-based sample from the Miami survey may favor the inclusion of larger households as opposed to smaller household sizes such as single-person students and retirees. Indeed, the Miami sample shows substantially higher percentages of households with three or more persons.

The income distributions are as expected with a large percentage of the households in both surveys comprising medium income households. In Miami, the percentage of low income households is found to be quite higher than that in San Francisco. However, this observation is tempered by the fact that these income values have not been corrected for cost-of-living differences. The average vehicle ownership is found to be 1.9 and 2.1 for the Bay Area and Miami samples respectively. Once again, these values must be compared with caution in light of the exclusive presence of commuters in the Miami sample. One would expect that car ownership levels in such households would be higher than in other households. 86 percent of the households in the San Francisco Bay Area survey have at least as many vehicles as the number of workers in the household indicating a rather high degree of car availability; the corresponding percentage is only 64 percent for the Miami sample. This difference in level of car availability per worker must be looked at in conjunction with the comparison in the number of workers per household. While the number of workers per household is only 1.4 in the Bay Area sample, it is 2.5 in the Miami sample. Once again, the exclusive presence of commuters in the Miami sample explains this rather large difference.

Table 1. Comparison of Household and Person Characteristics

Characteristic	San Francisco	Miami
Household Attributes		
Sample Size	3827	640
Household Size	2.3	3.2
1 person hhld	32.2%	12.8%
2 person hhld	34.5%	27.0%
3 person hhld	15.1%	22.0%
4 person hhld	11.9%	20.0%
5+ person hhld	6.3%	18.2%
Residence Type		
Single family detached	63.7%	56.1%
Single family attached	4.5%	15.9%
Apartment or condominium	29.4%	25.2%
Others	2.4%	2.8%
Income		
Low (<30k)	15.8%	29.4%
Medium (30-75k)	44.4%	40.9%
High (>75k)	26.7%	19.7%
Vehicle Ownership	1.9	2.1
0 car hhld	5.6%	3.9%
1 car hhld	34.4%	21.9%
2 car hhld	39.4%	49.4%
3+ car hhld	20.5%	24.8%
% Vehicles≥commuters	86.4%	64.4%
Number of Workers	1.4	2.5
0 worker hhld	16.5%	n.a.
1 worker hhld	40.4%	23.4%
2 worker hhld	37.0%	38.0%
3+ worker hhld	6.0%	38.6%
Number of Bicycles	1.3	1.4
0 bicycle hhld	39.8%	40.8%
1 bicycle hhld	22.6%	19.2%
2 bicycle hhld	20.1%	20.0%
3+ bicycle hhld	17.6%	20.0%
Owning Home of Residence	63.0%	73.1%
Years at Current Residence	4.7 years	9.0 years
Person Attributes	**Commuters**	**Commuters**
Sample Size	4331	589
Age (in years)	41.5	n.a.
Young (≤29)	18.8%	25.3%
Middle (30-49)	53.8%	48.9%
Old (≥50)	27.4%	22.3%
Employment Status		
Full time	81.5%	80%
Part time	12.1%	15%
Licensed	95.3%	93.0%
Student	13.3%	11.1%
Mode Choice for Journey to Work		
Single Occupant Auto	68%	72%
Pool	13%	18%
Transit	8%	3%
Non-motorized	11%	5%

In general, the differences found in the comparison of household characteristics between the two survey samples are consistent with expectations. Many of these differences are simply manifestations of the fact that the Miami sample consists exclusively of commuters while the San Francisco sample includes all types of households.

A comparison between commuter samples from the two surveys is also shown in Table 1. The age distribution for commuters appears quite comparable with nearly one-half of the individuals (both in San Francisco and Miami) in the middle age bracket. Nearly 80 percent of the commuter respondents in both regions are full-time workers. As expected, the percent of licensed drivers among commuters is quite high in both survey data sets. In general, the commuter samples in both surveys are quite comparable with respect to their personal characteristics. Variables representing age, employment status, drivers license holding, and student status are all quite similar between the two commuter samples. As such, it was felt that performing comparisons of stochastic frontier models of prism vertices between the two samples is quite appropriate.

5. RESULTS OF MODEL ESTIMATION

Commuter samples from the Miami and San Francisco Bay Area surveys are used to estimate stochastic frontier models of prism vertices. Models of the following prisms are presented in this chapter:

- Origin vertex of the commuters morning prism – Miami and San Francisco
- Terminal vertex of the commuters evening prism – Miami and San Francisco

As data are available for a two-day period in the San Francisco data set, separate models are estimated for each day and for the pooled data set so that day-to-day variability in time vertex locations can be explored.

The dependent variables of the models presented in this chapter are defined with the time of day expressed in minutes, with 12:00 A.M. (midnight) being 0; so 6:00 A.M. is expressed in the model as 360, and 6:00 P.M. as 1080. All models assume that v_i has a normal distribution and u_i has a half-normal distribution. The expected value of u_i is evaluated as

$$E[u_i] = \left(\frac{2}{\pi}\right)^{1/2} \hat{\sigma}_u \qquad (6)$$

where $\hat{\sigma}_u$ is an estimate of σ_u.

The model for the origin vertex of the Miami commuter's morning prism is presented in Table 3. Table 2 provides a definition of the variables used in the model. The model is a "cost frontier" model and is formulated as $\beta' X_i + v_i + u_i$. The model is found to offer plausible indications. The model shows that a full-time worker has a origin vertex about 86.5 minutes earlier than a non-worker while the corresponding figure for a part-time worker is about 57 minutes. On the other hand, those who work at home have origin vertices about 87 minutes later than those who work outside the home. Similarly, the variable representing students also has a negative coefficient, though not as much as those associated with full- or part-time workers. The origin vertex of the Miami commuters morning prism is pushed earlier as commute time increases - about ½ hour for every hour of commute. Greater car availability and the possession of a drivers license provide for origin vertices that are later in the morning; this is presumably because of the faster travel times and flexibility associated with the ability to drive alone. Older individuals and those in families with children have slightly earlier origin vertices than other groups. The E[u] is 141 minutes indicating that the first time of departure from home is, on average, about 2 hr 20 min after the origin vertex.

Table 2. Definition of Explanatory Variables for Miami Sample (N=569 cases)

Variable	Definition	Descriptive Statistic
Full-time worker	1 if working full time; 0 otherwise	69.8%
Part-time worker	1 if working part time; 0 otherwise	6.9%
Work at home	1 if works mainly at home; 0 otherwise	2.1%
Student	1 if 'student only' or 'student and works part-time'; 0 otherwise	19.2%
Commute time (hr.)	Distance from home to work (or school) (hr)	0.384 hr
Car availability	1 if number of cars ≥ number of drivers; 0 otherwise	83.3%
Driver's license	1 if holds driver's license ; 0 otherwise	91.6%
Young	1 if age < 30; 0 otherwise	26.0%
Middle	1 if 30 ≤ age < 50; 0 otherwise	48.7%
Old	1 if age ≥ 50; 0 otherwise	21.6%
Family with children	1 if family with members age 5-15; 0 otherwise	40.6%

Table 3. Stochastic Frontier Model of Miami Commuters' Morning Prism Origin Vertex

Variable	Coef.	t-stat
Constant	383.4	15.17
Full-time worker	-86.5	-3.69
Part-time worker	-57.1	-1.98
Work at home	86.8	3.38
Student	-47.7	-1.88
Commute time (hr.)	-31.4	-1.73
Car availability	19.3	1.65
Driver's license	51.9	3.35
Old	-21.7	-1.95
Family with children	-15.4	-1.62
R^2, Adjusted R^2	0.260, 0.248	
$L(C)^{\dagger}$, $L(\beta)$	-3592.1, -3464.2	
χ_c^2 (df)	255.9 (9)	
Var(v), E[u], Var(u)	1807.6, 141.4, 11404	
N	569	

†L(C) is evaluated by setting all coefficients to 0, except constant.

The model for the terminal vertex of the Miami commuter's evening prism is presented in Table 4.

Table 4. Stochastic Frontier Model of Miami Commuters' Evening Prism Terminal Vertex

Variable	Coef.	t-stat
Constant	1215.7	29.0
Full-time worker	76.1	2.50
Part-time worker	67.6	1.68
Work at home	95.2	2.10
Student	66.1	1.98
Driver's license	-48.4	-1.82
Young	73.7	3.40
Middle	27.8	1.46
R^2, Adjusted R^2	0.041, 0.029	
$L(C)^{\dagger}$, $L(\beta)$	-3744.0, -3731.4	
χ_c^2 (df)	25.4 (7)	
Var(v), E[u], Var(u)	20867, 120.9, 8344	
N	569	

†L(C) is evaluated by setting all coefficients to 0, except constant.

The model is a "production frontier" model and is formulated as $\beta' X_i + v_i - u_i$. The model is found to offer a substantially poorer overall goodness-of-fit than the model presented in Table 3. This may be due to the greater variance associated with the final home arrival when compared with the first departure from home. While the distributions of the first departure from home are clearly peaked and show a well-behaved pattern, the distributions of the final arrival at home are relatively flat and exhibit greater variance. This will be further discussed in the next section where distributions of observed times and predicted vertices are examined.

Despite the poorer goodness-of-fit, the model offers plausible indications. Workers and students have terminal vertices that are later in the day with full-time workers showing the latest terminal vertex. Working at home is associated with a terminal vertex that is 95 minutes later than for other individuals. This is potentially because these workers engage in more out-of-home activities in the evening as a way of compensating for staying and working at home all day long. This is also consistent with the finding in Table 3 that their origin vertex in the morning prism is pushed later by about an equivalent duration. Essentially, their "active" day is pushed in time by about 1 ½ hours relative to workers who commute to a location outside home. Younger individuals have terminal vertices later than middle-aged individuals presumably because they engage in more post-work activities outside the home and do not have the same home obligations as middle aged individuals. As in Table 3, the E[u] shows that the final arrival at home is, on average, about 2 hours prior to the terminal vertex of the evening prism.

Table 5 provides definitions for the variables used in the San Francisco Bay Area models.

Table 5. Definition of Explanatory Variables for San Francisco Sample
(N=6885 cases; Day 1 = 3606 cases; Day 2 = 3279 cases)

Variables	Definition	Descriptive Statistic (Pooled 6885 Cases)
Working day	1 if working day; 0 otherwise	70.7%
Working day (full-time worker)	1 if working day (full-time worker); 0 otherwise	61.6%
Working day (part-time worker)	1 if working day (part-time worker); 0 otherwise	6.2%
Multi jobs	1 if has 2 or more jobs; 0 otherwise	5.6%
School day	1 if school day; 0 otherwise	5.2%
Homemaker	1 if homemaker; 0 otherwise	0.6%
Commute time (min.)	Distance from home to work (or school)	23.5 min
Drive alone	1 if commuted by car (drive oneself); 0 otherwise	78.5%
Transit	1 if commute by public transit; 0 otherwise	7.1%
Age	Age in years	40.7
Male	1 if male; 0 otherwise	54.0%
Driver's license	1 if holds driver's license; 0 otherwise	94.3%
Hispanic	1 if Hispanic; 0 otherwise	10.5%
White	1 if White, non-Hispanic; 0 otherwise	69.0%
Black	1 if Black; 0 otherwise	5.8%
Household size	Household size	2.66
Single person	1 if single person; 0 otherwise	19.8%
No. of workers	Number of workers in the household	1.76
No. of cars	Number of vehicles in the household	2.09
No. of bicysles	Number of bicycles in the household	1.54
No. of mopeds	Number of mopeds in the household	0.025
Low income	1 if income is less than $30K; 0 otherwise	14.4%

Table 6 shows the model for the origin vertex of San Francisco commuter's morning prism. For the San Francisco commuters, two days worth of data is available. Therefore, model results are shown by day and for the pooled sample as a whole. In general, the model shows consistent indications across the two days with virtually every coefficient having the same sign despite small differences in magnitudes. Going to work or school is associated with earlier vertex locations as evidenced by the negative coefficients. Similarly to the Miami model, every hour of commute results in a shift of the origin vertex by about 25 minutes earlier in the day. Transit users have earlier origin vertices possibly because of the longer access and travel times associated with transit. Being older, male, Hispanic, or Black is associated with earlier vertex locations as evidenced by the negative coefficients exhibited by these variables. Low income commuters are found to have origin vertices about 15 minutes earlier than other commuters possibly due to their reliance on alternative modes of transportation, rigid work hours associated with lower paying jobs, and other constraints. Interestingly, the value of E[u] for the San Francisco sample is greater than that for the Miami sample by about 50 minutes. It is found that the first time of departure from home is, on average, about 3 hr 15 min later than the origin vertex for the San Francisco sample. Recall that the corresponding figure for the Miami sample was about 2 hr 20 min.

Table 6. Stochastic Frontier Model of San Francisco Commuters' Morning Prism Origin Vertex

Variable	Pooled		Day 1		Day 2	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constant	476.90	58.52	478.26	43.90	481.12	38.73
Working day	-80.34	-20.58	-90.96	-17.57	-71.66	-11.44
School day	-60.93	-7.15	-72.10	-5.41	-53.53	-4.76
Homemaker	39.16	1.94	53.27	2.03	26.08	0.83
Commute time (min.)	-0.41	-5.33	-0.26	-3.01	-0.58	-3.91
Drive alone	-19.53	-4.81	-14.92	-2.562	-24.09	-4.22
Transit	-28.81	-3.56	-31.31	-2.82	-24.59	-2.08
Age	-0.41	-3.21	-0.38	-2.21	-0.51	-2.55
Male	-22.84	-7.35	-20.45	-4.81	-24.70	-5.37
Hispanic	-33.99	-6.46	-30.88	-4.32	-37.69	-4.84
Black	-23.43	-3.93	-28.55	-3.27	-19.41	-2.37
Household size	-4.86	-3.87	-4.48	-2.66	-5.41	-2.87
No. of bicysles	-2.24	-2.00	-2.76	-1.85	-1.51	-0.88
No. of mopeds	19.34	2.90	17.87	1.78	21.31	2.29
Low income	16.34	3.85	16.15	2.76	16.80	2.67
R^2, Adjusted R^2	0.298, 0.297		0.302, 0.300		0.299, 0.296	
$L(C)^{\dagger}$, $L(\beta)$	-45843, -44041		-23812, -22897		-22005, -21114	
χ_c^2 (df)	3604 (13)		1831 (13)		1781 (13)	
Var(v), E[u], Var(u)	2660, 197.63, 22293		3017, 183.5, 19218		2346, 210.7, 25340	
N	6885		3606		3279	

†L(C) is evaluated by setting all coefficients to 0, except constant.

Table 7 shows the results of the model estimation effort for the terminal vertex of the commuter's evening prism of the San Francisco sample. As seen in Figures 3 and 4, the work end time and the final time of arrival at home for the San Francisco commuter sample show distributions that have high variance and less well-defined patterns when compared with the Miami sample. This is also evidenced in the model estimation results.

Table 7. Stochastic Frontier Model of SF Commuters' Evening Prism Terminal Vertex

Variable	Pooled Coef.	Pooled t-stat	Day 1 Coef.	Day 1 t-stat	Day 2 Coef.	Day 2 t-stat
Constant	1292.71	83.80	1286.12	61.80	1299.73	56.70
Working day (full-time worker)	8.94	1.57	22.59	2.92	-6.36	-0.75
Working day (part-time worker)	38.98	4.14	39.58	3.13	39.24	2.78
Multi jobs	26.11	2.93	30.20	2.51	20.90	1.59
School day	69.05	6.29	92.61	5.74	42.48	2.82
Commute time (min.)	0.46	4.03	0.49	3.06	0.43	2.58
Age	-2.11	-11.74	-2.09	-8.61	-2.16	-8.04
Hispanic	-19.23	-2.34	-26.44	-2.38	-10.60	-0.87
White	-8.56	-1.39	-14.50	-1.74	-1.72	-0.19
Black	-13.67	-1.40	-27.36	-1.99	0.05	0.00
Single person	41.05	6.25	43.83	4.95	38.98	3.99
No. of workers	6.04	2.06	10.96	2.70	1.15	0.27
No. of cars	5.50	2.50	4.96	1.64	6.02	1.88
No. of bicycles	-5.17	-3.33	-5.32	-2.52	-5.03	-2.20
Driver's license	43.26	4.90	35.00	3.00	52.67	3.93
Low income	-15.32	-2.36	-19.71	-2.29	-10.48	-1.07
R^2, Adjusted R^2	0.062, 0.060		0.078, 0.074		0.052, 0.048	
$L(C)^{\dagger}$, $L(\beta)$	-45922, -45631		-24045, -23854		-21875, -21761	
χ_c^2 (df)	583 (14)		381 (14)		228 (14)	
Var(v), E[u], Var(u)	18260, 166.8, 15873		16949, 169.9, 16485		19525, 162.6, 15089	
N	6885		3606		3279	

†L(C) is evaluated by setting all coefficients to 0, except constant.

For example, the effect of a working day for a full-time worker is minimal (and not significant for the second day). On the other hand, working day of a part-time worker and working multiple jobs shifts the terminal vertex by about ½ hour later in the day. Similarly, school also shifts the terminal vertex later in the day. For every hour of commute, the vertex is shifted later by about 25 minutes. This result is found to be very symmetric with that of the origin vertex of the morning prism where one hour of commute shifted the origin vertex 25 minutes earlier in the day. Being older or of minority status (Hispanic or Black) is associated with relatively earlier terminal vertices for the commuter's evening prism. On the other hand, being a single person and having a drivers license are both associated with later terminal vertices. This may be because of the greater flexibility for final home arrival that these individuals may have relative to those who have families and can not drive. A greater number of workers or cars is associated with marginally later terminal vertices, once again presumably due to the flexibility afforded by these variables.

As in the case of the Miami sample, the goodness-of-fit of the model of the evening prism terminal vertex is substantially poorer than that found for the morning prism origin vertex. The greater variability in the final arrival times at home may be contributing to this poor fit. The E[u] is found to be about 2 hr 45 minutes, indicating that commuters in the San Francisco sample, on average, arrive home about 2 hr 45 min prior to the terminal vertex. This is in comparison to the figure of about 2 hours obtained for the Miami sample.

Overall, it is seen that the stochastic frontier modeling methodology is capable of representing the terminal vertices associated with beginning or ending points of space-time prisms, at least for commuters who tend to have more structured weekdays. Further research is warranted in the context of estimating vertex locations for nonworkers (see Kitamura et. al. 2000, for some early work in this area).

6. COMPARISONS OF PRISM VERTICES

Comparisons are presented in this section for two items of interest:

- Comparisons between Miami and San Francisco commuter samples with respect to origin vertex of morning prism and terminal vertex of evening prism
- Comparisons between first and second days of the San Francisco commuter sample with respect to origin vertex of morning prism and terminal vertex of evening prism.

Figure 1 shows the distributions of expected vertex locations and observed time of first departure from home for the two samples (the San Francisco sample represents a pooled sample including both days observations). The two samples show strong similarities. For both San Francisco and Miami, the origin vertex peaks at about 6 AM while the observed distributions of first departure from home peak about two hours later at about 8 AM. Thus there is about a two hour difference between the expected vertex of the prism and the actual time of departure from home. The distribution of expected vertex locations for the Miami sample has a small secondary peak at about 7:30 AM while the San Francisco sample does not exhibit any such secondary peaks. Also, the observed distribution of departure times for the San Francisco sample appears to be relatively flatter in comparison to that of the Miami sample.

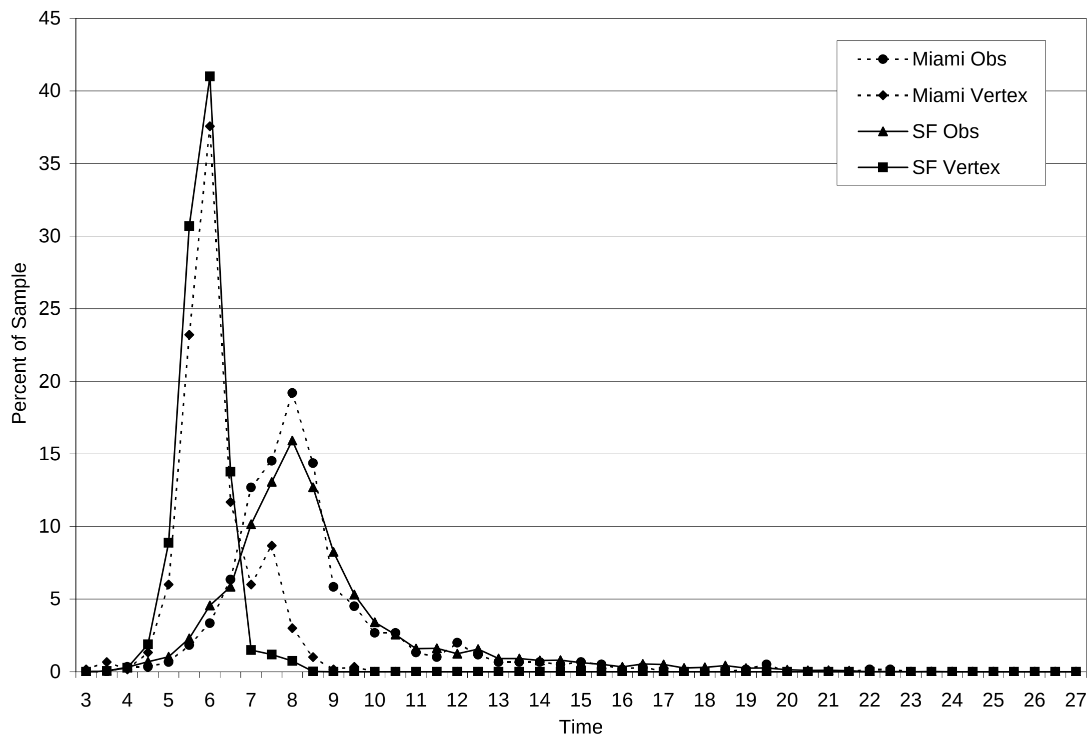

Figure 1. Distribution of Expected Vertex Locations and First Departure from Home

Greater differences between the Miami and San Francisco (pooled) samples are found in Figure 2 where distributions of expected vertex locations and observed final home arrival times are compared. Relative to first departure times (seen in Figure 1), the final home arrival times exhibit greater variation and the peaks are not as pronounced. Note that this greater variation associated with home arrival times may be contributing to the poorer model fit found in the previous section. The peak home arrival time for the Miami sample appears to be about 7 PM while that for the San Francisco sample appears to be about 30 minutes earlier at 6:30 PM. The distributions of expected vertex locations peak for both samples at about 9:30 PM with that of the Miami sample showing a more pronounced peak than the San Francisco sample. Greater household obligations (child care, etc.) associated with larger household sizes in the Miami area may be contributing to this difference. Thus it is found that most individuals arrive home about 2.5-3 hours prior to their vertex location.

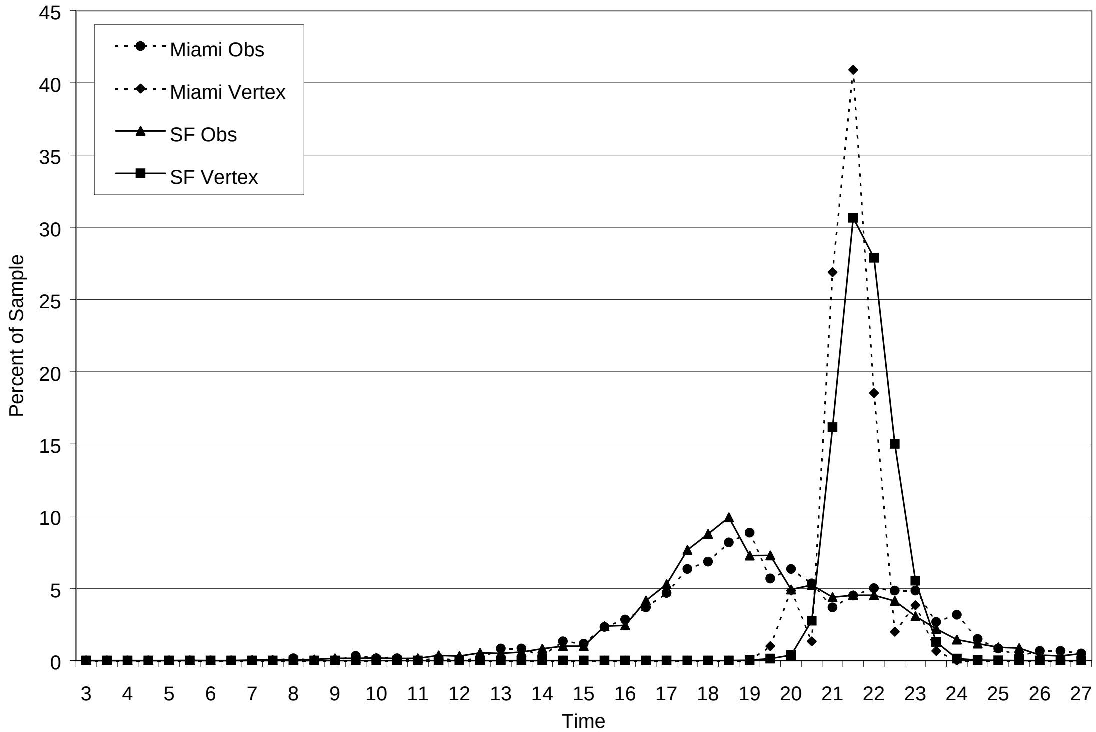

Figure 2. Distribution of Expected Vertex Locations and Final Arrival at Home

In addition to comparisons between geographic areas, comparisons were made between the first and second days for the San Francisco sample. Figure 3 shows the comparison for the origin vertex of the morning prism and the first time of departure from home. The distributions are strikingly similar. The peaks of the observed distributions are shifted about two hours to the right (later in the day) of the peaks associated with the distributions of the expected vertex locations. The distributions of the expected vertex locations are very similar between the two days as are the distributions of observed home departure times.

Similarly, Figure 4 shows the comparison between the first and second days for the terminal vertex of the evening prism. Once again, the distributions are strikingly similar. As expected, the distributions associated with the final home arrival are flatter and the peaks are less pronounced than in the case of the first home departure (in Figure 3). These differences are very consistent between the two days.

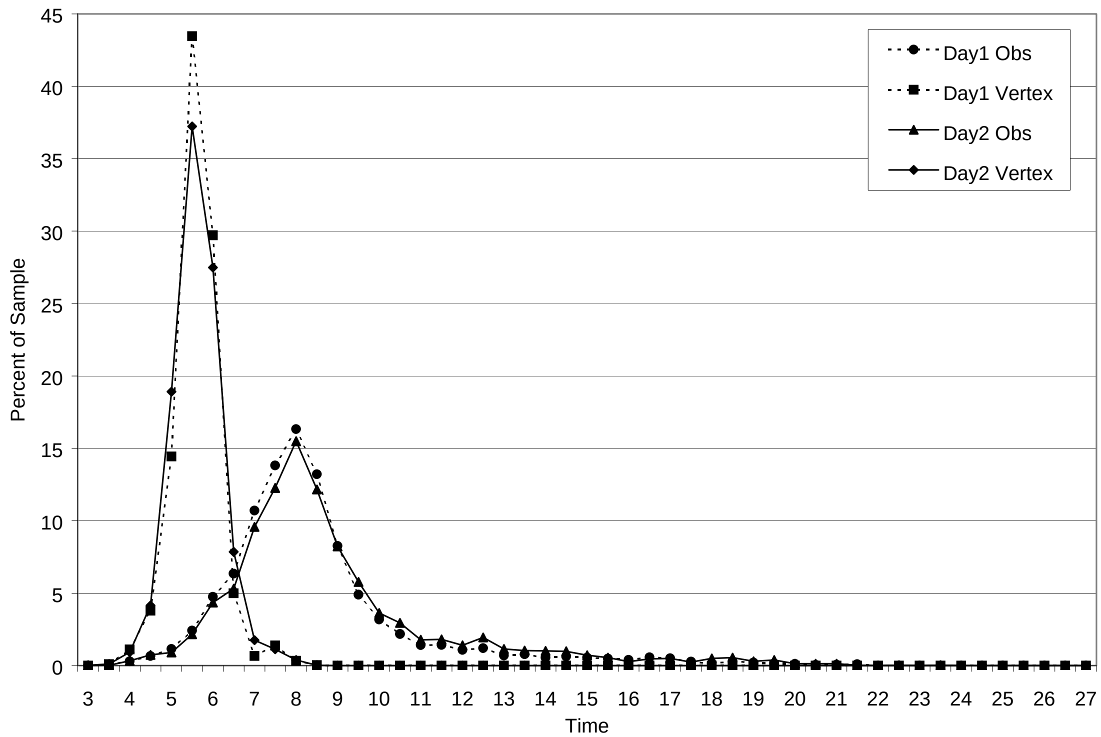

Figure 3. Distribution of Expected Vertex Locations and First Departure from Home: Comparison Between Day 1 and Day 2 for San Francisco Commuters

Overall, it appears that similarities across geographic areas are more pronounced in the case of origin vertices associated with the morning prism of commuters. The greater variability in home arrival times contributes to greater differences across geographical areas when one considers the terminal vertex locations of the evening prism. Also, comparisons between two days of travel show striking similarities between the distributions of expected vertex locations and observed departure/arrival times.

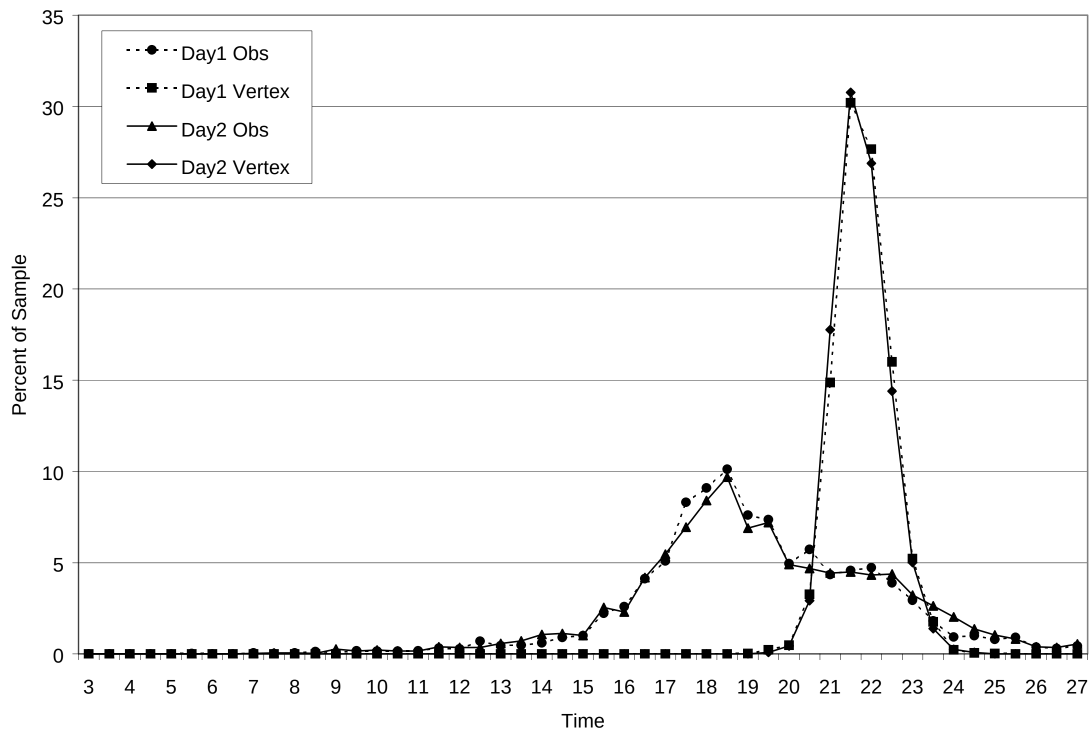

Figure 4. Distribution of Expected Vertex Locations and Final Arrival at Home: Comparison Between Day 1 and Day 2 for San Francisco Commuters

7. CONCLUSIONS

This chapter uses the stochastic frontier modeling methodology to represent the temporal vertices of space-time prisms within which people schedule their activities and trips. The stochastic frontier modeling method is found to be an effective method for modeling such temporal extremities. Estimation results provide strong indications that the temporal vertices associated with space-time prisms are significantly influenced by people's socio-economic, demographic, and commute characteristics. The chapter presents models for the origin vertex of the morning prism and the terminal vertex of the evening prism for commuter samples drawn from the Miami, Florida and San Francisco Bay areas.

The stochastic frontier model estimation results were utilized to perform two types of comparisons. First, a comparison was made between geographical areas and second, a comparison was made between two days for the same sample. The first comparison showed that the distributions of expected vertex locations and home departure/arrival times for commuters are remarkably similar across geographic areas. Marginally greater differences are found in the case of the terminal vertex location of the evening prism (final home arrival time distributions); whether or not these differences are statistically significant is yet to be determined. In general, however, it appears that there are substantial similarities between areas with respect to the locations and sizes of prism vertices. In comparing the models estimated using the two commuter samples, it was found that the coefficients associated with variables common to both models are similar with respect to their interpretation. While these findings may suggest the potential for applying models in multiple geographic contexts, considerable further research needs to be done before such conclusions can be drawn.

The second comparison showed that there are remarkable similarities across days with respect to the locations of prism vertices. The distributions of expected vertex locations and observed departure/arrival times show that day-to-day variability is minimal, at least on a sample-wide basis. However, as shown in the literature on day-to-day variability (e.g., Pas and Sundar 1995), individual travel behavior does show considerable variation from one day to the next. Even with a two- or three-day survey sample, it is found that there is considerable intraperson variability in trip rates by purpose, travel time, and vehicle miles traveled. One may then hypothesize that, while prism locations and sizes are very consistent from one day to the next (as found in this chapter), the scheduling and undertaking of activities and trips within those prisms varies considerably from one day to the next. Further research should focus on testing this hypothesis so that robust models of activity and travel scheduling under space-time prism constraints can be developed.

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A NESTED LOGIT MODEL OF ACTIVITY SCHEDULING
CHAPTER VII

SUMMARY

This chapter presents a nested logit model of activity scheduling behavior that can be used to predict a daily activity pattern for commuters. The behavioral paradigm embodied in the model suggests a two-stage decision process in which commuters first plan or identify the non-work activities that need to be undertaken during the day, and second, schedule these activities in relation to the work activity schedule. Three possible scheduling periods are considered in the model including before work, at work, and after work. Alternative nested logit model structures are estimated on the 1996 San Francisco Bay Area activity survey sample to identify a plausible and statistically acceptable structure. Numerical examples are presented in the chapter to show how the model, when combined with a Monte Carlo simulation and simple heuristics, can be used to generate daily activity schedules for commuters.

INTRODUCTION

The conceptual deficiencies of the conventional four-step trip-based travel demand modeling procedure combined with the shift in transportation planning and policy initiatives from transportation infrastructure development to transportation systems management, have led to the emergence of activity-based approaches to model individual travel behavior (Kitamura 1988; Axhausen and Garling 1992). Activity-based analysis is based on the premise that travel demand is a derived demand and resulting travel demand models are applicable to a wider range of situations than is the conventional four-step trip-based procedure (Ettema and Timmermans 1997). The activity-based perspective of travel can also reliably evaluate travel demand management policies since it explicitly models activity patterns and considers these patterns to be the fundamental influence on individual travel decisions (Golob 1998; Kuppam and Pendyala 2000).

The activity-based approach has seen substantial development in the past few years (Kitamura et al. 1998). Bhat and Koppelman (1999) have broadly classified these developments into activity time allocation studies and activity episode analysis studies. Activity time allocation studies classify activities into one of the several categories available and then examine the time allocated to these activity types based on socio-economic and demographic characteristics of individuals (Kitamura 1984). However, these approaches ignore the context in which individuals pursue activities, i.e., these approaches ignore the time of the day of activity performance, the sequence in which the activities are performed in a continuous temporal domain, and the location characteristics of activity participation (Kitamura et al. 1997b).

Activity episode analysis is closer to the original theory behind activity-based approaches. This approach analyzes activities and trips and their associated spatial and temporal constraints in a comprehensive model framework. These studies describe in detail, the sequence, context, and duration of activity participation thus leading to more detailed models of activity choice and travel behavior. Many of the earlier activity episode analysis studies focused on participation of individuals in one or more activity episodes, along with one or more accompanying characteristics of the episodes such as duration, location, or time window of activity participation (Damm 1982; Hamed and Mannering 1993; Bhat 1996, 1998).

Over the last decade, several researchers have developed models that attempt to microsimulate daily activity participation and trip schedules of individuals (Chen et al. 1999). Examples include, but are not limited to, STARCHILD (Recker et al. 1986), SCHEDULER (Garling et al. 1994), and AMOS (Kitamura et al. 1995; Pendyala et al. 1998). The development of such models has been further accelerated by the availability of data that captures household activity scheduling behavior (Doherty and Miller 2000). Another line of research in activity-based modeling has seen the development of tour-based model frameworks, where “tours” are considered to be the basic unit of travel. These approaches use a combination of multinomial logit and nested logit models to simulate activity-travel patterns in the context of tours (Bowman and Ben-Akiva 1998; Wen and Koppelman 1999, 2000).

Activity-based approaches form the basis of the next generation of travel demand models in the United States and other countries. The objective of this chapter is to contribute towards operationalizing the activity-based approach by proposing a simple analysis framework to generate weekday activity engagement and trip scheduling patterns of commuters. Using data from the 1996 San Francisco Bay Area activity survey, nested logit models of activity scheduling behavior are developed and estimated. The proposed nested logit models, though not comprehensive and exhaustive, offer practicality, provide a plausible behavioral basis, and represent activity scheduling and travel behavior of commuters in a simple model system. It is believed that the nested logit models of activity scheduling behavior proposed in this chapter can be effectively combined with other models of activity behavior (e.g., activity frequency models, activity duration models) and rule-based algorithms (e.g., Pendyala et al. 1998) to develop a full-fledged activity based model system.

The remainder of this chapter is organized as follows. The second section provides a brief description of the survey sample used in this chapter. The third and fourth sections describe the overall modeling approach and nested logit methodology respectively. The fifth and sixth sections describe the nested logit model specification and estimation results respectively. The seventh section provides an example of how the nested logit model can be used to predict a commuter's activity pattern. Finally, conclusions are drawn in the final section.

SAMPLE DESCRIPTION

This research chapter utilizes activity and trip information collected as part of the 1996 San Francisco Bay Area Travel Study (BATS). Gangrade, et. al. (2000) provide a detailed description of the survey and sample characteristics. As such, only a brief summary is provided here. A two-day activity-based time use and travel survey was conducted in the nine counties of the San Francisco Bay Area in 1996. Detailed information on both in-home and out-of-home activities and trips undertaken by an individual was recorded. The survey also collected data on the usage of the Bay Bridge in connection with a peak-period toll study; however, variables in the data set related to this aspect of the study are not used in the context of this chapter. While information was solicited for all out-of-home activities and trips undertaken by an individual, in-home activity information was requested for those activities at least 30 minutes in duration. However, it was found that many respondents provided detailed information on all in-home activities regardless of their duration.

The original survey data set includes a sample of 8,817 individuals residing in 3,919 households who provided detailed activity and trip information over a 48-hour period. After extensive data checking, cleaning, and merging/organizing, the final dataset obtained for use in this study included 7,982 individuals residing in 3,827 households. Among the 7,982 persons, 4331 were commuters and the remaining 3651 persons were non-commuters.

Sample Profile

Table 1 presents the demographic characteristics of households in the sample. The average household size is found to be 2.3 persons per household while the average number of workers is 1.4 workers per household. Forty percent of the households were single-worker households, while another 38 percent were multiple-worker households.

The income variable was categorized into low (less than $30,000), medium ($30,000 - $75,000), and high (greater than $75,000) groups. The distributions are as expected with a large percentage of the households in the survey comprising medium income households. Average car ownership in the sample is 1.9 vehicles per household. It should also be noted that over 87 percent of the households in the survey sample have vehicle ownership levels greater than or equal to the total number of commuters in the household. This is indicative of a high level of commuter auto availability.

Person characteristics (provided separately for commuters and non-commuters) of the sample are also shown in Table 1. The age of the respondents has been categorized into young (29 years or less), middle (30 - 49 years), and old (50 years or more) age groups. More than 50 percent of the commuter sample falls in the middle age bracket, while over 50 percent of individuals in the non-commuter sample fall in the young age group (non-commuter group includes children). More than 80 percent of the commuters are full-time workers. Also, as expected, the percent of licensed drivers in the commuter sample is substantially higher than that in the non-commuter sample (95% vs. 49%).

Table 1. Household and Person Demographic Characteristics

Household Attributes		
Sample Size	3827	
Household Size	2.3	
1 person hhld	32.2%	
2 person hhld	34.5%	
3+person hhld	33.3%	
Income		
Low (<30k)	19.6%	
Medium (30-75k)	43.3%	
High (>75k)	22.5%	
Vehicle Ownership	1.9	
0 car hhld	5.6%	
1 car hhld	34.4%	
2 car hhld	39.4%	
3+ car hhld	20.5%	
% Vehicles≥commuters	86.4%	
Number of Workers	1.4	
0 worker hhld	16.5%	
1 worker hhld	40.4%	
2 worker hhld	37.0%	
3+ worker hhld	6.0%	
Number of Bicycles	1.3	
Owning Home of Residence	63.0%	
Years at Current Residence	4.7 years	
Person Attributes	**Commuter**	**Non-commuter**
Sample Size	4331	3651
Gender		
Male	54.4%	42.8%
Female	45.5%	56.9%
Age (in years)	41.5	32.4
Young (≤29)	18.8%	54.0%
Middle (30-49)	53.8%	14.5%
Old (≥50)	27.4%	31.5%
Employment Status		
Full time	81.5%	n.a.
Part time	12.1%	n.a.
Licensed	95.3%	48.6%
Student	13.3%	44.8%

It can be seen that the non-commuter sample is quite different from the commuter sample. In light of these differences, one would expect non-commuters to have substantially different activity and time use patterns than commuters. These differences call for the development of separate models of activity scheduling behavior for commuters and non-commuters. In this chapter, out-of-home non-work activity engagement and trip scheduling behavior is modeled only for the commuter sample. As such, the remainder of this chapter focuses exclusively on the commuter sample.

Activity Participation and Trip Frequency Analysis

The original dataset had more than 30 categories describing the various activities performed by an individual. These numerous categories were broadly aggregated into 11 activity types to study activity and trip frequencies by purpose. Average frequencies (including both in-home and out-of-home activities) for the commuter sample are presented in Table 2. As mentioned earlier, the Bay Area travel survey was conducted over a 48-hour time period. The activity and trip frequencies presented in the table were obtained by averaging over the two-day survey period.

Table 2. Activity and Trip Frequencies

Activity	Commuters (N=4331)	Non-commuters (N=3651)
Work/Work Related	1.6	--
Eating/Meal Preparation	1.7	2.0
Shopping/Personal Business	0.6	0.7
Out of Home Entertainment	0.5	0.6
In Home Entertainment	1.2	1.8
Personal care and Child care	1.2	1.2
Sleep and Nap	1.0	1.1
In Home Maintenance/Other	0.7	1.1
Out of Home Other	0.4	0.4
School	0.1	0.7
Travel (Total Trips)	4.8	3.5
Work/Work Related	1.3	--
Return Home	1.6	1.3
Meal (out-of-home)	0.4	0.2
Shopping/Personal Business	0.5	0.6
Out of Home Entertainment	0.5	0.5
Child Care	0.1	0.1
Out of Home Other	0.4	0.4
School	0.1	0.4
Total Activities and Trips	13.9	13.1

The average number of work and work related activities is 1.6 activity episodes per day for the Bay Area commuter. This value is along expected lines because many commuters undertake two work activity episodes in a day; one work activity before lunch break and one work activity immediately after lunch.

As expected, eat-meal, in-home entertainment, personal and child care, and sleep/nap activities average one or more activity episodes per day. On the other hand, shopping and personal business, out-of-home entertainment, and out-of-home other activities average less than one activity episode per day.

With respect to travel, it is found that commuters, on average, undertake 4.8 trips per day. Table 2 shows trip rates by purpose for both commuter and non-commuter samples in the data set. Work/work related and return home trips comprise almost 50% of the trips undertaken by commuters over a day. The average trip frequency for out-of-home shopping/personal business, entertainment, and maintenance/other related activities is found to be about 0.5 trips per day for each purpose. The average trip frequency associated with child care is rather low at 0.1 trips per day.

Overall, it can be seen that the work activity is a major part of a commuter's daily activity and travel pattern. In the case of commuters, one may conjecture that other non-mandatory and discretionary activities (such as shopping, personal business, recreation, child care, etc.) are scheduled and performed around the relatively fixed and less flexible work schedules. This hypothesis, which is consistent with the literature on activity-based approaches (see e.g., Damm 1982) forms the basis for the nested logit model of activity scheduling developed in this chapter.

A FRAMEWORK FOR ACTIVITY SCHEDULING BEHAVIOR

In this chapter, nested logit models are formulated with a view to predict activity and trip schedules of commuters over a day. This section provides the behavioral framework underlying the specification of the nested logit models of commuter activity scheduling behavior.

There is increasing interest in the application of microsimulation approaches for activity-based travel demand forecasting (Kitamura et al. 1997a; Pendyala et al. 1998). In microsimulation approaches, one is often attempting to simulate, at the level of the individual traveler, an entire activity schedule and travel itinerary over the course of a day. This involves the modeling of a series of choices that travelers make during the day including those related to activity type choice, activity duration, timing and scheduling, location and destination choice, and path choice. Considering that many of these choices are made under constrained situations, one can argue that there are finite spatio-temporal action spaces or space-time prisms within which one can engage in activities and travel (Pendyala et al. 2002).

Space-time prisms provide a means of representing the spatial and temporal constraints that influence activity and travel patterns. For example, from a spatial standpoint, one can conjecture that home and work locations are potential anchors that constrain the potential range of destinations a person can visit. Because of data limitations, this chapter does not consider the spatial aspect of commuter activity scheduling behavior.

From a temporal standpoint, there may be several events in time that constrain the range of activity-travel patterns that an individual can pursue. These events and their associated beginning and ending times can play an important role in determining how individuals schedule, sequence, and plan their activities and trips. In this chapter, six temporal events that might dictate how a commuter schedules and plans activities are identified. These temporal events are as follows:

1. Wake up time
2. First time of departure from home
3. Work start time
4. Work end time
5. Final time of arrival at home
6. Sleep time

Gangrade et al. (2000) have provided detailed descriptions of these temporal events for the commuter and non-commuter groups in the survey sample. These six events potentially define five temporal prisms within which commuters schedule their activities. For example, wake up time and first time of departure from home define an “initial at-home prism”. Similarly, work start time and work end time define an “at-work prism”. In reality, these events may not truly describe the temporal dimension of a prism. The real vertices (or extremities) of a prism are unobserved (e.g., earliest wake up time, latest possible work arrival time, earliest possible work departure time, latest possible sleep time) and therefore the observed events are used as surrogates to represent the temporal dimensions of prisms.

A commuter can engage in out-of-home activities within prisms that lie between the first time of departure from home and the final time of arrival at home. Only in-home activities can be pursued prior to the first home departure and following the last home arrival. The period between the first home departure and the final home arrival may be further subdivided into:

- *Before-work time period*: This time period comprises time available between the first departure from home and work start time. During this period, a commuter may pursue activities on the way to work and/or pursue activities and return home prior to departing to work.

- *During-work time period*: This time period is defined by the work start time and work end time of commuters. On average, work accounts for approximately 30 percent of a commuter’s day and 50 percent of the waking hours. As such, this prism is likely to be an important determinant of a commuters daily activity pattern. Commuters are often temporally constrained by their work schedules. Non-work activity engagement typically occurs during the lunch break (that constitutes about one hour for most commuters).

- *After-work time period*: The time period available to a commuter after work ends and prior to final time of arrival at home constitutes the after-work time period. During this time period, a commuter may undertake non-work activities such as shopping, running errands, recreation, etc. either on the way home from work or separately after a temporary home sojourn. The latter choice of activity engagement would generate another set of trips before the commuter finally returns home.

Within the framework adopted in this chapter, it is postulated that commuters choose to engage in out-of-home non-work activities within one or more of these broad prisms. For example, a commuter may choose to undertake shopping before work, during work, or after work including the possibility of undertaking multiple shopping activities in the same or different time prisms. By scheduling out-of-home non-work activities in various prisms (periods of the day), a commuter's activity schedule can be identified.

For purposes of model development and estimation, the various out-of-home non-work activities undertaken by commuters in the 1996 Bay Area survey sample are broadly aggregated into eat-meal, shopping/personal business, and entertainment/social recreation. In addition, in an attempt to capture temporary home sojourns that occur between the first home departure and last home arrival, an additional activity category called "return home" is included in the model formulation. It should be noted, however, that "return-home" really represents in-home activity engagement by commuters in the survey sample. Previous research has clearly shown that there are significant trade-offs and complementarity between in-home and out-of-home activity engagement (Kitamura 1984; Kuppam and Pendyala 2000). Within the model framework of this chapter, relationships between in-home and out-of-home activity engagement and the identification of specific activities pursued during home sojourns are not explicitly included. Future efforts will involve the integration of such models with the model developed in this chapter. However, the inclusion of "return-home" sojourns as an explicit category in the model framework helps determine the activity sequencing and trip chaining behavior of commuters (for example, does a commuter do shopping on the way home from work or after returning home from work?).

In summary, the behavioral framework adopted in this chapter takes the form of a two-stage process. In the first stage, commuters are choosing among activities to be pursued (outside home and work) and in the second stage, they are choosing to place the activity within a time prism. Such a two-step process may be conveniently represented using nested logit model structures. For example, in one postulated structure, the various out-of-home non-work activities pursued by individuals, namely eat-meal, shopping/personal business, entertainment/social recreation, and return-home comprise the upper-level (composite) alternatives. The three time periods available to pursue these activities form the lower-level (elemental) alternatives available to an individual. Figure 1 provides a visual depiction of this postulated behavioral structure.

However, it should be noted that the two-stage behavioral paradigm suggested in this chapter is not necessarily the only factor motivating the adoption of a nested logit modeling methodology. A nested logit model is usually adopted when there is a potential for shared unobservable attributes across alternatives, if they were to be arranged in a simple multinomial structure. The potential for shared unobserved attributes across alternatives coupled with the two-stage behavioral paradigm motivated the adoption of the nested logit methodology in this chapter.

As the behavioral framework adopted in this chapter does not include in-home vs. out-of-home activity substitution and utilizes a rather aggregate activity-type categorization, it is not comprehensive in its treatment of commuter activity and travel behavior and constitutes a simplification of the behavioral process underlying activity and travel pattern formation. Nevertheless, it provides a practical and convenient way to extract activity schedules and sequences and trip chains of commuters given standard socio-economic variables.

NESTED LOGIT MODELING METHODOLOGY

The nested logit model is a widely used form of discrete choice models and has been extensively presented and described in the literature (see e.g., Ben-Akiva and Lerman 1985; Lerman 1984; Train 1986; and Ortuzar and Willumsen 1994). There are at least two ways to express the nested logit structure, namely, the Non-Normalized Nested Logit model (NNNL, described by Daly 1987) and Utility Maximizing Nested Logit model (UMNL, described by McFadden 1978). A detailed discussion of both the model structures would be beyond the scope of this chapter. The merits and demerits of the two model structures have recently been discussed in the literature (Koppelman and Wen 1998; Hensher and Greene 2000).

Despite the potentially more appealing nature of the UMNL model, the NNNL model specification is used in this research primarily because of the availability of convenient software to estimate it (e.g., LIMDEP). Also, from a behavioral interpretation standpoint, it was considered sufficient to adopt the NNNL modeling methodology.

The lower level choice in a nested logit model is a multinomial logit choice and can be expressed as:

$$P(k \mid i) = \frac{e^{V_{ik}}}{\sum\limits_{l \in D_i} e^{V_{il}}} = \frac{e^{\beta'_{ik} x_{ik}}}{\sum\limits_{l \in D_i} e^{\beta'_{il} x_{il}}}$$

where

$P(k/i)$	is the probability of alternative k from subset D_i to be chosen on the condition that alternative i on the upper level has been chosen
D_i	is the lower level choice set, which is associated with alternative i on the upper level
V_{ik}	is the deterministic portion of the utility associated with choice k in nest i
β	is a vector of model parameters
x	is a vector of exogenous variables.

An inclusive value I_i (or logsum) associated with the upper level alternative i is defined as follows:

$$I_i = ln \sum_{l \in D_i} e^{\beta'_{il} x_{il}}$$

The upper level choice probability is then expressed as:

$$P(i) = \frac{e^{\delta'_i z_i + \tau_i I_i}}{\sum\limits_{j \in C} e^{\delta'_j z_j + \tau_j I_j}}$$

where

$P(i)$	is the probability of choosing alternative i
δ	is a vector of model parameters
z	is a vector of exogenous variables.

The parameter τ is referred to as the inclusive value parameter. The value of this parameter should lie between zero and one. When the parameter equals unity, the structure collapses to a multinomial logit model without a nested structure. The levels are separated and present independent and separate choice situations if the value of the parameter is equal to zero. If τ

< 0, an increase in the utility of an alternative in the nest, which should increase the probability of the nest being chosen, would actually diminish the probability of selecting the nest. In virtually all choice modeling situations, this is implausible. If $\tau > 1$, an increase in the utility of an alternative in the nest would not only increase its selection probability but also the selection probability of the rest of the alternatives in the nest. That is, improvements in one alternative could increase not only the probability of that alternative to be chosen, but some substitutive alternatives would also gain a bigger share (Ortuzar and Willumsen 1994). While this may be plausible under certain limited conditions, it is generally not applicable to a wide variety of choice modeling situations. Therefore, the nesting structure that provides inclusive value parameter estimates between zero and one is generally adopted as long as the structure offers a plausible behavioral framework and interpretation.

NESTED LOGIT MODEL ESTIMATION RESULTS

There are several possible alternative nesting structures that may describe the activity scheduling behavior of commuters. This section describes the alternative nested logit model structures that were tested and presents model estimation results for the structure that provided desirable statistical and plausible behavioral indications.

Figure 1 illustrates the nested logit model structure that is most consistent with the behavioral framework postulated earlier in the chapter. This structure suggests that a commuter, in formulating an activity schedule, first chooses the out-of-home non-work activities to be pursued in a day. The choice of the appropriate time period in which to undertake each of the chosen activities comprises the second step in the choice process.

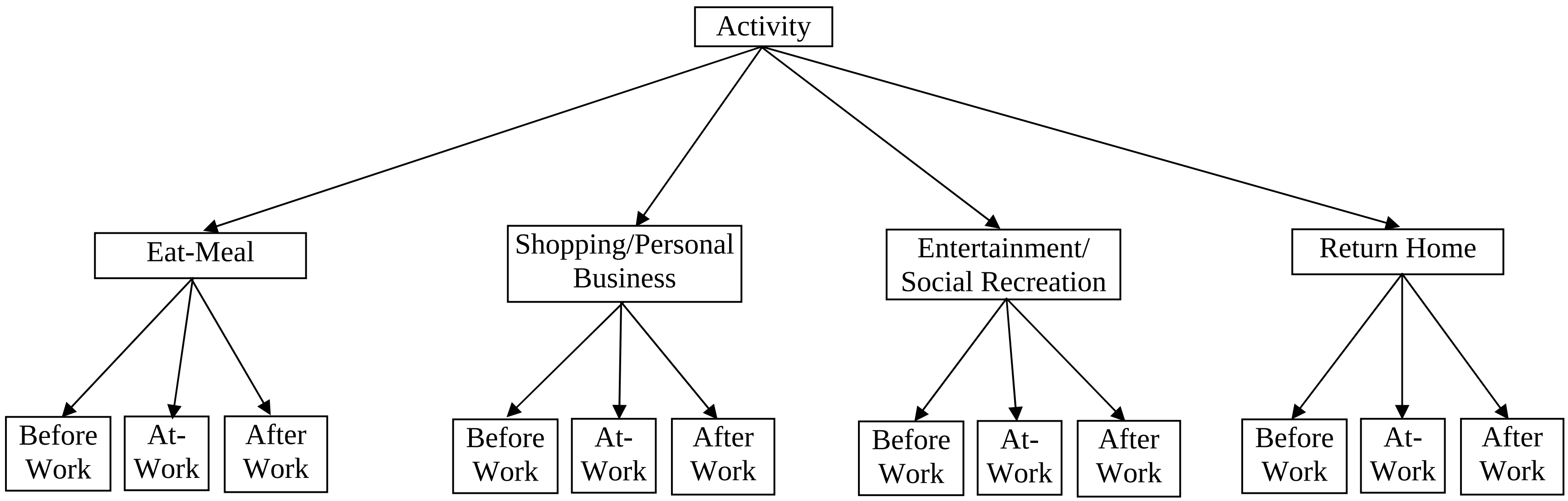

Figure 1. Activity Schedule Structure 1

Nested logit model estimation results for this structure are found to offer plausible coefficient estimates, except for those associated with the inclusive value parameters. As the model did not offer acceptable inclusive value parameter coefficients, this model was not adopted and therefore detailed model estimation results and parameter estimates are not included in the chapter. The inclusive value parameter estimate for the nest comprising eat-meal alternatives was found to be 1.45, while that for the nest comprising shopping/personal business alternatives was found to be 1.09 (significantly different from one). These two inclusive value parameter estimates suggest that when the probability of a commuter pursuing either an eat-meal activity or a shopping/personal business activity in one of the three time periods increases, then the probability that the commuter undertakes the same activity in a different time period (on the same day) also increases simultaneously. While this result may hold true for a few commuters, it is not likely to hold true across the sample. The inclusive value parameter estimate for the nest comprising entertainment/social recreation activities is found to be 0.51. This value indicates that there is a potential trade-off involved when pursuing entertainment/social recreation activities during different time periods in a day. This inclusive value is certainly behaviorally intuitive as one would expect commuters to trade-off the pursuit of entertainment activities across different time periods.

As the nested structure shown in Figure 1 provided counter-intuitive inclusive value coefficient estimates for two nests, an alternative structure as shown in Figure 2 was developed. This framework proposes a bottom-up decision-making process where a commuter first breaks up the day into various periods (prisms) and then chooses the activity (or activities) to be undertaken in each period. In Figure 2, before-work time period, at-work time period, and after-work time period comprise the three composite alternatives that are placed at the upper level in the nest structure. The various out-of-home non-work activities undertaken by individuals namely eat-meal, shopping/personal business, and entertainment comprise the elemental alternatives in each nest. However, return-home is still retained as an upper level choice as this alternative pertains to the choice to return home during the day for a temporary sojourn. As it was considered appropriate to distinguish between out-of-home activity scheduling (in the other three nests) and trip scheduling (for in-home activities), return-home was retained in a manner similar to that in the first nesting structure in Figure 1.

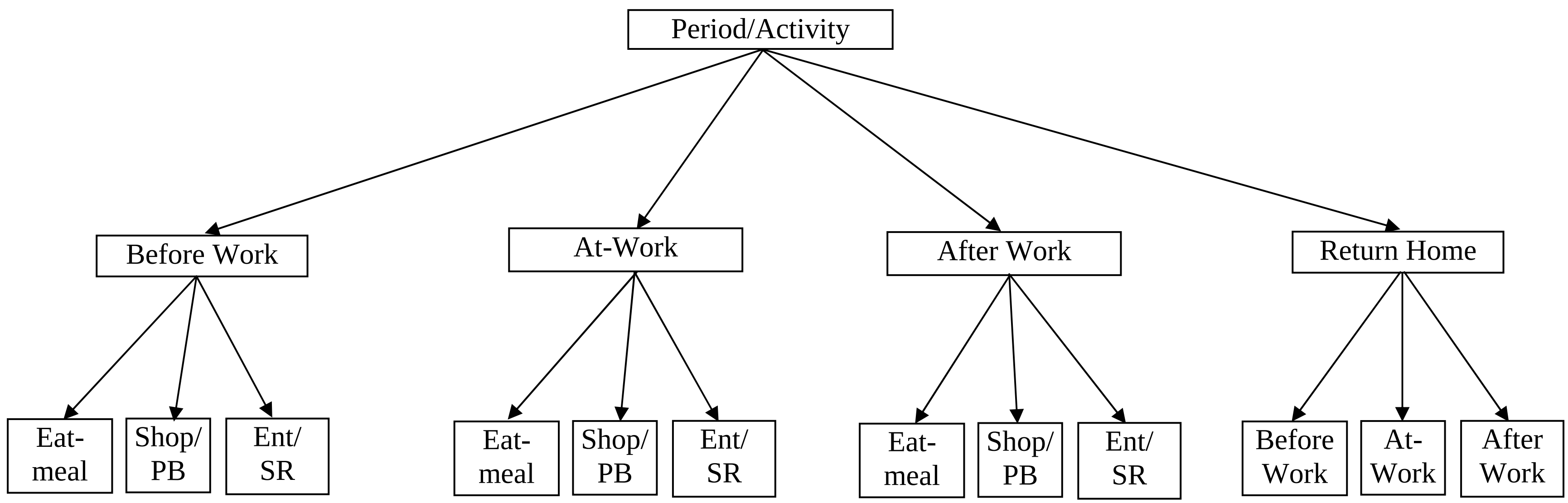

Figure 2. Activity Schedule Structure 2

This model offered plausible coefficient estimates and acceptable goodness-of-fit measures. However, similar to the first structure, the inclusive value coefficient estimates for two nests significantly exceeded one. For the nest comprising activities undertaken before work, the inclusive value coefficient estimate was found to be 1.40, while that for the nest comprising activities pursued after work was found to be 1.29. These inclusive values imply that commuters who are likely to engage in a non-work activity before work or after work are also likely to simultaneously engage in other activity types during the time period under consideration.

One could posit that these model results are plausible, particularly in the context of the after-work period. During the after-work periods (typically in the evenings), quite a few commuters are found to engage in multiple activities suggesting that elemental choice alternatives in the after-work nest are not competing but complementary in nature. However, in the presence of household, work, and other institutional and temporal constraints, it is unlikely that this will apply across the entire sample. Also, with respect to the before-work period (typically in the morning), it is very unlikely that commuters treat activities as complementary to one another (with possibly a few exceptions). Then, the inclusive value parameter estimate for the before-work nest should be less than one, even if that for the after-work period is acceptable.

In addition, it was found that the inclusive value coefficient estimate for the nest comprising activities undertaken while at work was 1.03. This was not significantly different from one at the 95 percent confidence level, suggesting that activities undertaken while at work are independent of one another (no trade-offs) and do not belong in a nesting structure. Similarly, the inclusive value for the nest comprising return home trips was also one, suggesting that various return home trips undertaken by commuters over a day are independent of one another. Again, both of these findings are not very consistent with behavioral expectations. Even if the finding that activities undertaken while at work are independent of one another is potentially acceptable, the finding that return home trips are independent across time periods is behaviorally inconsistent. For a commuter, work and other temporal constraints would undoubtedly result in interdependence (and therefore trade-offs) among various time periods for undertaking return home trips. This would call for the nest comprising return home trips to have an inclusive value coefficient estimate of less than one. The behaviorally inconsistent inclusive value coefficient estimates prompted the rejection of this structure and the search for a structure that is both behaviorally plausible as well as statistically acceptable.

Upon extensive exploratory analysis of commuter activity engagement patterns in the data set, it was found that the most prevalent activity participation behavior included an eat-meal activity pursued while at-work, shopping/personal business pursued (in the evening) after work, and entertainment/social recreation pursued after work. Other types of activity participation behavior, where individuals pursue activities before work or while at work, occur less frequently in the sample possibly because constraints do not allow the scheduling of activities during those periods for most commuters or simply because they are less preferred scheduling alternatives.

This activity scheduling behavior of commuters may be captured by placing the more prevalent alternatives as separate and independent choices. All of the less prevalent activity scheduling alternatives may be combined into a single nest to represent their rare nature and the fact that, if a commuter does participate in one of those less prevalent alternatives, the likelihood of he or she participating in another less prevalent alternative (in the same nest) is virtually none. Eat-meal activity engagement while at-work, shopping/personal business activity engagement (in the evening) after work, and entertainment/social recreation activity engagement (in the evening) after work are the more prevalent alternatives. They are all treated as separate and independent choice alternatives. Once again, as in the previous case, return home trips are placed in a separate nest to distinguish between activities and trips. Figure 3 shows this nesting structure for representing activity scheduling behavior of commuters.

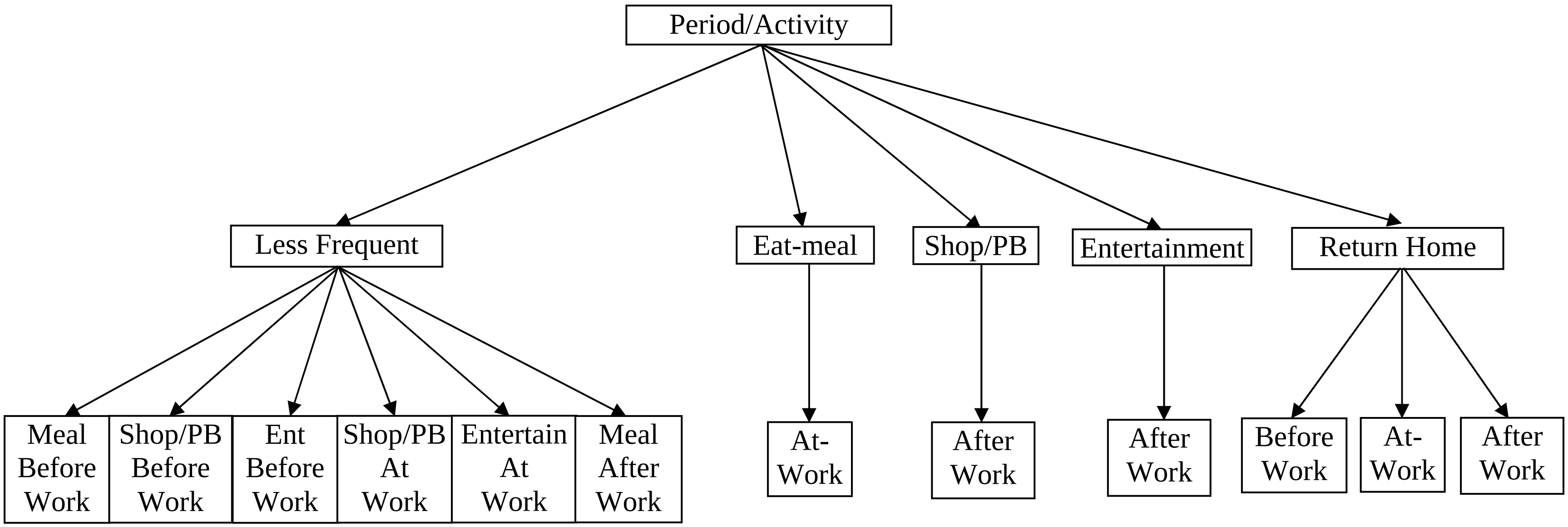

Figure 3. Activity Schedule Structure 3

Variables used in this nested logit model are defined in Table 3. They include a series of socio-economic variables describing the individual and the household. There are two inclusive value parameters for this nesting structure, one associated with the "less frequent" nest and the other associated with the "return home" nest. Model estimation results for the proposed structure are presented in Table 4. This model offered plausible and behaviorally sound coefficient estimates for the inclusive value parameters. In addition to this, it offered the same level of goodness-of-fit as the prior two structures considered in this effort and provided coefficient estimates on all other explanatory variables according to expectations. Although several coefficients had low t-statistics from a statistical standpoint, they were retained in the model as they offered behaviorally plausible interpretation and sensitivity. This model structure was finally chosen for representing activity scheduling behavior of commuters in the San Francisco survey sample.

Table 3. Definition of Explanatory Variables

Variable	Definition	Descriptive Statistic
Male	1 if male; 0 otherwise	54.3 %
Young	$18 \leq$ age ≤ 29	18.8 %
Middle	$30 \leq$ age ≤ 55	54.4 %
License	1 if licensed; 0 otherwise	94.4 %
Jbfull	1 if employed full-time; 0 otherwise	82.6 %
Student	1 if student; 0 otherwise	13.4 %
Single	1 if single; 0 otherwise	20.1 %
SinPar	1 if single parent; 0 otherwise	4.3 %
Couple	1 if couple with no children; 0 otherwise	27.8 %
Cwkid	1 if couple with children; 0 otherwise	28.1 %
Linc	\$5,000 $\leq$ income $\leq$ \$29,999	19.6 %
Minc	\$30,000 $\leq$ income $\leq$ \$74,999	43.3 %
Hinc	Income $\geq$ \$75,000	22.5 %
Drvwk	1 if drive to work; 0 otherwise	67.4 %
White	1 if white; 0 otherwise	69.2 %
CGC	1 if No. Cars $\geq$ No. Commuters in hhld	86.4 %
Const	Constant	
IV	Inclusive Value Parameter for nest	
Eat-meal	Eat-meal activity	
Shp/PB	Shopping/Personal Business/Serve Child activity	
Ent	Entertainment/Social Recreation	
Return Home	Return Home trip	
Before Work	Activity undertaken before work start	
At-work	Activity undertaken during work	
After Work	Activity undertaken after work end	

Table 4. Estimation Results for Activity Schedule Structure 3

Episode	Const	Male	Young	Middle	License	JbFull	Student	Single	SinPar	Couple	Cwkid	Hinc	CGC	Wht	Drvwk	IV
LESS FREQ																0.80 (8.8)
Meal Before Work	-1.58 (-12.7)						2.0 (7.5)		-1.82 (-1.8)							
Shp/PB Before Work		0.14 (1.4)				-0.45 (-4.4)	0.4 (1.4)		0.68 (3.3)						-0.18 (-1.9)	
Ent Before Work	-1.49 (-12.3)						1.4 (4.4)									
Shp/PB At-work	-1.30 (-3.0)		-0.59 (-3.1)	-0.25 (-2.4)	1.18 (2.8)		-1.0 (-1.6)			0.26 (2.3)	-0.27 (-2.1)					
Ent At-work					-1.41 (-10.8)						-0.52 (-2.8)					
Meal After Work	-0.43 (-3.8)						1.1 (4.0)				-0.67 (-5.1)					
MEAL																1.00
At-work		0.12 (2.0)	0.48 (5.4)			0.71 (9.8)		-0.16 (-2.3)				-0.14 (-2.4)				
SHP/PB																1.00
After Work		-0.36 (-5.1)	-0.03 (-0.3)		0.06 (0.5)								0.08 (0.8)	0.13 (1.75)	0.26 (3.5)	
ENT																1.00
After Work		0.16 (1.9)	0.78 (5.7)	0.26 (2.5)			0.5 (2.6)	0.19 (1.9)			-0.24 (-2.4)	0.10 (1.1)	0.11 (1.0)	0.12 (1.3)		
RETURN HOME																0.72 (9.8)
Before Work						-0.93 (-11.8)	1.64 (7.9)		0.57 (2.4)							
At-Work	-0.72 (-2.5)	0.22 (2.5)	-0.26 (-1.6)		0.68 (2.4)	-0.09 (-0.8)					-0.23 (-2.4)				0.40 (3.9)	
After Work			0.30 (2.2)													
L(0): -17805.3				L(β): -16663.7			χ^2 (df): 2283.1 (56)			ρ^2 [1-L(β)/L(0)]: 0.06			N: 4188			

Note: Values in parentheses are t-statistics.

The inclusive value coefficient estimate of the nest comprising the less frequent activities is found to be 0.80, while that for the nest composed of return home trips is found to be 0.72. Both of these inclusive value parameter estimates are found to be statistically significant at the 99% confidence level and significantly less than one. The inclusive value parameter estimate of 0.80 for the nest comprising rare and less frequent activities indicates that the activities in this nest share unobservable attributes and that there are considerable trade-offs involved when pursuing these activities. The inclusive value parameter estimate of 0.72 for the nest comprising return home trips indicates that return home trips typically undertaken by commuters over a day share unobserved attributes. If a commuter returns home temporarily during a certain time period during the day, then the same commuter would show less preference to again return home temporarily at some other time period in the day. This inclusive value is consistent with behavioral expectations that commuters are temporally constrained and are rarely inclined to make multiple return home trips during the day.

With respect to socio-economic variables, the model offers very consistent coefficient estimates. In general, male individuals in the sample are more likely to engage in eat-meal activity while at work. On the other hand, females are more likely to engage in shopping/personal business activities after work. However, males are found more likely to pursue entertainment and other social recreation activities after work compared to their female counterparts. These findings are consistent with traditional gender-based differences in household roles and obligations. Strangely, males also exhibit a greater tendency to return home while at work. This finding clearly indicates the importance of integrating models of in-home activity engagement with models of out-of-home activity engagement such as that developed in this chapter. The reasons for males return home trips while at work merits further investigation.

Younger commuters in the sample are found to be more likely to eat-meal while at work and undertake entertainment/recreation activities after work. It appears that they are more likely to undertake their after work activities after a temporary home sojourn as indicated by the positive coefficient associated with the return home after work alternative. Licensed individuals, who presumably have access to an automobile, are found to be more likely to pursue shopping/personal business activities during the day and more likely to return home in the middle of the work day. As expected, commuters employed full-time are found to be less inclined to undertake return home trips during the day, but are more inclined to undertake an eat-meal activity while at work. Students are found to be more prone to undertake activities in the prior to work period (they are more likely to be part-time workers who have the flexibility to undertake before work activities).

Single persons show a greater propensity to engage in entertainment/recreation activities in the after-work period than other household types. Single parents are more likely to return home during the day, presumably to take care of child care or other household obligations. Commuters in households with children show a negative propensity to engage in recreation and other out-of-home non-work activities during the day. This is presumably because these individuals devote much time in-home to child care activities and other household obligations. As expected, high income commuters and commuters in households with high car availability are more prone to undertake entertainment activities in the after-work period (though these coefficients are not statistically significant at the 95% confidence level, they have been retained because of their behaviorally intuitive interpretation). Those who drive to work appear to have the flexibility and therefore positive propensity to return home during the day (while at work) and undertake shopping/personal business activities after work (possibly on the way home from work).

In summary, the final adopted model structure provides model parameter estimates consistent with behavioral and empirical expectations. Most of the model coefficients are statistically significant at the 95% confidence interval. The inclusive value parameter estimates are also found to be behaviorally plausible. Therefore, it may be conjectured that this nesting structure provides a reasonable representation of activity scheduling for commuters. However, this conclusion is drawn with caution because this nested logit structure generated consistent inclusive value parameter estimates in the context of the 1996 San Francisco Bay Area survey sample. Alternate nesting structures estimated on several different sample datasets should be examined and tested before drawing conclusions regarding the behavioral paradigm underlying commuter activity scheduling behavior.

NESTED LOGIT MODEL APPLICATION

The previous section described a nested logit model structure that intended to represent commuter's activity scheduling behavior. In this section, a sample numerical simulation is provided to show how the model can be used to predict activity scheduling patterns of commuters in a practical and simple manner.

For the purpose of this exercise, six hypothetical individuals are considered. Their characteristics in relation to the socio-economic variables included in the nested logit model are shown in Table 5. In general, the six hypothetical individuals cover a range of socio-economic characteristics thus providing a means of examining whether the model is truly sensitive to differences among individuals. Prior to the application of the nested logit model of activity scheduling behavior, the total number of out-of-home non-work activities (including temporary return home trips) pursued by each commuter is predicted using poisson- and negative-binomial regression-based activity frequency models similar to those developed by Ma and Goulias (1999). These activity frequency models provide a basis for determining the number of activities that need to be drawn and included in the commuters activity schedules. The predicted activity frequency for each individual is provided in the last column of Table 5.

Table 5. Characteristics of Six Hypothetical Individuals

Person No.	Male	Female	Young	Middle Age	Low Income	High Income	Single	Single Parent	Couple-no child	Activity Freq[a]
1	1		1		1		1			2
2	1		1			1	1			5
3		1	1		1			1		3
4		1	1			1		1		6
5	1			1	1				1	3
6	1			1		1			1	6

[a]Activity frequency refers to the number of out-of-home non-work activities undertaken by an individual in a day including return-home sojourns. These frequencies were obtained from a poisson regression model of activity frequency not presented in this chapter.

Table 6. Predicted Activity Episode Probabilities and Simulation Draws for Person Number 4

Activity	Predicted Probability	Activity Draws
Meal – Before Work	0.01	
Meal – At - Work	0.11	X
Meal – After Work	0.09	X
Shop/PB – Before Work	0.14	X
Shop/PB – At - Work	0.01	
Shop/PB – After Work	0.08	X
Entertain – Before Work	0.04	
Entertain – At - Work	0.01	
Entertain – After Work	0.12	X
Return home – Before Work	0.32	X
Return home – At - Work	0.03	
Return home – After Work	0.05	

The nested logit model includes a total of 12 different alternatives as shown in the first column of Table 6. In this table, predicted probabilities associated with each alternative are shown for person number 4 from Table 5. This person is a female high-income young single parent. The predicted probabilities for the 12 alternatives are shown in the last column of Table 6. In order to determine the activities that need to be included in this person's schedule, a simple Monte Carlo simulation method is adopted. Using a random number generation process, random numbers between 0 and 1 are repeatedly drawn to determine the choices according to the predicted probability distribution of the alternatives for each individual. The number of draws is equal to the predicted activity frequency as provided by the poisson- or negative binomial regression-based activity frequency model.

For this individual, the activities that were drawn in the simulation include return home before work, shop/personal business before work, entertainment after work, eat-meal at work, eat-meal after work, and shop/personal business after work. In order to develop the pattern, we start at the beginning of the day and assume that the person is at home (initial location). According to the model, this person undertakes shop/personal business before work. During the aggregation of activity types, serve child activities were combined with shopping and personal business activities. As this person is a single parent, it is conjectured that this must be a serve child activity. Also, the person returns home before work. Then, it appears that this person drops off a child and then returns home prior to work. So far, the pattern is as follows: Home → Child drop → (Return) Home.

Next the individual goes to work. While at work, the individual undertakes an eat-meal activity. No other activities are undertaken while at work. The individual presumably returns to work after undertaking an eat-meal activity while at work. The pattern thus far has become: Home → Child drop → Return Home → Work → Eat-meal → Work.

There are a total of three activities undertaken in the after-work period. They are shopping/personal business (presumably serve or pick-up child), entertainment, and eat-meal. There is no temporary return home trip in the after-work period. Thus, it appears that this individual undertakes all of these activities after work prior to returning home. The question then becomes: how are these three activities sequenced? Many factors influence the sequencing of activities and one would need richer preference data and possibly rule-based heuristics to determine activity sequencing (Pendyala et al. 1998). At this point in the model development, a simplified heuristic rule is being adopted to determine the activity sequence. Utilizing the values of predicted probabilities in Table 6 as an ordering mechanism, the individual would first proceed to an entertainment activity, then to an eat-meal activity, and finally picks up the child (shop/personal business after work) prior to returning home. The final pattern then becomes: Home → Child drop → Return Home → Work → Eat-meal → Work → Entertainment → Eat-meal → Child pickup → Home.

Figure 4 shows the activity scheduling patterns generated for the six different hypothetical individuals considered in Table 5. It is found that the model offers very plausible and reasonable activity schedules. For example, person number 2 is a high-income single male. Consistent with one's expectations, this person undertakes several after-work activities including eating out, shopping/personal business, and entertainment/recreation. On the other hand, person number 1 who is a low income single male, undertakes fewer activities and does not engage in out-of-home entertainment. Person number 3 is very similar to person number 4 except for the fact that she is a low-income individual. The difference between their activity patterns reflects their income difference. Whereas person number 4 eats out and pursues entertainment after work, person number 3 does not.

It is possible that the model might predict activity scheduling patterns that are not possible due to situational or institutional constraints (Kitamura et al. 2000). For example, an individual may be constrained to pickup a child prior to engaging in other after-work activities. These aspects of activity pattern generation need to be incorporated by combining this model with other models of activity behavior including rule-based, econometric, or behavioral decision approaches. By combining this model with models of activity sequencing and prioritization, activity duration, departure time choice, prism constraints, etc., realistic and plausible activity patterns (with detailed time-of-day information) that do not violate various constraints can be generated.

CONCLUSIONS AND FUTURE RESEARCH

This chapter has presented a simple and practical nested logit model that can be used to predict the daily activity schedule of a commuter. The model schedules non-work activities in relation to the work activity, thus explicitly recognizing the limited spatial and temporal flexibility associated with the work schedule. The model schedules various non-work out-of-home activities in three possible periods (or prisms), namely, before work, at work, and after work. In addition to scheduling out-of-home non-work activities, the model includes the capability of scheduling temporary return home sojourns, thus facilitating the identification of both home-based and work-based trip chains for commuters.

The behavioral paradigm suggested in this chapter is that individuals first plan the activities (non-work) that they need to accomplish in a day, and then schedule these activities in relation to their work activity. Several alternative nested logit structures were estimated on the 1996 San Francisco Bay Area activity survey sample data set in an attempt to operationalize the behavioral paradigm. The two-stage decision process embodied in the behavioral paradigm is found to be supported by the estimation results, albeit with some modifications to account for the fact that some activity scheduling patterns are far more prevalent than others.

Person No.	Predicted Activity-trip Pattern
1	Home → Work → Eat-meal → Work → Shop/PB → Home
2	Home → Work → Eat-meal → Work → Home → Eat-meal → Shop/PB → Enter-tain → Home
3	Home → Child drop → Work → Eat-meal → Work → Child pickup → Home
4	Home → Child drop → Home → Work → Eat-meal → Work → Enter-tain → Eat-Meal → Child Pickup → Home
5	Home → Work → Eat-meal → Work → Home → Shop/PB → Home
6	Home → Enter-tain → Home → Work → Eat-Meal → Work → Home → Shop/PB → Enter-tain → Home

Note: Shaded activities are those drawn in the Monte Carlo simulation.

Figure 4. Predicted Activity-Trip Patterns for Six Hypothetical Individuals

The chapter includes a numerical example to illustrate how the model can be used to predict a daily activity schedule for commuters. The model includes the capability of scheduling return home sojourns that may occur during the day, thus facilitating the identification of home-based trip chains (in addition to work-based trip chains). Six hypothetical individuals with different socio-economic characteristics were considered and their activity schedules were simulated using the nested logit model. This was done by combining the application of the nested logit model with a Monte Carlo simulation method and simple heuristics that facilitated the identification and sequencing of activities in the schedule. A quick check in which predicted schedules were compared against actual observed schedules of very similar (but not always exactly identical) individuals in the data set showed that the model predictions were virtually identical to observed schedules.

The model presented in this chapter is only a small piece of an overall activity based model system. The model needs to be combined with other models of activity behavior including models of activity sequencing, activity frequency, activity duration, activity timing, and in-home vs. out-of-home activity substitution/complementarity to fully identify and describe an individual's activity-travel pattern. In addition, appropriate rule-based heuristics need to be incorporated to ensure that the predicted pattern is plausible, feasible, and satisfies all constraints.

The nested logit model presented in this chapter may itself be improved in several ways both from an empirical as well as a methodological standpoint. In this effort, several activity purposes were aggregated into composite categories (e.g., shopping/personal business/serve child). However, it would be preferable to retain the differentiation among activity categories so that their unique characteristics may be better reflected in the model and the identification of specific activities in the pattern becomes easier. The inclusion of accessibility variables would be another important enhancement to the model as activity generation and time-of-day scheduling are highly influenced by spatio-temporal activity accessibility. In addition, it would be helpful to test and estimate alternative structures on different data sets to see whether a more robust and unified theory of activity scheduling behavior can be developed.

The assumptions implicit in the nested logit model (for example, the IIA assumption holds at each level of the nested structure) should be tested to ensure that the nested logit modeling methodology and the nested structure adopted are appropriate for modeling activity scheduling behavior. Also, the nested logit model structure proposed in this chapter does not accommodate multiple episodes of the same activity type in one time period. However, it is possible that individuals will pursue multiple episodes of the same activity (say, shopping) in one time period (this was found to be extremely rare in the San Francisco Bay Area data set, but nevertheless worthy of accommodation in the model structure). Finally, another issue that merits improvement is concerned with the use of the nested logit model in the presence of inter-related choice alternatives.

From an application standpoint, the model should be enhanced to incorporate the capability of responding to a range of transportation policy scenarios. A major benefit of the activity-based approach is that it offers a behaviorally robust framework in which the impacts of transportation policies on individual travel behavior can be assessed (Pendyala, et. al., 1997). Increases in congestion, travel demand management strategies, transportation control measures, or new transportation investments (highway or transit expansion) may lead to adjustments in daily activity schedules. In its current form, the model is not wholly sensitive to such variables. Either the model needs to incorporate such variables so that it is sensitive to the changes brought about by alternative transportation policies or it needs to be combined with another model capturing such sensitivities (for example, a stated preference model). The development of such models would, however, also place greater demands with respect to data requirements.

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MODEL FRAMEWORK FOR MEASURING THE IMPACT OF TRAVEL DEMAND STRATEGIES
CHAPTER VIII

SUMMARY

A conceptual framework is presented that may be utilized when analyzing changes in household travel behavior arising from the range of potential measures available to policy makers. The proposed framework draws on goal setting theory in order to understand how the impact of various travel demand measures (TDMs) on time, cost, and convenience of travel option, influence behavior. This behavior is understood from a perspective assuming that it is controlled by negative feedback functioning to minimize deviations from goals nested at different levels. The conceptual framework, with its basis in goal setting and control theories, is then applied to understanding habitual travel, strategic choice, and operational choice related to travel. Finally, the proposed conceptual framework is used to highlight and focus attention on key research issues that ought to be addressed if our understanding of the impact of TDMs on travel behavior, and private car use in particular, is to improve.

1. INTRODUCTION

Increased environmental and societal costs of private car use such as congestion, noise, air pollution, and depletion of energy are likely future consequences of the worldwide increasing trend in car ownership and use (Goodwin, 1996; Greene & Wegener, 1997; Sperling, 1995). In many metropolitan areas these consequences are in fact already urgent problems that need to be solved. This has resulted in suggestions of a large number of policy measures.

The potential efficiency and success of various policy measures for eliminating or reducing traffic problems in metropolitan areas largely depends on how people will respond to them. Lack of public acceptance is an important issue that has been highlighted in recent years (Emmerink, Nijkamp, & Rietveld, 1995; Jakobsson, Fujii, & Gärling, 2000; Jones, 1995).

Whether and how travel actually changes is, however, an equally important issue that is far from settled. As has been previously highlighted by leading travel-behavior researchers (e.g., Axhausen & Gärling, 1992; Jones, Dix, Clark, & Heggie, 1983; Gärling, Kwan, & Golledge, 1994; Root & Recker, 1983; Vilhelmson, 1999), it has become increasingly evident that travel results from choices people make that are both interdependent and dependent on desires or obligations to participate in activities. It may therefore be a mistake to focus any measure solely on a target behavior such as car use. In an alternative approach (Gärling, A. Gärling, & Johansson, 2000; Gärling, A. Gärling, & Loukopoulos, 2002; Kitamura & Fujii, 1998; Pendyala, Kitamura, Chen, & Pas, 1997; Pendyala, Kitamura, & Reddy, 1998), travel choice is viewed as an adaptation to changes where people try out different choice options over time.

In this chapter we propose a conceptual framework grounded in behavioral theories that may be used to analyze changes in travel behavior due to a wide range of different policy measures designed to influence the travel choices people make. In the next section we first discuss the possible measures that can be used. We then offer an overview of the conceptual framework. Since the conceptual framework identifies individuals' goals and implementation plans as important elements, a section follows that is devoted to an analysis of behavioral research on goal setting. This is followed by the presentation of a control theory of behavior that is a refinement of the conceptual framework. How this theory can be applied to understand travel choice is discussed in the next section. The following section is then devoted to an analysis of the role of habit as an impediment to changing travel behavior. The chapter closes with a discussion of research directions based on the preceding analyses.

2. TRAVEL DEMAND MANAGEMENT MEASURES

There are many conceivable measures that may improve transportation with respect to reduced levels of congestion and air pollution in metropolitan areas. Some of these (e.g., increased capacity of road infrastructure, improved car technology, or limiting speed) do not necessitate a reduction in car use, at least not in the immediate future. A general assessment of the current state is, however, that measures that reduce demand for car use must be implemented in metropolitan areas (e.g., Hensher, 1998). In addition, it is desirable to change car use with respect to when and where people drive, particularly at peak hours in city centers. Since the proposed measures focus on changing or reducing demand for car use, we refer to them as travel demand management (TDM). We are aware that this term, coined in the 1970's (Kitamura, Fujii, & Pas, 1997; Pas, 1995), is frequently not used as broadly as we intend. Other terms with similar meanings include transport system management (Pendyala et al., 1997), mobility management (Bradshaw, Cooper, Ferril, & Serwill, 2001), and travel blending (Rose & Ampt, 2001).

Widely proposed policies for reducing car use include discouraging car owners from driving, making driving less attractive, improving alternative travel modes such as public transport, biking, or walking, and changing the relative locations of homes, work places, and shopping and recreational facilities so that driving distances are reduced. These policies differ in efficiency, cost, technical feasibility, and political feasibility. Vlek and Michon (1992) suggest that the following categories of TDM measures may be feasible ways of implementing car-use reduction policies (ordered from more to less coercive): *physical changes* such as, for instance, closing out car traffic, providing alternative transportation; *law regulation*; *economic incentives*; *information, education, and prompts*; *socialization and social modeling* targeted at changing social norms*;* and *institutional and organizational changes* such as, for instance, flexible work hours, telecommuting, or "flexplaces." As they further note, the more coercive strategies may have negative side-effects outweighing the expected benefits, whereas the less coercive strategies may be based on untenable assumptions about determinants of car use.

TDM measures may also be classified in terms of those that discourage car use (push measures) and those that encourage the use of alternative modes (pull measures) (Steg & Vlek, 1997). Exhibit 1 presents many examples ordered on a continuum from primarily push to primarily pull measures. It should be noted, however, that the list is not based on behavioral evidence and that the continuum is more of a heuristic, conceptual guide than a precise continuum with clear differences in effects between adjacent TDM measures. However, there is empirical evidence that is attitudinal, but not behavioral, in nature. Stradling, Meadows and Beatty (2000) surveyed English motorists providing them with a list of push and pull measures that overlapped substantially but were not identical with those provided by Steg and Vlek (1997). Conducting a factor analysis on participants' ratings of effectiveness of these measures at reducing their own car use, Stradling et al. (2000) extracted two factors that almost perfectly corresponded with Steg and Vlek's (1997) push-pull distinction. The exception was "public information campaigns about negative effects of car use” which respondents grouped together with other push measures.

Exhibit 1. Travel Demand Management Measures Varying from Push to Pull Measures (Adapted from Steg & Vlek, 1997)

- Taxation of cars and fuel
- Closure of city centers for car traffic
- Road pricing
- Parking control
- Decreasing speed limits
- Avoiding major new road infrastructure
- Teleworking
- Land use planning encouraging shorter travel distances
- Traffic management reallocating space between modes and vehicles (e.g., bus and high occupancy vehicle lanes)
- Park and ride schemes
- Improved public transport (e.g., frequency, comfort, retrievability of information about public transport, no price increases)
- Improved infrastructure for walking and biking
- Public information campaigns about the negative effects of driving
- Social modeling where prominent public figures use alternative travel modes

We conclude that the different classifications of TDM measures are promising ways of conceptualizing and means of understanding potential reasons for behavioral change (or lack thereof) and, to this end, need to be followed up with in-depth empirical analyses of the behavioral effects. The conceptual framework will be possible to apply in such analyses. A necessary first step is to specify how the TDM measures affect people's travel options with respect to cost, time, and convenience, then to find out how they react to these changes.

3. OVERVIEW OF CONCEPTUAL FRAMEWORK

The general aim is to understand whether and how TDM measures affect private car use. To this end we propose a conceptual framework that will be elaborated on in the following sections. In this section we present an overview of the conceptual framework with reference to Figure 1.

We define travel options as bundles of attributes describing trip chains (purposes, departure and arrival times, travel times, monetary costs, uncertainty, and convenience). It is generally assumed that trip chains rather than trips constitute choice options (e.g., Axhausen & Gärling, 1992). Our intuition is that trip chains should be defined subjectively, that is, with respect to what users perceive a trip chain (or travel option) to be. Such a definition reflects the process of forming choice sets (Thill, 1992). Yet, in any empirical study an objective definition must be given. In order to do this, it is necessary to empirically find principles for how trip chains are conceptualized by users. This is one important research issue that we identify.

A closely related research issue is how to assess the effects of other users of the transportation system who also respond to the TDM measures (Kitamura, Nakayama, & Yamamoto, 1999). This is important since these other users are likely to respond in such a way that the travel options for a target user are changed over and above the effects that a particular TDM measure (or combination of measures) would otherwise have. A case in point is changes in congestion caused by a wider dispersion of departure times or mode switching. Such an interdependence analysis also needs to include the fact that users sometimes take into account (and are concerned about) choices by other users (Van Lange, Van Vugt, & De Cremer, 2000).

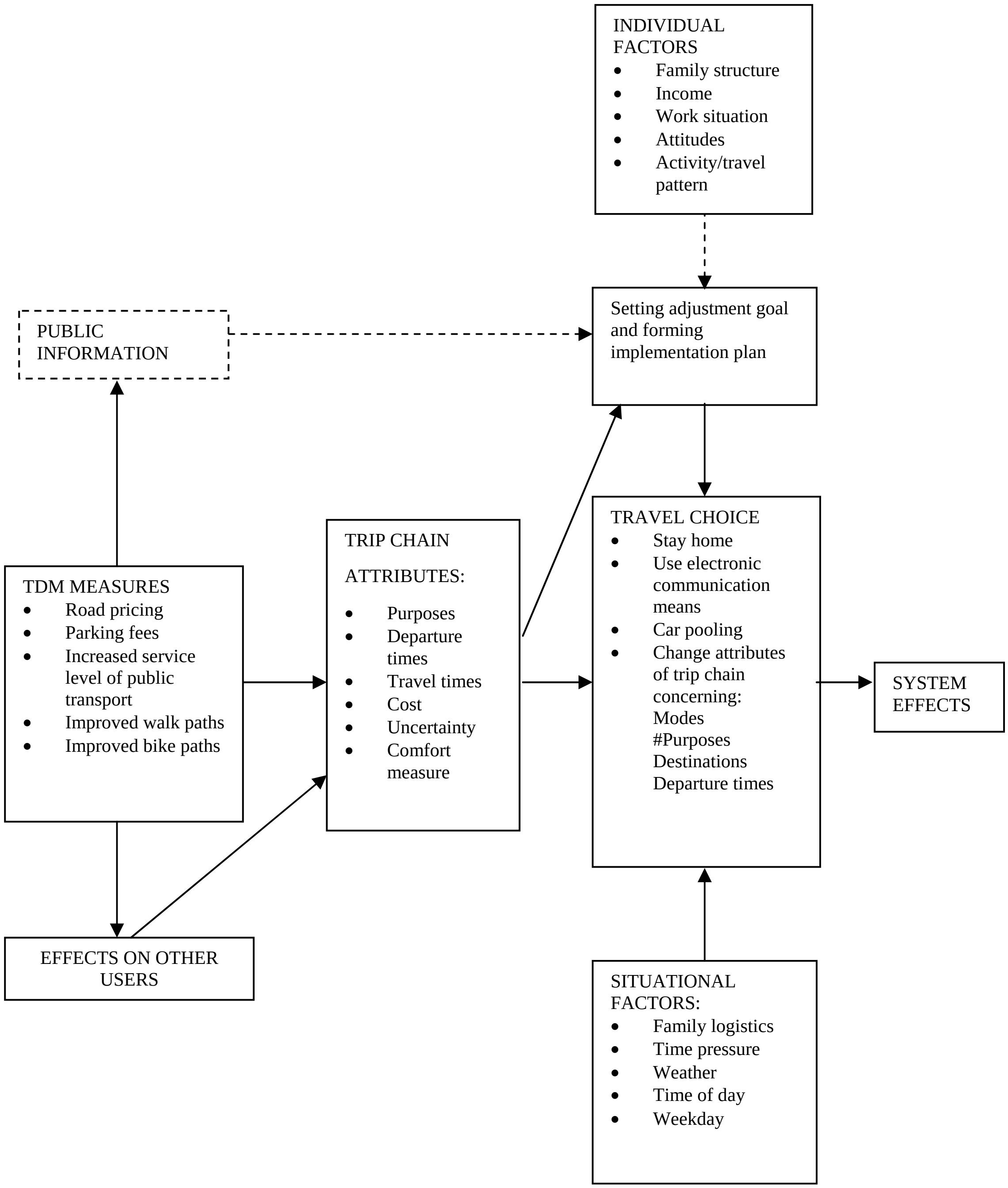

Figure 1. Proposed Conceptual Framework

As will be elaborated on in the following sections, we hypothesize that choices of travel options have two classes of determinants: the bundles of attributes characterizing the travel options included in the choice set that households form, and the goals and implementation intentions that households form over time in response to evaluations of monetary costs, time, and convenience of current travel. In addition, choices may be determined more immediately in response to public information leading to expectations about adverse consequences. These goals may take the form of a specified desired reduction in travel cost and/or car use. Such goals, and the implementation intentions contingent on them, are partly determined by several relatively static factors including income, family structure, work situation, activity/travel pattern, and attitude (e.g., environmental concern).

Implementation intentions consist of a plan for how to achieve the goals given the choice options (Gärling & Rise, 2001). Such a plan in turn consists of sets of predetermined choices contingent on specified conditions (Hayes-Roth & Hayes-Roth, 1979; Payne, Bettman, & Johnson, 1993). As will be discussed further below, in making plans households may consider a wide range of possibilities such as staying at home, using electronic communications means, car pooling, or changing attributes of trip chains (e.g., modes, departure times) (Gärling et al., 2000). They may also consider longer-term strategic changes such as moving to another residence, selling the car, or changing work place or hours. Choices among these possibilities are likely to be made sequentially over time such that some are tried out and evaluated before others are, starting with less costly and continuing with more costly changes (Gärling et al., 2002).

4. GOAL SETTING

In theories of motivation it is assumed that people have needs (e.g., Alderfer, 1969; Maslow, 1954) and desires (e.g., Pinder, 1984; Vroom, 1964) that they strive to satisfy. In some theories, needs and desires are thought of as choice outcomes or goals (e.g., Locke, 1968; Locke & Latham, 1984, 1990; see also Heath, Larrick, & Wu, 1999). Goals are assumed to have two primary attributes, content and intensity. Lee, Locke, and Latham (1989) divide goal content into four separate parts: difficulty, specificity, complexity, and conflict. Difficulty refers to the skills required to obtain the goal, specificity to whether or not the goal is quantitative, complexity to the number of different outcome dimensions, and conflict to the degree to which the achievement of one goal inhibits achievement of another goal. The second primary attribute, intensity, entails commitment, perception of goal importance, and the processes engaged by goal attainment.

Research on goal setting has focused on the relationship between goal difficulty and performance. An important finding is that setting more difficult goals leads to better performance than setting goals that are easier to attain, provided that they are not set too high since then there will be less commitment to the goal and the positive relationship will level off or even become negative. As suggested by Yearta, Maitlis, and Briner (1995), when individuals have multiple and distal goals, they may choose to invest effort in attaining those goals from which they can expect to obtain more positive outcomes. Therefore, people may choose to work to attain goals with a higher rate of progress so that they experience positive rather than negative affect (Carver & Scheier, 1990). A second finding is that a specified goal leads to better performance than an unspecified ("do-your-best") goal. These findings are robust and have been replicated in many different settings (Lee et al., 1989; Locke, Shaw, Saari, & Latham, 1981).

There are, however, several factors that moderate the effects of goal setting. One such factor is feedback about goal progress. A difficult, specific goal leads to better performance if the person receives feedback about how well he or she is doing. Another facilitating factor is goal commitment. A goal is a motivator only if one is committed to it. The source of the goal (e.g., whether the person participates in setting the goal or the goal is provided) does not seem to be important (Locke, Latham, & Erez, 1988).

Goal setting theory (Locke & Latham, 1984, 1990) suggests that an accepted goal directs people's attention and actions toward activities that are relevant to that goal. Furthermore, goals mobilize energy to work towards goal attainment, with the mobilized energy or effort being proportional to goal difficulty. More difficult goals lead to more sustained effort or persistence than more easily attained goals. Direction, effort, and persistence are assumed to be activated almost automatically based on past experience.

In the conceptual framework (Figure 1), TDM measures are assumed to affect specific trip-chain attributes (e.g., increased travel costs and/or travel times). These attribute changes are proposed to both directly affect people's travel choices, and indirectly through people setting a goal of adjusting to the attribute changes. For instance, if road pricing is introduced, a person will experience increased travel cost. Individual factors, such as income, are assumed to affect whether or not a goal is set to reduce travel costs (i.e., those who can afford to pay the increased travel costs are less likely to set the goal of reducing them than are those who cannot afford the costs). Thus, provided that the increased travel costs are perceived as necessary to reduce, the person will set the goal of reducing them.

In summary, we propose that various TDM measures change trip-chain attributes (e.g., travel costs) which, in turn, encourages setting goals to counter such changes (e.g., to reduce travel costs). The achievement of such goals is influenced by a variety of factors including goal commitment, goal difficulty, goal specificity, and information about progress.

5. STRATEGIC CHOICE

Borrowing from control theory (Ashby, 1956; Clark, 1996; Wiener, 1948), a useful refinement of the conceptual framework is to introduce the concept of negative feedback that minimizes deviations from a goal or reference value. That is, over time people perceive the present situation and compare it to a reference value or goal. If there is a difference between the two, some action is carried out on the environment, thereby minimizing the discrepancy. The model proposed here, illustrated in Figure 2, draws on Carver and Scheier (1982, 1998) based on Powers' (1973) theorizing.

Reference values or goals are assumed to be hierarchically organized (Austin & Vancouver, 1996; Carver & Scheier, 1982, 1998). The uppermost level of the hierarchy is termed the system concept by Powers (1973) in that it represents people's ideal image of themselves that they wish to emulate. The reference value at the next level is that of principle control. Structures at the system concept level provide input in the form of principles for how to act at this level. Yet, these principles are essentially content-free in that they do not specify a detailed plan (Carver & Scheier, 1982, 1998). It is consequently claimed that control at the principle level requires output in the form of programs or plans. The hierarchy of control extends to lower levels. However, since these become progressively more perceptual-motor based, the program level is for our purposes the lowest level in the hierarchy.

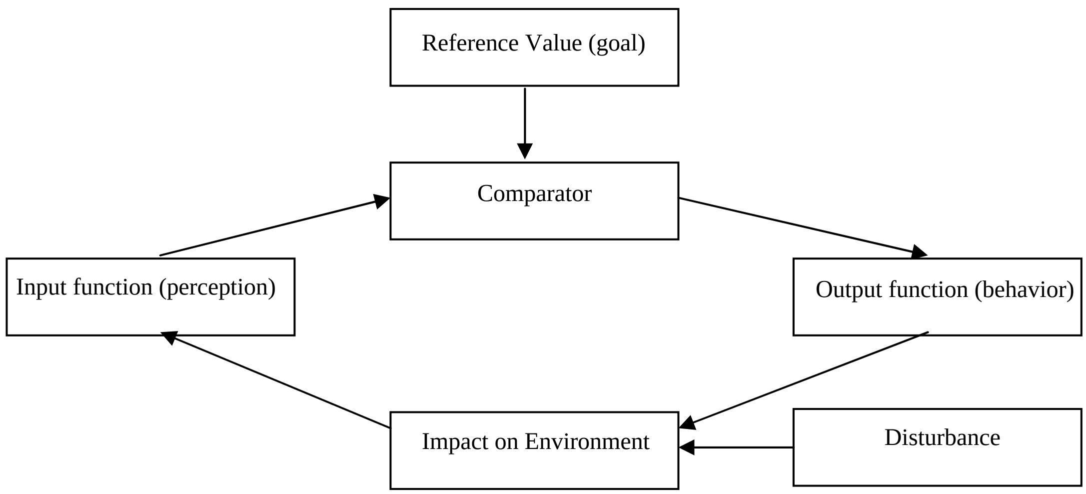

Figure 2. Goals Conceptualized as Part of a Negative Feedback Loop

To summarize, a control theory of behavior may be particularly useful in understanding changes of travel choice over time in response to TDM measures. It is also consistent with research findings in many areas showing that behavior is frequently controlled by negative feedback. Negative feedback control can be found at the neural (e.g. Leibowitz & Alexander, 1998) and motor levels (e.g. Ebenholtz, 1986). However, it is clearly not limited to these lower levels of functioning. Of particular relevance is that control theory has been employed in research on dynamic decision making which requires a decision maker to make a series of real-time, interdependent decisions in an environment that changes both autonomously and as a result of the decision maker's actions (Brehmer, 1990). How successful people are depends on factors, such as negative feedback delay and time pressure, which have been systematically varied or measured in emergency management tasks (e.g. Brehmer, 1990, 1992; Brehmer & Allard, 1991; Omodei & Wearing, 1994) or market scenarios (e.g. Paich & Sterman, 1994; Sterman, 1989). While it is beyond our present scope to detail the findings of this research, the point to note is that researchers have found that people attempt to reduce the discrepancy between their present state (e.g., a bushfire raging in a certain district or insufficient stock) and a goal state (e.g., an extinguished fire with housing saved or a balance between insufficient and excess stock). In the following we specify how the control theory can be applied to the issue of how TDM measures impact private car use and we give some views of the policy implications of the adopted framework.

Figure 3 illustrates possible reference values or goals and subgoals related to car use reduction. At the system concept level, the uppermost level of the hierarchy representing a person's ideal image of himself or herself, the reference value is one of "being a good member of society". People would like to and do tend to see themselves as being concerned about the problems facing the society of which they are part — for example, environmental deterioration or crime. Part of being a good and valued member of society might involve reducing car use because doing so implies that one does not contribute to air pollution and congestion problems. A policy initiative directed at this level could consist of information campaigns or campaigns using role models. These would need to be pull measures as it is difficult to see how a push measure would provide information about an alternative system concept; it would merely inform people of what is not acceptable and this may indeed risk alienating commuters as Stradling et al. (2000) noted. They conjectured that motorists do not like being labeled polluters and as part of the problem when it comes to environmental and traffic problems.

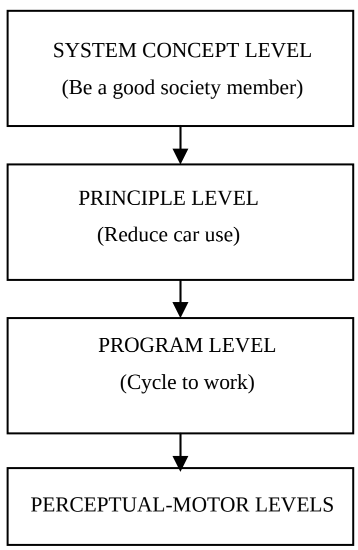

Figure 3. An Application of the Control Theory Model to Changes of Private Car Use

Reducing car use is a principle-level reference value because it is not a specific behavioral action plan. The next level, the program level, is such a plan and may include cycling to work, taking the bus to work on rainy days, or walking to the local grocery store when only a few items need to be purchased. Policy initiatives leading to the establishment of mobility management centers or travel blending assistance (e.g., Rose & Ampt, 2001) could assist commuters to form travel plans (i.e., specific behavioral action plans) where car use is reduced. Of crucial importance to the understanding and prediction of the success, or lack thereof, of various TDM measures is the principle-program connection, discussion of which will be deferred until the section on habits.

Programs at the program level are similar to scripts (Schank & Abelson, 1977; Verplanken, Aarts, Van Knippenberg, & Van Knippenberg, 1994) in that they consist of a list of actions. However, programs are also general courses of action incorporating decision points where many details are left out (Carver & Scheier, 1982, 1998). The details are not specified since what is done at any given point depends on the circumstances that are encountered. Thus, using the example in Figure 3, one may cycle to work via a different route if public works are encountered on the way. In the case of driving to the local store, one may stop to refuel if the car is low on fuel. Such decisions are made in order to match behavior to the goal of reducing car use (Figure 3). Additionally, Carver and Scheier (1982, 1998) argue that within-program variations such as those described also assist one to conform to other goals (e.g., safety by not cycling through a public works area, or not being stranded by not running out of fuel on the way to the store).

Power's (1973) and Carver and Scheier's (1982) reference-level hierarchies are steeped in notions of an ideal self and idealized images of oneself. This may not be true of every person and in any case may vary from person to person such that reducing car use may not be the guiding principle. For example, one system concept may be behaving responsibly and the guiding principle to come out of this may be to preserve one's safety (e.g., not traveling alone by public transport at night). This may lead to driving at the program level (in the worst case) or car pooling. Alternatively, behaving responsibly may entail that one is punctual with respect to work commitments and this, in turn, may lead to one choosing to drive to work..

The way system concepts and principles actually emerge and are formed, and the way they vary from person to person and within persons, is something that needs to be researched more closely.

6. OPERATIONAL CHOICE

Within the control theory framework specified in Figure 2, it is argued that the output function or behavioral choice occurs in a manner outlined by Gärling et al. (2002). If people must make changes to their car use that have costs (monetary costs, mental costs, or inconveniences), then they will prefer and actively seek out alternatives that have smaller costs. This has been consistently demonstrated in research on cost-benefit tradeoffs in decision making (Payne, et al., 1993). As a consequence of striving to minimize costs (or disutility), the preference is to maintain the status quo in terms of commitments, activities, and travel arrangements. Indeed, one can even speak of a status-quo bias implying that retaining the status quo is not always rational. Kahneman and Tversky (1984) propose that the status quo is the reference level for all attributes and, as such, the disadvantages of alternatives will be evaluated as losses (costs) and the advantages as gains.

If it is not possible to immediately attain the goal, a decision following a lexicographic rule may be implemented. The first step, then, may be to switch modes to public transport or a bicycle or to walk as these leave the activity schedule relatively unaltered. However, for such mode switching to be possible, there needs to be sufficient time between activities allowing one to commute with an alternative slower mode. Even if such time windows exist, the person may no longer be satisfied with the resultant increase in time pressure that he or she is likely to experience (Gärling, Gillholm, & Montgomery, 1999).

If the above step fails, a further step is to attempt to combine activities or to coordinate activity schedules with others or both. Combining activities so that they are performed at the same time or in sequence at spatially proximate locations is one option. Thus, a person may drive to a location and complete several activities and then return home, having made less car trips than would have otherwise been the case. Coordinating activity schedules with others is an option allowing people to car pool (e.g., going to sporting events together, going shopping or to work together), or allowing one's activities to be carried out at the same time as the activities of others (e.g., a father shopping while his daughter is at the dentist).

If an activity schedule can no longer be maintained or if the travel arrangement is unsatisfactory, then eliminating or substituting activities become potential options. However, not all activities (work is an obvious example) are possible to eliminate or substitute. Leisure activities are perhaps most likely to be removed from the schedule or at least postponed, as may be shopping activities.

The above is a description of a hierarchy of change grounded in the application of key principles that have been identified to characterize human behavior (i.e., status-quo bias, cost-benefit tradeoffs, disutility minimization, and a lexicographic decision rule). However, it is only a suggested, plausible hierarchy of change. To identify the hierarchies that households try is an important research task, as is specifying the criteria that determine these changes.

According to our conceptual framework (Figure 1), travel choice is influenced through the setting of goals, changes in trip-chain attributes, and the influence of situational factors. TDM measures are assumed to mainly affect travel choice by influencing trip-chain attributes and goals, whereas situational factors influence choices through disturbances (Figure 2). According to Carver and Scheier (1982, 1998), disturbances can either create deviations from a reference value, which need to be countered, or be sufficiently important so that the reference value changes. Consider a person who has decided to go to work or go out to see a film. Ordinarily, the control system may have ultimately led to the choice of bicycle. If the activities were not planned, then they could also be construed as disturbances (e.g., a friend telephones and asks if you want to go out and see a film). The environment consists of a myriad of disturbances that bombard the person in a largely unpredictable way. So, if it begins to rain heavily, then the system registers another disturbance which (despite having the same reference value) may lead to a different output function: stay at home, choose public transport, or drive rather than walk. For the drive option to occur, the rain must be perceived as a sufficiently strong disturbance so that another grouping of reference values is called up — perhaps safety or comfort. Alternatively, going to work or seeing a film must be valued greatly (or be a sufficient obligation) so that staying at home is not the option chosen.

While it is possible for disturbances to lead to new reference values, it is also possible that the situation is perceived as being novel, never before experienced. Let us return to the previous example concerning the offer to go out with a friend after work to see a film. Assuming this is a novel situation, then some planning needs to be made which involves determining the goals to be attained, the means for attaining those goals and the level at which a decision should be made (there are according to Svenson, 1998, four ranging from automatic and habitual to conscious and planned decision making in a new situation where decision alternatives need to be created). In any case, the next step is searching for information concerning alternatives (e.g., travel options). Having obtained the list of decision alternatives, how does one actually make operational decisions related to travel? It is proposed that some decision rule needs to first be applied in order to eliminate non-acceptable alternatives. In this way cognitive effort is saved such that resources may be allocated to the more detailed processing of remaining alternatives. Satisficing (Payne, et al., 1993; Simon, 1982) leads to the rejection of decision alternatives with aspects below certain criteria on different attributes. Thus, if one important attribute in our example is convenience, then some alternatives (e.g., walking or cycling) may be eliminated because of the possibility of getting wet in the rain. Other alternatives may not be feasible or applicable to the situation (e.g., car pooling if nobody has a car). In this way, the alternatives are eliminated such that there is only one alternative left or such that a comparison can be made between the two final alternatives (or the most promising two alternatives if more than two alternatives are left).

Disturbances need not be only environmental. They can take the form of family logistics or time pressure (see Figure 1). An unexpected meeting at work or an after-hours event may cause one to anticipate time pressure that may lead to attempts to change the behavior or may lead to a different set of reference values being adopted. That is, a prosocial person may first maintain the reduce car-use principle but, if the car must ultimately be used, then he or she may abandon it in favor of the principle of, for example, adhering to one's commitments or getting work done. That is, if the behavior cannot be changed, which will result in a goal-action inconsistency, cognitive change may ensue such that the referent is changed, thereby eliminating the aforementioned inconsistency (Campion & Lord, 1982; Carver & Scheier, 1982, 1998) and avoiding the motivational conflict of cognitive dissonance (Festinger, 1957). Of course, it may not be the case that such a change in reference value occurs only when the person is incapable of making another choice. The convenience of the car has in itself the potential of acting as an incentive.

How situational factors prevent car-use reduction goals from being implemented is yet another important research issue. Extensive research (for review, see Gärling & Rise, 2001) suggests that goals are frequently not implemented. Gärling, Gillholm, and A. Gärling (1998) suggest that there are three main reasons for this. Firstly, when setting goals people are unrealistic because they overlook obstacles to their implementation, in effect believing that they have more control than they actually have. Secondly, people change their minds because they do not have sufficient commitment to the goal. Finally, if a goal cannot be implemented until later, it may be forgotten. As illustrated in Figure 4, these reasons may lead to false positives (failure to implement a goal). However, behaviors may also be performed although they are not related to a goal or even in conflict with a goal. Habitual and impulsive behaviors are examples of such false negatives.

	Behavior	No behavior
Goal	**TRUE POSITIVE**	**FALSE POSITIVE** *No or unrealistic plan* *Weak goal commitment* *Forgetting*
No goal	**FALSE NEGATIVE** *Habitual behavior* *Impulsive behavior*	**TRUE NEGATIVE**

Figure 4. Four Possible Relationships Between Goal and Behavior

Although the theories of planned behavior (Ajzen, 1988, 1991) and trying (Bagozzi, 1992) attempt to deal with the question of how goals are implemented, more recent work related to attitude theory (reviewed in Gärling et al., 1998) has focused more directly on the issue. Gollwitzer (1990, 1993) introduced the distinction between goal and implementation intentions.

A person with a goal intention has stopped deliberating about alternative goals or end-states since he or she is committed to pursuing one alternative. A choice of implementation route must also be made, consisting of choices of time or sequence and place of instrumental behaviors. When the situational contexts specified by the implementation intention materialize, the intended behavior is triggered by features in the environment activating a chapterry representation of the goal. Indirect evidence comes from studies demonstrating augmented readiness to perceive relevant situational cues, promotion of attentional strategies for searching such cues, and reduced forgetting of intentions (e.g., Gollwitzer, Heckhausen, & Steller, 1990; Gollwitzer & Kinney, 1989; Heckhausen & Gollwitzer, 1987).

As similarly argued by Eagly and Chaiken (1993), planning is an important component of the implementation of a goal. A general definition of planning is "the predetermination of a course of action aimed at achieving some goal" (Hayes-Roth & Hayes-Roth, 1979, p. 275-276). According to Gollwitzer (1990, 1993), planning consists of finding implementational routes to the goal. Consistent with what was stated above, he further postulated that planning "ties" a behavior to a situation. Planning is therefore referred to as "mental practicing" since it is similar to the development of a habit through actual practice. A more general definition may be "reduction of uncertainty" by means of various activities (e.g., information search). This definition was adopted by Gärling and Fujii (2001) in a study showing that commitment to the goal and perceived control were important determinants of planning. Other research (reviewed in Gärling & Rise, 2001) has shown that if participants plan they are much more likely to perform a particular behavior. In fact, the positive effect of setting specific goals (Lee et al., 1989) is probably, to a large extent, the result of the implementation of such goals being easier to plan.

Research reported in Gärling et al. (1998) and Gärling, Ettema, Gillholm, and Selart (1997) demonstrates that planning has a positive effect on actual car-use reduction. In Jakobsson, Fujii, and Gärling (2001) this effect was even stronger than a substantial increase of the monetary cost of driving. It was also shown that situational factors (e.g., weather, being sick) had an impact on both increases and decreases of car use. An important old insight emerging from this research is that knowledge is a necessary complement to motivation (Locke, 2000). An urgent research question is how such knowledge can be conveyed on a large scale? Public information about the implementation of TDM measures is likely to be more effective if it provides useful knowledge, for instance, about alternative modes and departure times. Likewise, general appeals may only be effective if augmented with information about alternative courses of action.

7. HABITS

With repeated occurrence, the principle-program connection (see Figure 3) may become habitual so that whenever a typical situation arises, the program which is the output from the principle level of control is immediately retrieved. An example would be that choosing to drive has become a habitual program (Gärling, Fujii, & Boe, 2001). This will make the implementation of a new goal (reducing car use) more difficult. A general finding is that intentions and attitudes are not enacted if they are interfered with by habits (Verplanken & Faess, 1999). That is, they become progressively worse predictors of behavior when habit increases in strength and vice versa. As habit strength increases, depth of predecisional information search decreases (Verplanken, Aarts & van Knippenberg, 1997). Individuals with a strong habit apparently do not require as much information about the pros and cons of available options. They may, therefore, have false negative beliefs about alternatives (Fujii, Gärling, & Kitamura, 2001). All these points suggest that planned, thoughtful decision making is not wholly applicable in these cases.

More specifically, the implication is that drivers, despite entertaining the goal of reducing car use, may not be able to supplant the previous principle-program control of using the car as often as they are accustomed to. In the control theory framework, one possible reason is that the input function (perception of the environment) calls up an entirely different set of reference values in the given situation. Another possibility is that the output function (partly because of habit and partly because of inability to search for alternatives) fails to minimize the difference between the reference value and input function (as gauged by the comparator, see Figure 2). That is, changing behavior may not be seen as feasible despite the principle encouraging the change in behavior.

Yet, it may not only be an inability to search for information but also an unwillingness to do so that prevents the replacement of an old principle-program connection. Any public information campaigns that attempt to alter behavior by communicating either the advantages or disadvantages of the behavior to be promoted or by referring to norms and values may not be successful. Such strategies work on the assumption that the relevant behavior (i.e., driving a car) is guided by attitudes and intentions (Ajzen, 1991; Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975). As is argued here and demonstrated in many empirical studies (e.g., Verplanken, Aarts, van Knippenberg, & Moonen, 1998), even if such campaigns successfully alter attitudes and behaviors, these changes may not be reflected in the occurrence of new, different behavior to the extent that the old behavior is habitual (Wright & Egan, 2000).

The relevant question is how a habit can be overruled. Verplanken et al. (1997) provided evidence that this can be done by forcing experimental subjects to pay attention to the decision options or by increasing the functional importance of information acquisition (e.g., being in a new geographical area). However, the effect was temporary with subjects reverting back to their habitual car driving choices. The researchers concluded that consequences of habit can be overruled only temporarily until the habit once again imposes itself on the decision making process. Still, this may not be completely true. Many habits are functional and convenient, and the above experiment did not alter this. The extent to which a habitual behavior is functional can be changed by implementing various policy decisions (e.g., reducing parking spaces). Thus, attitude-based influence attempts may only be useful when habits are broken as a result of such policy measures (Fujii et al., 2001), or, of course, when new habits are yet to be formed, as is the case when new residential areas are built.

The implications are that the type of information required to break a habit may not be the same information required for the formation of a habit. Furthermore, the suggestion is that the various TDM measures available to policy makers are differentially effective in breaking car-use habits. A research issue is to assess these measures with respect to their effectiveness in this respect, perhaps seeing how differences in effectiveness map on to the push-pull conceptualization present in Exhibit 1. The research reviewed thus far suggests that policy initiatives comprised of push measures would be more effective in breaking a habit but not necessarily in yielding a new behavior. Policy initiatives utilizing TDM measures that fall towards the pull end of Exhibit 1 could potentially do this, but only after the push measures have been successfully implemented.

8. CONCLUSIONS

To this point we have introduced and discussed the proposed conceptual framework (Figure 1), elaborating on the various components and processes assumed to function within the framework. Thus, we mentioned the predicted impacts of TDM measures on people and how the measures themselves could be variously classified. The focus then shifted to an analysis of goal setting with some links drawn between TDM measures and the setting of goals. Control theory was applied for understanding of changes in travel choice. It was argued that people have a hierarchically organized set of reference values or goals that they seek to achieve. Finally, habits were discussed within the control theory framework given that much research has indicated the role they play in preventing changes to travel behavior.

Throughout the chapter, key research issues and areas have been highlighted. These may be summarized as follows:

- How do TDM measures influence attributes of trip chains in terms of cost, time, and convenience?
- Related to the above point is the need to empirically determine the principles by which trip chains are described by people themselves.
- Research into the effects of other users on the transportation system is vital, given the interdependencies present in the system. Users do not operate in a vacuum and their actions affect the actions of others, and the actions of others may affect a target user in ways other than intended by a particular TDM measure.
- Does the content of a goal (i.e., its difficulty or the level of specificity that it possesses) influence the likelihood of its achievement?
- A potentially fruitful research path is to examine and determine the guidelines that influence the emergence and formation of system and principle concepts. Additionally, the way such concepts vary from person to person and from situation to situation (i.e., within a person) should shed light upon the reasons behind people's travel choice.
- A potential change hierarchy was introduced. However, it is only hypothetical, based on well-established principles that are known to guide behavior. Research is needed to identify the various potential hierarchies of change that households attempt and to specify criteria influencing such changes.

- How situational factors can prevent people from achieving their car-use reduction goals is an important research question. Are there situation types that are more likely to cause this than others? Or are the goals that certain people set in the first place unrealistic? The implication is that knowledge and motivation go hand in hand and, as such, research aimed at determining the most effective means of conveying such knowledge on a large scale is likely to be valuable.
- An important question is if and how car-use habits can be overruled. It has been suggested that attitude-based influence attempts are not likely to be successful on individuals having strong habits. Research into the effectiveness of TDM measures in breaking habits and fostering new behaviors is vital.

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VALIDATION OF ACTIVITY-BASED ANALYSIS OF TRANSPORTATION CONTROL MEASURE IMPACTS

CHAPTER IX

SUMMARY

This chapter describes the development and application of an activity-based microsimulation model system capable of simulating changes in individual travel patterns in response to a transportation control measure. A unique activity-based time use survey was conducted to obtain information on people's activity and travel patterns and their likely behavioral adjustment in response to various transportation control measures. This chapter describes the survey and the use of the ensuing data set in estimating various components of the simulator, called AMOS. The validation of the model is performed on a data set obtained from the Washington D.C. area demonstrating the capabilities of AMOS as a transportation policy analysis tool. Sample results from the Washington D.C. validation are presented.

1. INTRODUCTION

Over the past several decades, the emphasis of transportation planning has shifted from the construction of new infrastructure to the effective management of travel demand. This shift has been brought about by rising social, environmental, and economic concerns coupled with a realization that building one's way out of congestion is only a temporary solution to serving the increasingly complex patterns of travel demand that evolve over time. Federal legislative acts such as the Clean Air Act Amendments, 1990 and the Intermodal Surface Transportation Efficiency Act, 1991, serve as key examples of this shift in transportation planning emphasis.

In this regard, the decade of the 1980s saw an increased interest in the development and implementation of Travel Demand Management (TDM) strategies. These strategies were aimed at effectively managing and distributing travel demand, both in the spatial and temporal dimensions. For example, flexible work hours helped shift commute related peak-period trips to off-peak periods (temporal shift). However, these strategies alone were not able to alleviate air quality, traffic congestion, noise, and safety problems associated with an ever-increasing travel demand. As a result, new strategies termed Transportation Control Measures (TCM) have been embraced by the transportation planning community. These measures are sophisticated and complex in nature, the exact impacts of which are unknown. However, they are not only intended to effectively manage travel demand, but also to reduce travel demand through the suppression and selective elimination of trips. Specifically, these measures tend to target peak-period commute trips and single-occupant vehicle (SOV) automobile trips, the two types of trips that contribute most to traffic congestion, fuel consumption, and emissions on a per capita basis.

As increasing numbers of urban areas began considering TCMs, it became apparent that traditional travel demand forecasting and planning methods, that are primarily derived from trip-based four-step procedures, are not able to address the complex questions raised by TCM implementation. Relationships among human travel behavior patterns and the attitudes, values, and constraints that determine these patterns are extremely complex in nature, and traditional forecasting models do not explicitly model these relationships in a theoretically sound framework.

Consequently, activity-based approaches to travel demand forecasting were conceived and proposed in the travel behavior research arena (Kitamura, 1988). Activity-based approaches explicitly recognize that travel demand is derived from the need to pursue activities that are dispersed in time and space. Moreover, these approaches recognize the interaction among various members of a household as households tend to allocate and coordinate their activities. As such, it has been argued that activity-based approaches provide a theoretically and conceptually stronger framework for modeling travel behavior in the current planning context.

Activity-based approaches focus on the timing, destination, duration, and constraints in human activity engagement. Implementation of these approaches requires activity and travel behavior data that is not collected in traditional household travel surveys. If the activity-based approach is going to be used in the context of evaluating or forecasting the impact of a proposed TCM, revealed activity-travel behavior data will have to be combined with stated adjustment data.

Stated adjustment data provide information on how people may adjust their current travel patterns in response to hypothetical scenarios of TCM implementation.

This chapter reports on the results of implementing an innovative activity-based microsimulation model to TCM impact evaluation in the Washington D.C. metropolitan area. A unique activity-based travel data set combining revealed preference and stated adjustment information was used in the model development and implementation phases of the effort. The model simulates changes in travel behavior for each individual and generates modified travel patterns that may be adopted in response to a TCM.

This chapter consists of eight more sections. The next section provides a brief description of the activity-based microsimulation model and its components and operation. The third section describes the survey that was conducted in conjunction with this validation study while the fourth section summarizes key characteristics of the respondent sample. The fifth section provides an analysis of the stated responses offered by survey participants in response to hypothetical TCM scenarios. The sixth section describes model estimation results. In the seventh section, the validation of the model using the Washington D.C. area data set is described in brief. The detailed TCM policy analysis results are offered in the eighth section while conclusions are drawn in the ninth section.

2. DESCRIPTION OF AMOS

The activity based microsimulation model that was developed and implemented in this effort is referred to as AMOS, an acronym for Activity Mobility Simulator. In its prototypical application, AMOS was intended to serve as a short term transportation planning and policy analysis tool. AMOS is an activity-based microsimulator of daily human activity and travel patterns, which focuses on the adaptation and learning process that people exhibit when faced with a change in the transportation environment. AMOS simulates a new activity engagement and travel behavior pattern that a person is likely to adopt in response to a TCM and implements, to the extent possible, the conceptual framework presented in the previous chapter. This is accomplished through the implementation of several modules. The modules comprising AMOS are briefly described in this section.

The first module is called the Baseline Activity-Travel Analyzer. The baseline activity-travel analyzer reads individual trip records from a typical travel diary data set and compares them with network data for logical consistency and missing information. It then generates a coherent baseline activity-travel pattern for each individual. In addition, for commuters, it examines for the presence of stops on the way to or from work and for the use of a personal vehicle while at work. These commute characteristics will be used in ensuing components of AMOS to constrain the choice of mode to work.

The second component of AMOS is the TDM Response Option Generator. This module creates the “basic” or “primary” response of an individual to a TDM strategy or TCM. The generator consists of a neural network model that is trained using survey responses obtained from hypothetical TCM scenarios. The baseline activity-travel pattern from the previous module, demographic and socio-economic attributes, and the characteristics of the TCM under investigation serve as inputs to this module. The output of this module is defined by the basic behavioral response that a person is likely to exhibit in response to a TCM. The TCMs may be characterized by changes in cost, travel time, modal attributes, and/or constraints that they bring about.

The Activity-Travel Pattern Modifier constitutes the third module of AMOS. This module lies at the heart of AMOS and consists of an activity-trip resequencing and rescheduling algorithm. It furnishes one or more modified but feasible alternative activity-travel patterns based on the primary level response provided by the TDM Response Option Generator. For example, if the response option generator indicated a mode shift to transit as the possible primary level response that an individual may exhibit, the modifier will deduce the secondary and tertiary changes that will be brought about in the travel pattern due to the mode change. It then constructs a coherent modified activity-travel pattern that will be evaluated for possible adoption by the individual. The inputs of this module include the baseline activity-travel pattern, network data, land use data, socio-economic and demographic data, and the response option from the TDM Response Option Generator. The output of this module is a modified activity-travel pattern. The feasibility of the modified activity-travel pattern is checked for consistency and logic against a set of rule-based constraints that people must adhere to. There are physiological constraints (e.g., a person must sleep and eat), spatial constraints (e.g., destination of one trip serves as the origin for the next trip), temporal constraints (e.g., a day consists of 24 hours), modal constraints (e.g., one can not drive if no vehicle is available), and institutional constraints (e.g., business establishments are open during certain hours).

The modified but feasible alternative activity-travel pattern generated by the modifier must be evaluated for potential adoption. The fourth component of AMOS, namely, Evaluation Module and Acceptance Routine, serves this purpose. This component evaluates the utility associated with an activity-travel pattern based on the time allocated to various activities and travel in the pattern (Kitamura, et al., 1995a). Operationally, its built-in acceptance routine assesses whether a modified activity-travel pattern will be accepted or rejected on the basis of a human adaptation and learning model incorporating a set of search termination rules. The search termination rules are defined so as to permit the acceptance of sub-optimal choices of travel patterns. This is based on the notion of "satisficing" which postulates that an individual will experiment with a limited set of alternatives before choosing one that is satisfactory. The model recognizes that people do not have perfect information, can not exhaustively enumerate and experiment with all possible alternatives, and are often unable to select the optimal choice.

The final module in AMOS serves as an output device. This module, called the Statistics Accumulator, reads all feasible and accepted activity-travel patterns provided by the Evaluation Module and Acceptance Routine to generate descriptive measures of travel on a daily basis. These measures include vehicle miles traveled, trip frequencies by purpose and mode, number of stops, number of trip chains by type, activity duration by purpose, travel times by purpose, vehicle occupancy, cold and hot starts, etc. In addition, all of these measures are provided by time-of-day. In conjunction with the baseline activity-travel patterns, the accumulator is able to provide measures of change in travel demand as a result of a TCM implementation.

As such, AMOS consists of a series of inter-related components that collectively serve as a comprehensive transportation planning and policy analysis tool. Detailed operational descriptions, assumptions, and underlying algorithms of all AMOS components can be found in Kitamura, et al. (1995b). A review of other activity-based travel modeling tools can be found in Pendyala, et al. (1995).

3. AMOS SURVEY

The development and validation of AMOS involved an elaborate survey effort (hereafter, AMOS survey) involving the collection of both revealed preference and stated adjustment data. The survey furnished the data needed to train the neural network in the TDM Response Option Generator module of AMOS. Upon completion of neural network training, household travel diary data from the Washington D.C. metropolitan area provided the baseline activity-travel patterns to which AMOS could be applied. This section describes the AMOS survey methodology and administration.

The objective of the AMOS survey was to obtain a data set that could be used to model individual responses to various TCMs. To this end, the survey included an activity-based time use section to obtain revealed preference information on daily activity and travel behavior, and a stated adjustment (or stated adaptation) portion to obtain information on how individuals would respond in the event of a TCM implementation. As the initial development of AMOS and the TCMs considered were primarily targeted at commuters, the target population for the survey consisted of adults who commuted (to/from work or school) at least three days a week. Only one commuter was interviewed in each household, thus precluding the ability to capture interactions among household members.

The survey was administered in three phases using computer aided telephone interview (CATI) techniques. In the first phase, a CATI was conducted to screen survey participants, obtain information on commute characteristics, work schedules, and demographics, and to assign a travel day for which the respondent would report his or her activity/travel pattern in ensuing phases of the survey. In the second phase, a chapterry jogger was mailed to the participants so that they could record their activities and travel for the assigned day. In the third phase, the activity and travel information was retrieved over the phone using CATI.

The stated adaptation portion of the survey was also administered in the third phase. TCM scenarios were customized to each individuals' commute situation so that they were meaningful and realistic to the survey participants. Participants were presented with six TCMs (one scenario per TCM). The TCMs included in the survey are:

- *TCM #1: Parking Pricing*

  An incremental parking surcharge imposed at the work place with ranges $1 to $3 per day in suburban areas and $3 to $8 in downtown areas.
- *TCM #2: Improved Bicycle/Pedestrian Facilities*

  A description of improved bicycle and pedestrian friendly facilities including well-marked and well-lit bicycle paths and sidewalks and a secure place to park a bike wherever a person went.
- *TCM #3: Parking Pricing & Improved Bicycle/Pedestrian Facilities*

  A combination of TCM #1 and TCM #2.
- *TCM #4: Parking Pricing & Employer Supplied Commuter Voucher*

  A monthly parking surcharge imposed at the work place along with an employer supplied commuter voucher that could be used to cover transportation costs. Both had ranges of $40 to $80 per month.
- *TCM #5: Congestion Pricing & Travel Time Reduction*

  Peak period congestion pricing imposed along entire commute route with a range of $0.15 to $0.50 per mile together with a travel time reduction of 10% to 30%. Peak period defined as 6:00-9:00 am and 4:00-7:00 pm.
- *TCM #6: Parking Pricing/Employer Voucher & Congestion Pricing/Travel Time Reduction*

  A combination of TCM #4 and TCM #5.

After presenting a scenario, the respondent was asked what he or she would do as a consequence of the TCM implementation. The respondent was not prompted with a list of possible changes unless necessary. The respondents' stated adjustments were coded into one of eight possible response options:

- Do nothing different
- Change departure time to work or school
- Walk to work or school
- Bicycle to work or school
- Car/Van pool to work or school
- Take transit to work or school
- Work at home
- Other

Upon the respondent providing a stated adjustment, a series of follow-up questions were presented to the individual to determine the impacts of the stated adjustment on their activity-travel pattern. For example, suppose an individual indicates that he or she will switch to transit in response to congestion pricing. Then, if the individual currently stops to drop off a child at school on the way to work, a follow-up question is posed asking how that stop would be handled after the switch to transit. In this manner, the survey derived information about likely secondary and tertiary changes in the activity-travel itinerary and ensured that the respondents thought about their entire itinerary when providing a stated response to a TCM scenario.

Considering the length and complexity of the survey, the response rates obtained were as expected. A total of 2,664 calls were answered by a person. 48% or 1,283 persons completed Phase 1 of the survey. 1,003 of the 1,283 persons qualified and agreed to participate in Phase 2. Out of the 1,003 persons, 65% or 656 commuters responded to all phases of the survey and provided complete information. The analysis in this chapter is done using the sample of 656 commuters who provided complete data.

4. SAMPLE CHARACTERISTICS

This section provides a brief overview of the sample characteristics. The respondent sample consisted of 656 commuters belonging to 656 households. The average household size is 2.7, while the average number of commuters per household is 1.7. On average, there are two vehicles and 1.4 bicycles per household. About 90% of the households have at least one vehicle per commuter indicating a high degree of vehicle availability for commuting purposes. About one-fifth of the households have at least one child less than five years of age.

Table 1 provides further details regarding the characteristics of the commuter sample which was used to develop AMOS. Almost all of the respondents are licensed and employed. Nearly 58% of the respondents are male. About 70% of the respondents indicate driving alone (SOV) as their usual mode of transport to work (used 3 or more days per week). Average commute distance for the sample is 15.2 miles while the average commute time (measured as direct home-to-work travel time) is found to be 31.7 minutes.

TABLE 1
Respondent Characteristics
(N=656 Respondents)

Characteristic	Average Value
% 30-49 years of age	60%
% Drivers License	98%
% Male	58%
% Employed (outside home)	99%
Modal Shares: Work Trip	
% Drive Alone (SOV)	70%
% Car/Van Pool	16%
% Transit (Bus + Rail)	10%
% Bike + Walk	3%
Commute Distance (miles)	**15.2**
% <5 miles	22%
% 5-25 miles	61%
Home-Work Travel Time (min)	**31.7**
% <10 min	12%
% 10-30 min	48%
Trip Chaining Patterns (1+ days)	
Home-Work: Serve Child	13%
Home-Work: Other Activity	28%
Work-Home: Serve Child	14%
Work-Home: Other Activity	49%
At Work: All Activities	40%

Quite a few of the respondents indicated that they trip chained at least one day the previous week (either during the journey to or from work). About 13% of the respondents stopped on the way to or from work to serve a child on one or more days. Nearly one-half of the respondents indicated that they stopped on the way home from work for an activity other than serving a child. In this context, it is important to note that the implementation of a TCM may bring about changes in trip chaining patterns, which in turn, may affect how an individual responds to that TCM.

5. ANALYSIS OF STATED ADJUSTMENTS TO TDM STRATEGIES

As mentioned previously, the respondents were presented with six hypothetical customized TCM scenarios and asked how they would respond in the event of their implementation. Their responses were coded into one of eight possible categories. In this chapter, only a few representative sample results are provided for the sake of brevity.

Table 2 provides the distribution of stated responses for TCM #4: Parking Pricing with Employer Commuter Voucher, TCM#5: Congestion Pricing with Travel Time Reduction, and TCM #6: Combination of TCM #4 and TCM #5. In addition, statistical tests examining the null hypothesis of equality across response distributions are also presented.

An examination of the response distributions indicates that, for these TCMs, about 60 to 70 percent of the respondents would not change their current travel choices even after the introduction of the TCM. Congestion Pricing yields the largest percentage change (nearly 40 percent would either change departure time or mode to work). In general, the indications provided are as expected. Parking pricing has little impact on departure time, but substantial impact on mode switching. The response distribution for TCM #4 is significantly different from that of TCM #5 at the 0.05 level of significance. On the other hand, neither the response distribution of TCM #4 nor that of TCM #5 is significantly different from that of the combination TCM (TCM #6) at the 0.05 level. The respondents who indicated that they would not change in response to congestion pricing also indicated that they would not change in response to the combination TCM. It appears that this 60% of the sample can not or will not respond to a TCM, regardless of the TCM implemented.

TABLE 2
Distribution of Stated Responses to TCM Scenarios
(N=656 respondents)

Response Option	Parking Pricing w/ Voucher TCM #4	Congestion Pricing w/ Travel Time Red TCM #5	Combination TCM TCM #6
No Change	71%	61%	62%
Change Departure Time to Work	1%	20%	12%
Switch to Transit	10%	8%	10%
Switch to Car/Van Pool	9%	4%	6%
Switch to Bicycle	6%	4%	5%
Switch to Walk	1%	1%	1%
Work at Home	1%	1%	1%
Other	2%	2%	3%

χ^2 test-statistic for TCM #4 vs. TCM #5 = 20.5, df=7, p=0.0046
χ^2 test-statistic for TCM #4 vs. TCM #6 = 10.8, df=7, p=0.1474
χ^2 test-statistic for TCM #5 vs. TCM #6 = 2.94, df=7, p=0.8908

Interesting results were obtained when the response distributions were cross-tabulated against various socio-economic, demographic, and travel characteristics. An example of a cross-tabulation indicating the effects of trip chaining on the response distribution is presented in this chapter. Table 3 shows the distribution of responses to congestion pricing for those who made no stops on the way from home to work versus those who made one or more stops on at least one day (during the previous week).

TABLE 3
Congestion Pricing Response Distribution by Trip Chaining

TCM Response Option	Stops on 0 Days (N=430)	Stops on 1+ Days (N=226)
No Change	57%	67%
Change Departure Time to Work	19%	20%
Change Mode	*20%*	*11%*
Switch to Transit	9%	5%
Switch to Car/Van Pool	5%	3%
Switch to Bicycle	5%	2%
Switch to Walk	1%	1%
Work at Home	1%	0%
Other	2%	1%

χ^2 test-statistic = 13.406; df=7; p=0.0628

Of the 656 respondents, 226 indicated that they stopped on at least one day the previous week during the home-to-work trip. These commuters are found to be more resistant to changing their mode when compared with those who did not stop at all the previous week. However, they are almost equally inclined to change their departure time. It appears that trip chaining acts as a deterrent to mode shifts, but not to departure time shifts. Approximately, one-fifth of the sample responded with a change in departure time whether or not they trip chained at least one day the previous week. On the other hand, with regard to mode shifts, 20% of those who did not trip chain were willing to change mode. The corresponding percentage for those who trip chained was only 11%. Trip chaining is found to be significantly related to the response distribution at a p-value of 0.0628.

The descriptive tabulations provided in this section provide insights into the types of relationships that can be explored using the AMOS survey data set. Further exploratory analysis of the data set revealed the set of variables significantly affecting response distributions to various TCMs. These variables were used to train the neural network in the TDM Response Option Generator. The neural network training and its calibration results are described in the next section.

6. NEURAL NETWORK TRAINING

The TDM response option generator consists of a neural network that provides the primary level basic response of an individual to a TCM. This section provides a brief overview of the neural network specification and training results.

A neural network may be considered a general-purpose function estimator or pattern recognizer. It is an assembly of artificial neurons that is intended to mimic the learning behavior of the human mind. These neurons are usually arranged in several layers, namely, an input layer, an output layer, and one or more intermediate hidden layers. Neurons in the input layer accept inputs and re-transmit them to each neuron in the next layer. If one or more hidden layers is included, each neuron in a hidden layer accepts a weighted set of inputs from the previous layer and transmits a signal to all neurons in the next layer. Finally, neurons in the output layer accept inputs from the last hidden layer and produce the output of the neural network.

A neural network methodology is adopted in AMOS as it draws from the theory of connectionism postulated in the field of cognitive sciences. According to that theory, humans process information by breaking it down into a multitude of inter-connected elements. Through the use of an assembly of inter-connected neurons, a neural network is able to depict the connectionist behavior of humans (Benjafield, 1992).

Training the neural network involves the estimation of weights associated with each of the neuron links. Once it is trained, a neural network can provide an appropriate output in response to various patterns of inputs. In AMOS, baseline travel characteristics, land use and socio-economic data, transportation supply data, demographic characteristics, and attributes of the TCM under investigation serve as inputs. The output comprises a set of behavioral responses defined by the eight response option categories mentioned in the previous section.

The neural network was trained using data from the AMOS survey. However, as the trained neural network was going to be applied to the household travel diary data of the Metropolitan Washington Council of Governments (MWCOG), only those variables in the AMOS survey database that were also available in the MWCOG database could be used for training purposes. Based on this criterion and the desire to maximize the use of the information in the database, a set of 36 input nodes (variables) together with 8 output nodes (one node for each response option) were identified.

Broadly, the 36 input nodes encompassed an array of demographic, socio-economic, land use, transportation network, and TCM characteristics in addition to the baseline travel patterns. The method of backpropogation was used to adjust the weights associated with the links in the network so as to maximize the predictive accuracy of the network. The data set was divided randomly into two subsets; one subset was used for estimation (training set) and the other for validation (validation set). The predictive accuracy is measured in terms of the percentage of cases in the validation set whose output nodes are correctly classified when compared against their stated response. Based on considerations of complexity and predictive sensitivity and accuracy, a network with two hidden layers was chosen for implementation within AMOS.

When the training is complete, a certain output node (of the possible eight) corresponding to one behavioral response option is activated for each respondent. This deterministic activation level is then converted to a probability measure using standard econometric maximum likelihood estimation procedures. A conversion function is statistically estimated such that the neural network best replicates the observed responses in the training data set. In this way, the stochastic nature of human travel choice processes is explicitly captured in AMOS.

7. APPLICATION OF AMOS

This section discusses the implementation of AMOS and provides an example of how a baseline travel itinerary may be modified in response to a TCM. AMOS was first implemented in the MWCOG study area using the MWCOG traffic analysis zone (TAZ) system and zone-to-zone network skim tree travel time matrices by mode. AMOS therefore has the level of geographical resolution that equals that of the MWCOG's TAZ system. The implementation effort thus utilizes as much spatial and modal information as available from the MWCOG planning databases.

Baseline travel patterns were obtained from the MWCOG household travel diary survey. MWCOG provided complete data (with trip origins and destinations geocoded at the TAZ level) for a small subsample of 98 commuters. AMOS has been applied to this subsample of commuters to analyze the impacts of various TCMs on a sample-wide basis (the subsample is too small to permit a rigorous regional analysis).

A few selected characteristics of the MWCOG survey subsample are highlighted below:

- The average age of the sample 38 years, with about 90% between the age of 16 and 65 years.
- About 50% of the sample resides in households with 2 vehicles. Only two commuters reported a vehicle ownership of zero.
- About 80% of the households are one- or two-commuter households. On the other hand, the household size is more uniformly distributed, with about 50% of the sample indicating a household size greater than 2. These households were characterized by the presence of young children.
- The average commute time (including any stops) for the sample is about 30 minutes with the distribution slightly skewed in favor of travel times below the average value.
- About 60% of the sample commutes by SOV, 15% by car or van pool, and only 2% by transit (bus or rail). Bicycle and walk modes, when combined, were second only to SOV with a combined share of 17%. As such, this sample under-represents the presence of transit users in the population.
- From the baseline travel patterns, it was found that about 40% of the 98 commuters report at least one stop either on the way to or from work indicating a substantial presence of trip chaining.

The neural network that was trained using the AMOS survey data was applied to the MWCOG survey subsample of 98 commuters to first predict their basic (primary) response to a TCM. However, this response alone does not provide the necessary information for computing changes in travel characteristics such as trip frequencies by mode and purpose, cold and hot starts, travel durations, and vehicle miles traveled. In order to obtain such statistics, the basic response option must be used to deduce secondary and tertiary changes that may be brought about in an individuals' activity-travel pattern.

As described in the second section of this chapter, the activity-travel pattern modifier uses a rule-based algorithm to determine alternative, but feasible activity-travel patterns that a commuter may adopt in the new travel environment. In applying AMOS to the MWCOG survey subsample, the activity-travel pattern modifier was applied to the 98 commuters' baseline travel patterns to obtain modified activity-travel patterns that may occur as a consequence of the basic response (generated by the neural network).

Several assumptions were made to facilitate the implementation of the modifier. Some of the assumptions were institutional in nature; for example, business hours for offices were assumed to be 9:00 am to 5:00 pm. Also, work durations were assumed to be fixed according to the baseline travel pattern. Similarly, assumptions were made regarding store hours for shopping, destination locations, activity schedules, and non-work activity durations.

Table 4 presents an example of a baseline travel pattern and a modified, but feasible pattern generated by AMOS in response to congestion pricing (TCM #5). The table presents only one among the several alternative patterns generated by the modifier. The evaluation module and acceptance routine determines the specific pattern that may ultimately be adopted.

TABLE 4
Baseline and Modified Travel Pattern for Sample Case
TCM #5: Congestion Pricing with Travel Time Reduction

Household ID: 10196665; Person ID: 2; Age: 38; Sex: Male

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
BASELINE PATTERN								
1	217	7	Home	Work	8:18	8:38	Auto	Driver
2	7	217	Work	Home	17:30	17:50	Auto	Driver
3	217	209	Home	Social	18:50	19:00	Auto	Passenger
4	209	217	Social	Home	21:45	21:55	Auto	Passenger
5	217	110	Home	ChldCare	22:00	22:12	Auto	Passenger
6	110	217	ChldCare	Home	22:13	22:25	Auto	Driver

Summary Characteristics

Auto Psgr Trips:	3	Work Trips:	1	Peak Trips:	2
Auto Drvr Trips:	3	Home Trips:	3	Total Trips:	6
Commute Mode:	Auto Driver				

Trip No.	Origin TAZ	Destn TAZ	Origin Locn	Destn Locn	Depart Time	Arrive Time	Mode	Driver/ Passenger
MODIFIED PATTERN **Response Option: Change Departure Time to Work**								
1	217	7	Home	Work	9:00	9:20	Auto	Driver
2	7	217	Work	Home	18:12	18:32	Auto	Driver
3	217	209	Home	Social	19:32	19:42	Auto	Passenger
4	209	217	Social	Home	22:27	22:37	Auto	Passenger
5	217	110	Home	ChldCare	22:42	22:54	Auto	Passenger
6	110	217	ChldCare	Home	22:55	23:07	Auto	Driver

Summary Characteristics

Auto Psgr Trips:	3	Work Trips:	1	Peak Trips:	0
Auto Drvr Trips:	3	Home Trips:	3	Total Trips:	6
Commute Mode:	Auto Driver				

This commuter travels to work by automobile as a driver during the peak period. The TDM response option generator (neural network) provided a primary level response option as “change departure time to work” as one probable choice in response to peak period (7-9 am and 4-6 pm) congestion pricing. As such, the response option generated by the neural network is consistent with the TCM under investigation. In the baseline pattern, the individual makes two trips in the peak period that would be subject to congestion pricing. The modifier shifted both of these trips out of the peak period to avoid the congestion pricing. The trip to work in the morning now commences at 9:00 am instead of 8:18 am; and the trip from work commences at 6:12 pm instead of 5:30 pm (note that the work duration is kept fixed). As a result of the TCM implementation, both peak period trips are eliminated. However, neither the total trip frequency (by purpose) nor the travel mode changes.

This section has illustrated how the activity-travel pattern modifier, in conjunction with the TDM response option generator, provides alternative activity-travel patterns that may be adopted in response to a TCM. The modified patterns can be compared against the baseline patterns to obtain measures of changes in travel characteristics. The procedure described here was applied to the entire sample of commuters to perform a sample-wide policy analysis of TCM impacts. This is described in the next section.

8. POLICY ANALYSIS

As noted in the previous section, trip diaries are available from the MWCOG survey for conducting a policy analysis from only a very small sample of 98 commuters who are not representative of the population. Considering potential magnitudes of sampling errors associated with such a small sample, the results presented in this section should not be considered to represent an assessment of the merits of the TCM analyzed. Rather, the results presented in this section should be taken as numerical examples which illustrate how the activity-based policy tool applies to TCM analysis and how it evaluates TCM impacts while considering daily travel patterns in their entirety. The small sample size also precludes performing an analysis of TCM impacts by commuter market segment.

The example in the previous section showed how a commuter’s daily itinerary is reconstructed based on the TDM response option predicted by the neural network. Several evaluation measures are used in this study to assess the impacts of a TCM. Changes in daily travel patterns are aggregated and sample-wide mean values are obtained for the following measures:

- Daily trip frequencies by purpose and mode
- Travel time by mode
- Modal shares
- Peak period trip frequencies by purpose and mode
- Peak period travel time
- Peak period modal split

The first step in the policy analysis is to define parameter values that characterize the TCM under investigation. In this chapter, policy analysis results are presented for only one TCM, namely, TCM #5: Congestion Pricing with Travel Time Reduction. For the sake of brevity, policy analysis results for the other TCMs are not presented here. For conducting a congestion pricing policy analysis, two parameter values had to be established. First, the congestion price was set at $0.50 per mile and second, the travel time reduction was set at 30%.

A total of twenty simulation runs were performed to analyze the impacts of congestion pricing. An average value over all simulation runs was used to measure changes in travel characteristics. Table 5 presents results of the policy analysis by comparing baseline travel characteristics with those obtained from the activity based microsimulation analysis.

The overall distribution between work and non-work trips does not show any substantial changes with the TCM in place. This applies to all time periods, whether peak or off-peak. During the peak periods (when congestion pricing is in effect) a slight increase in the percentage of work trips is noted. This is expected as discretionary non-work trips may be rescheduled and moved out of the peak period to avoid congestion pricing while work trips may not exhibit the same degree of flexibility.

TABLE 5
AMOS Simulation Results for Congestion Pricing

Travel Indicator	Total		AM Peak		PM Peak		Off-Peak	
	Baseline	Simulation	Baseline	Simulation	Baseline	Simulation	Baseline	Simulation
TRIP PURPOSE								
Work	42.2%	43.0%	64.0%	64.4%	31.1%	35.6%	36.6%	36.5%
Non-work	57.8%	57.0%	36.0%	35.6%	68.9%	64.4%	63.4%	63.5%
TRAVEL MODE								
Auto-Driver	54.0%	50.2%	65.1%	56.3%	54.7%	51.9%	45.5%	39.7%
Auto-Psgr	18.4%	17.0%	10.5%	10.3%	18.9%	18.3%	23.6%	22.2%
Other	27.6%	32.8%	24.4%	33.4%	26.4%	29.8%	30.9%	38.1%
TRIP DURATION (min)								
Total	18.5	19.0	21.7	23.0	22.0	22.6	13.4	13.5
Auto-Driver	21.6	21.4	24.5	23.5	24.9	24.5	15.2	16.1
Auto-Psgr	17.0	17.3	16.4	16.4	21.4	21.8	14.2	14.5
Other	13.6	16.2	16.4	24.2	16.2	19.9	10.1	10.2
PERCENT HOT STARTS	37.7%	36.8%	34.9%	34.5%	35.9%	36.5%	37.8%	34.9%
PERCENT OF TRIPS	100%	100%	27.3%	26.9%	33.7%	32.2%	39.0%	41.0%
TRIPS PER PERSON	3.21	3.30						

Analysis of modal shares shows substantial effects of the TCM. The share of auto-driver and auto-passenger trips (which are subject to congestion pricing) decrease during all time periods with the greatest decrease seen during the AM peak period. During the PM peak period, the decrease is not as pronounced, possibly due to the constraints associated with activity engagement (trip chaining while serving children, personal business, shopping, etc.). The decreases seen in the auto-driver mode are larger than those seen in the auto-passenger mode, where passengers share the cost of the congestion pricing.

In general, average trip durations show virtually no change between the baseline case and the simulation runs. Similarly, the percentage of hot starts also showed virtually no change except in the off-peak period where it decreased from 37.8% to 34.9%. This may be attributable to the decrease in auto-driver mode share for the work trip. If a person chooses to use transit and the automobile is left at home, the individual may undertake shopping and other activities in a separate home-based trip chain which will entail a cold start.

Interestingly, the total trip frequency shows a slight increase from 3.21 to 3.30. This may be explained by the breaking up of trip chains as people abandon their automobile for the trip to work. When using the automobile for their commute, individuals could link their other activities (shopping, etc.) on the way to or from work. If they were to use transit (say, after the introduction of congestion pricing as in this case), then such activities are more easily pursued after returning home where an automobile is available. The generation of a separate trip chain to undertake these activities will drive up the overall trip frequency. The decrease in the percentage of trips in the peak periods and the concomitant increase in the off-peak period (39.0% vs. 41.0%) serves as further evidence of this phenomenon.

The exercise here shows that activity-based microsimulation models such as AMOS serve as practical tools capable of analyzing transportation policies while simulating daily travel patterns in their entirety. However, as noted earlier, the results in this section are merely illustrative of the capabilities of AMOS. The size of the subsample used in the validation warrants neither a generalization of the results obtained here nor a general assessment of the relative effectiveness of the TCM scenario examined here.

9. CONCLUSIONS

This study reports on the development and implementation of a full-fledged activity-based model system for transportation policy analysis. Despite the theoretical arguments that warrant their practical application, activity-based approaches remained within the domain of academia for nearly two decades. The development of AMOS and its implementation in the Washington D.C. area represent significant steps forward in moving these approaches into transportation planning practice. The development is especially significant considering the importance of travel demand management in the current planning contexts set forth by the Clean Air Act Amendments and Intermodal Surface Transportation Efficiency Act.

AMOS, an activity-based microsimulation model system, has been applied to the evaluation of a set of transportation control measures using a small sample of trip diaries from the household travel diary survey of the Metropolitan Washington Council of Governments. The effort demonstrated that the model system can be implemented in a metropolitan area using data available from a typical MPO, such as trip diary data, network travel time data, and land use inventory data. The only additional data needed for AMOS are stated adjustment survey results from the area which are used to customize a component of AMOS to the area residents' responsiveness to TCMs.

The effort also showed that travel forecasts can be developed while treating the daily travel patterns of individuals in their entirety, without breaking them up into a series of independent trips and compromising the interdependencies and continuities that exist across a series of trips. This allows the assessment of TCM impacts in a more coherent framework while accounting for secondary and tertiary changes in a traveler's daily itinerary that are brought about as a result of a primary change in response to a TCM. For example, if a person switches from the auto mode to transit for the commute trip (primary change), then stops previously undertaken on the way to or from work may have to be rescheduled into separate home-based trip chains (secondary and tertiary changes).

Research activities are currently ongoing on several fronts to further enhance the capabilities of AMOS and transform it from a short term policy analysis tool into a complete long range forecasting system. New features that are being incorporated into AMOS include the ability to model household vehicle transactions, utilization, and allocation, and perform synthetic generation of households and their activity-travel patterns. Future research activities will attempt at incorporating models of inter-personal interaction and multi-day behavior.

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OVERVIEW OF FAMOS
FLORIDA'S ACTIVITY MOBILITY SIMULATOR
Chapter X

SUMMARY

This chapter provides a brief description of the various modules of the FAMOS package. The description here is designed to provide an outline of the capabilities, data requirements, and structure of each module. The final package accompanying this report is completely based on the Southeast Florida region with the flexibility to accommodate alternative data formats, structures, and networks.

1. SYNTHETIC HOUSEHOLD GENERATOR

1.1 Need for Synthetic Households

Micro-simulation of individual behavior often calls for the generation of synthetic households and their members. There are several reasons why synthetic households are desired. Firstly, applying a disaggregate choice model, which have been proven to be an extremely powerful tool for travel demand forecasting, to predict future behavior requires that the future values of the model's explanatory variables be given at a disaggregate level. Namely, values of all the household and person attributes used as the model's explanatory variables must be obtained for each household or individual for which a prediction is prepared. No planning agencies currently provide such data for forecasting. One approach to obtaining such disaggregate data is to synthetically generate future households and their members along with their attributes. In particular, aging sample households obtained from a survey into the future, presents itself as a logical methodology for forecasting future household and person attributes.

There may be cases where a larger number of households are desired to obtain a necessary level of spatial or temporal resolution in micro-simulation results. In particular, the spatial distribution of trips will be much smoother when trips are simulated for a large number of households. The number of households from a survey, however, may not be sufficient, calling for the generation of synthetic households. Likewise, a survey sample may not offer large enough a number of households or individuals that fall in the particular categories in which the analyst may be interested. Finally, it may be the case that a survey sample is biased, under-representing certain groups of households or individuals. In such a case, under-represented households or individuals may be synthetically generated to supplement the survey sample.

1.2 HAGS

The Household Attributes Generation System, or HAGS (Nishida et al., 2000), is a model system developed to generate synthetic households. HAGS populates each geographical zone with synthetic households while observing marginal distributions of pertinent variables in census and other data, then produces their future demographic and socio-economic attributes for long-range forecasting. The original version of HAGS consists of three components: Household Distributor, Household Ager, and Fixed Activity Generator, as shown in Figure 1(a). The structure may be modified according to data availability as Figure 1 illustrates. Described in this section are these three components of HAGS.[1]

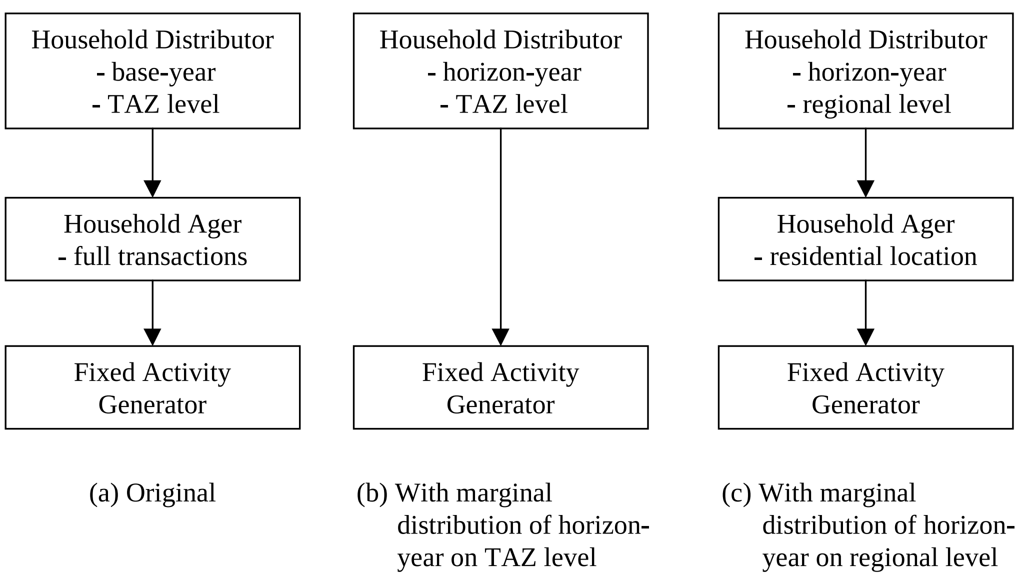

Figure 1. The Structure of HAGS

[1] Details are reported in Nishida et al. (2000).

Household Distributor determines the distribution of attributes of households in the respective zones based on data from the census, travel surveys and other sources. An iterative proportional fitting (IPF) method (Beckman et al., 1996) is applied to base-year marginal distributions of pertinent household and person attributes in each zone and their area-wide joint distribution, to yield a frequency distribution of households by their attributes for each zone. The base-year marginal distributions are obtained from the census and other data, while their area-wide joint distribution is obtained from base-year travel survey data. Each zone is then populated by cloning households from the travel survey data according to the distribution obtained for the zone.

Household Ager simulates the aging of the base-year households generated by the Distributor through the horizon year. Simulated events include: birth, death, marriage, divorce, employment, and residential relocation. The probabilities of these events are obtained from the census and other available statistical data. Pertinent trends, e.g., decreasing household size, increasing single-person households, and increasing labor force participation by women, are accounted for when preparing these probabilities for future years. Household vehicle ownership is endogenously determined using models estimated on the base-year travel survey data. Future driver's license holding by individuals is estimated using a simple cohort model. New households generated through these events are assumed to stay in the study area with those probabilities that replicate observed social changes in the regional population.

Fixed Activity Generator determines the beginning vertex of the morning prism, the ending vertex of the evening prism, the beginning and ending times of fixed activities, for each household member generated by the Household Ager. For non-workers without any fixed activities, there will be just one prism for the entire day, and the Generator determines the beginning and ending vertices for this prism. The location of prism vertices are estimated using the stochastic frontier models developed by Kitamura et al. (2000) and Pendyala et al. (2000). These models incorporate as explanatory variables: person attributes, household attributes, land use characteristics, and attributes of commute trips. Since only work (including work-related business) and school activities will be considered as fixed activities in the Florida implementation effort, work/school starting and ending times are generated probabilistically for each worker or student based on their distributions observed in the base-year travel survey data. Work/school zones are determined for respective workers/students using multinomial logit models of work/school location choice. The models may be viewed as a version of production-constrained gravity models. Their explanatory variables include land use characteristics, measures of separation between zones, and some of the variables used in the stochastic frontier models.

1.3 Modification of the HAGS Structure

The original version of HAGS does not presuppose any marginal distributions for the horizon year, and the Household Ager generates the future distributions endogenously. To accomplish this, however, the Household Ager needs to be developed based on extensive and detailed data on socio-demographic changes that are needed to determine probabilities of events that cause transitions in various household attributes, including: birth, death, marriage, divorce, employment, and residential relocation (Figure 1 (a)).

If the marginal distributions of household attributes can be obtained for the horizon year at the TAZ level, the Household Distributor is capable of directly generating households for the horizon year for respective TAZs to fit the marginal distributions. The Fixed Activity Generator, then, can be deployed to determine fixed activity patterns for each household member generated by the Distributor (Figure 1 (b)). In this case, the Household Ager is not needed, eliminating the need to collect data on transitions in household attributes.

If the horizon-year marginal distributions of household attributes are available only at the regional level, the Household Distributor can be deployed to generate the region-wide distribution of households for the horizon year, then the Household Ager can be applied to determine the residential location for each household. Residential location choice models may be developed using static information contained in typically available travel survey data (Figure 1 (c)).

1.4 Data Requirements

Assuming marginal distributions of pertinent household attributes are available for the horizon year, each component of HAGS requires the data as indicated below.

The Household Distributor requires:

- The Southeast Florida survey data to produce sample joint distributions of demographic and socio-economic variables, and
- Marginal distributions of demographic and socio-economic variables, including: population, household life cycle, employment, and housing type, for the horizon year, by TAZ (or region-wide if distributions by TAZ are not available).

The Household Ager (applied as in Figure 1(c)) and the Fixed Activity Generator require:

- The Southeast Florida Travel Survey data to estimate the model components,
- Socio-economic and land use data, including the number of dwelling units, the number of employees, the number of business establishments, and the number of schools by type, as explanatory variables of the residential location choice models and the work/school location choice models. The data for the base year are used for model estimation and data for the horizon year are used to generate the residential location and work/school location for each synthesized individual in the horizon year, and
- Network data, including uncongested and congested skim tree data by auto, carpool, transit, walk, for the base year to estimate the residential location choice models, the work/school location choice models and the prism vertices models; and horizon year skim tree data to generate residential and work/school locations and trip timings for each synthesized individual in the horizon year.

1.5 Sample Estimation Results

An example of application results is shown for a randomly selected zone in Table 1. A joint distribution obtained from a 1990 travel survey sample (Table 2(a)) and marginal distributions obtained from the census data (Table 2(b) - (d)) were used as inputs. The objective of the exercise was to generate a joint distribution of households that match the marginal distributions obtained form the census data, while utilizing the joint distribution obtained from the travel survey. The results (Table 2(e)) show that the marginal distributions of the estimated joint distribution match those from the census while preserving the information about the correlations among the attributes (e.g. odds ratio) obtained from the travel survey.

Table 1. Estimation of the Joint Distribution of Housheolds by Household Size, Presence of the Elderly and Children, by IPF

		Household size						
		1	2	3	4	5	6+	total
Household with member(s) of age 65+								
Age of youngest member	0-5	0	0	0	2	1	6	9
	6-17	0	1	1	1	1	3	7
	18+	66	62	27	8	1	2	166
Household without member(s) of age 65+								
Age of youngest member	0-5	0	2	25	14	16	5	62
	6-17	0	10	34	47	8	1	100
	18+	255	81	39	27	4	1	407
Total		321	156	126	99	31	18	751

(a) Joint distribution obtained from travel survey data

	1	2	3	4	5	6+	Total
Census	15653	8216	5288	5429	2002	881	37469
(%)	41.8%	21.9%	14.1%	14.5%	5.3%	2.4%	100.0%
Survey	321	156	126	99	31	18	751
data (%)	42.7%	20.8%	16.8%	13.2%	4.1%	2.4%	100.0%

(b) Marginal distributions of household size by census and travel survey

	With	Without	total
Census	8296	29173	37469
(%)	22.1%	77.9%	100.0%
Survey	182	569	751
data (%)	24.2%	75.8%	100.0%

(c) Marginal distribution of household with and without member(s) of age 65+ by census and travel survey

	0-5	6-17	18+	total
Census	3191	5422	28856	37469
(%)	8.5%	14.5%	77.0%	100.0%
Survey	71	107	573	751
data (%)	9.5%	14.2%	76.3%	100.0%

(d) Marginal distribution of the age of youngest household member by census and travel survey

		Household size						
		1	2	3	4	5	6+	Total
Household with member(s) of age 65+								
Age of youngest member	0-5	0	0	0	80	51	252	383
	6-17	0	43	36	47	60	149	334
	18+	2853	3016	1102	426	68	113	7579
Household without member(s) of age 65+								
Age of youngest member	0-5	0	84	885	647	947	244	2808
	6-17	0	497	1417	2558	558	58	5088
	18+	12800	4576	1848	1671	317	65	21277
Total		15653	8216	5288	5429	2002	881	37469

(e) Estimation result of joint distribution

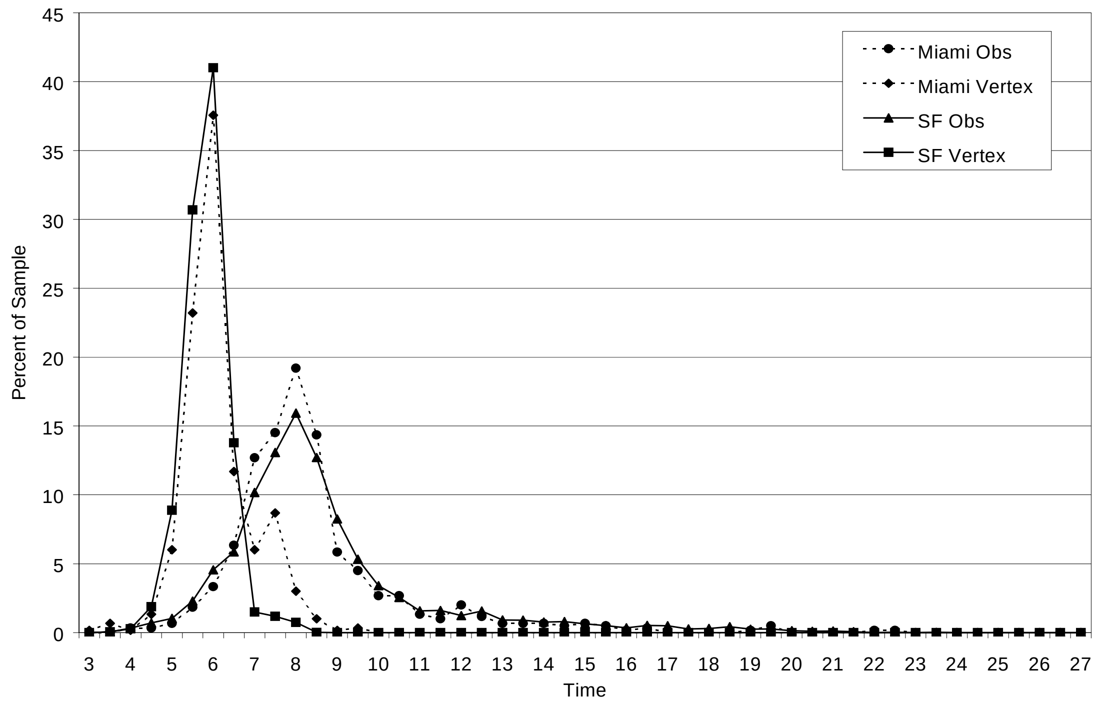

Figure 2(a). Distribution of Expected Vertex Locations and First Departure From Home

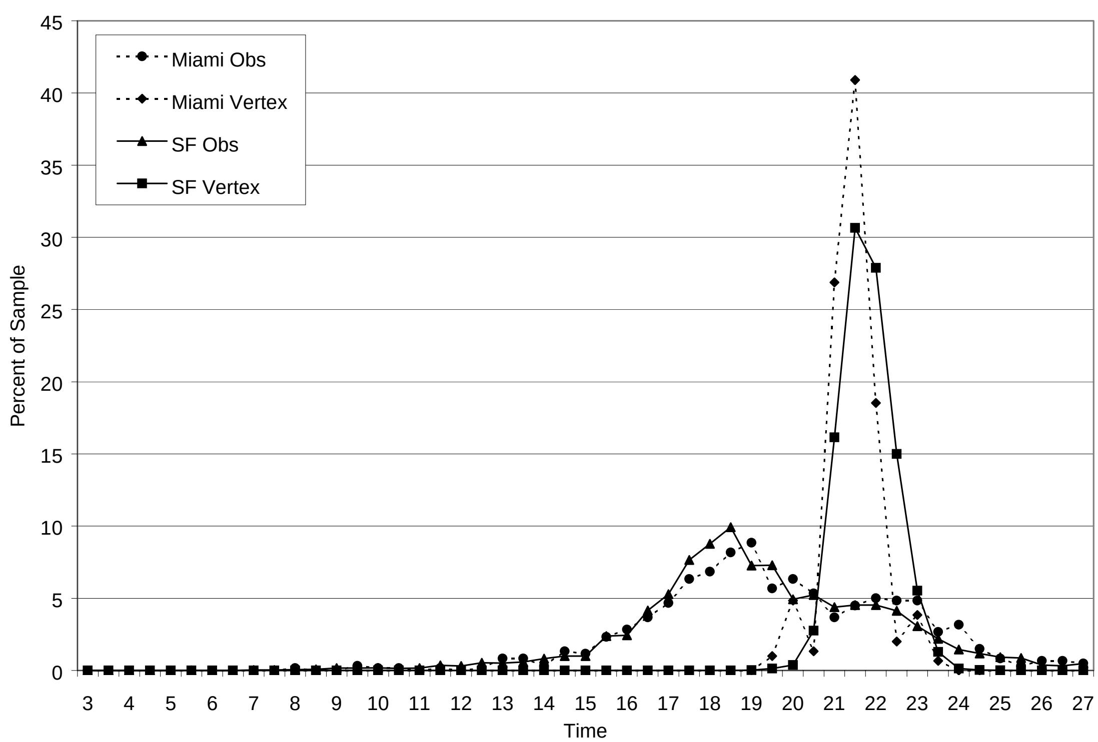

Figure 2(b). Distribution of Expected Vertex Locations and Final Arrival at Home

As components of the Fixed Activity Generator, the stochastic frontier models of the beginning vertex of the morning prism and the ending vertex of the evening prism were estimated. This estimated used results of the travel surveys conducted in the nine counties of the San Francisco Bay Area in 1996, and in the Miami-Dade County area of Florida in 1998. The results shown in Figure 2 suggest: the two samples show stronger similarities in the distributions of expected vertex locations and observed times of the first departure from home, than in those of expected vertex locations and observed final arrival times. It can also be observed that: there is about a two-hour difference between the expected vertex of the prism and the actual time of departure from home; the distributions of expected ending vertex locations peak at about 9:30 PM; most individuals arrive home about 2.5 to 3 hours prior to their vertex locations.

2. ACTIVITY-TRAVEL SIMULATOR: PCATS

2.1 Objectives of Activity-Travel Simulator

PCATS (Prism-Constrained Activity-Travel Simulator) is a system of behavioral models that together simulate individuals' activity and travel in urban space. All model components are statistically estimated and adjusted using household travel survey results. The Florida implementation of the PCATS/DEBNetS system is based on the 1999 Southeast Florida survey.

PCATS simulates behaviors of sample households in time and space over a one-day period. Results of the simulation may be visualized as a set of trip records for each household member, with information on trip purpose, starting and ending times, origin and destination zones, and travel mode.[2] These data are accompanied with information on person and household attributes that are typically contained in travel survey data. An example of an individual's simulated daily travel pattern is shown in Figure 3.

[2] Efforts are ongoing to simulate parking behavior in PCATS.

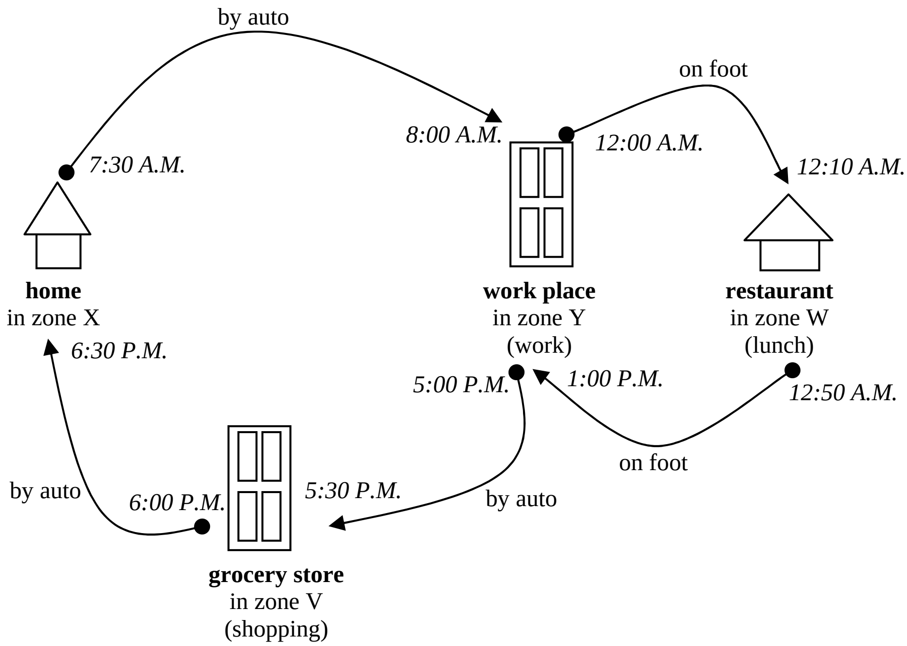

Figure 3. An Example of Daily Travel Patterns Simulated by PCATS

Sample households may contain synthetic households, generated based on census data and travel survey results and distributed over the study area to represent its current, or future, population. As noted earlier, the number of sample households can be adjusted to achieve desired levels of precision and spatial/temporal resolution in simulation results. In general, more precise results can be obtained by increasing the number of sample households by generating additional synthetic households. If certain segments of the population are targeted in the analysis, then these segments may be over-represented in the sample, again by generating more synthetic households that belong to these segments.

2.2 Representing Constraints on Travel

The development of PCATS was motivated by the recognition that various constraints imposed on individuals' activity and travel, are not well represented in conventional models of travel behavior.[3]

[3] For details, see Fujii et al. (1997) and Kitamura & Fujii (1997). The latter reference contains validation results of PCATS.

Emphasized in PCATS, therefore, are the constraints imposed on the individual's movement in geographical space along time. Because the speed of travel is finite while the time available for travel and activity is limited, the individual's trajectory in time and space is necessarily confined within "Hägerstrand's prism." This is shown in Figure 4. In the figure, point A represents the time point through which the individual must stay at location H. For example, this may be the earliest possible time that a commuter can leave home. Point B represents the time point by which the individual must be at location W. This may be the time by which the commuter must report at his work place. If urban space can be represented one dimensionally as in the figure, and if the commuter can travel at speed v, then the domain in time and space that the commuter can occupy can be represented by the parallelogram as shown in the figure. This parallelogram is Hägerstrand's prism.

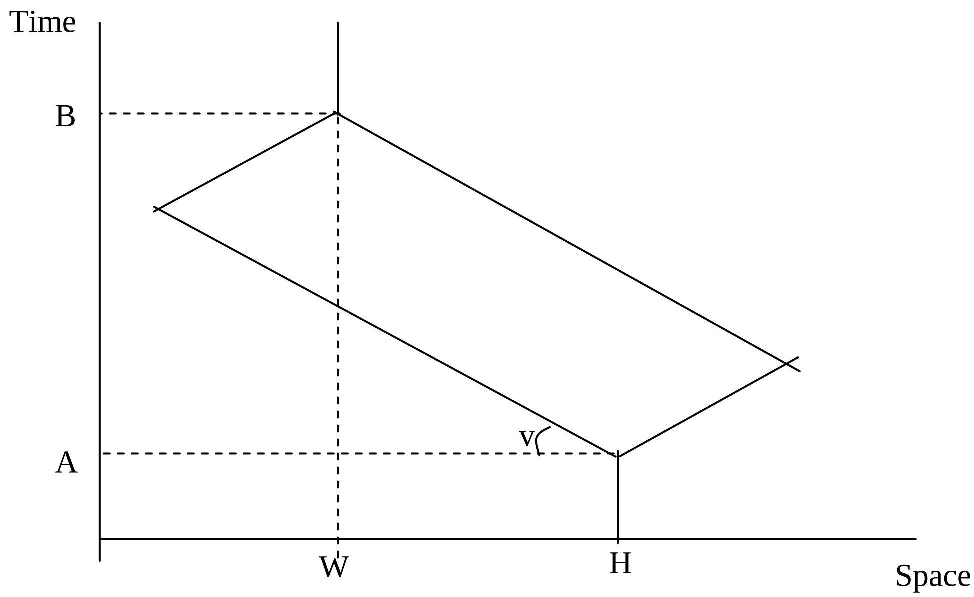

Figure 4. Hägerstrand's Prism

Prior to the simulation of activity-travel behavior, PCATS identifies the set of prisms that govern an individual's behavior, then generates activities and trips within each prism while observing constraints involving private travel modes and operating hours of public transit. Prisms are defined over a system of traffic zones (TAZs). PCATS first determines for each individual the periods in which the individual is committed to engage in a certain activity, or a bundle of activities, at a predetermined location.[4] These periods are called "blocked periods" in this report. For example, a worker's work hours may constitute blocked periods.

The complement of a set of blocked periods for an individual is a set of "open periods." For example, the lunch break of a worker constitutes an open period. A Hägerstrand's prism is established for each open period that an individual has. This is done through the following procedure. Given the mode of travel being used, it is determined for each zone whether the zone can be visited within the open period and, if so, how much time can be spent in the zone before starting to move to the location of the next committed activity. This is repeated for all zones to identify the earliest possible arrival time at, and the latest possible departure time from, each zone. These arrival times and departure times comprise a prism for the open period.[5]

Blocked periods for workers are typically determined by work schedules, e.g., between 8:00 A.M. and 12:00 noon and between 1:00 P.M. and 5:00 P.M. would be typical blocked periods (see Figure 5). As in Damm (1982), then, a worker's day may be assumed to include three prisms: one before work, one during the lunch break, and one after work (Figure 5). The beginning time of the first prism before work and the ending point of the last prism after work are not well defined. In the Florida implementation of PCATS, models have been developed to estimate unobserved prism vertices (Kitamura et al., 2000; Pendyala et al., 2000).

Another set of constraints incorporated into PCATS is concerned with the availability of travel modes. As noted earlier, the availability of public transit is determined by its operating hours. Outside the operating hours, public transit is eliminated from the choice set of the destination-model choice models described later. PCATS also tracks the location of private travel modes such as the automobile and bicycle. For example, if a private automobile is not located at the origin of a trip, then it will be eliminated from the choice set of the destination-mode choice models.

[4] In this report the set of activities pursued at a location is called an activity bundle, and the activity bundle is treated as the unit of analysis. Therefore there always is a trip between two successive activity bundles. It is in general unknown from standard travel survey data if an activity bundle is fixed in time and location. In the exercises presented in this paper, work, work-related business and school activities are treated as fixed activities.
[5] Prisms are defined for auto and public transit, respectively. The set of zones contained in a prism by travel mode defines the choice set in the mode-destination choice models described later.

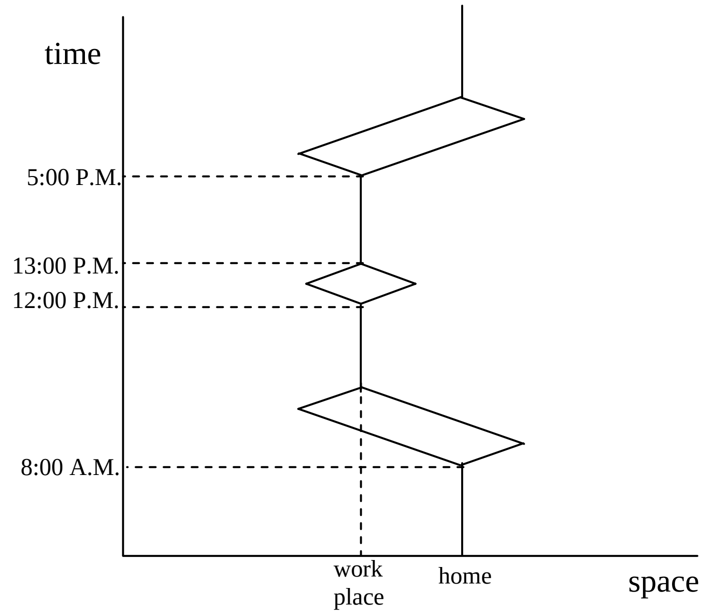

Figure 5. Typical Worker's Prisms

Generation of Activities

In PCATS, the probability that a particular daily activity-travel pattern will be made is decomposed into a series of conditional probabilities, each associated with one activity bundle and the trip to reach the location where it is pursued. The conditional probability of an activity bundle is further decomposed to yield the following three sets of model components: 1) activity type choice models, 2) destination and mode choice models, and 3) activity duration models. These models are applied repeatedly to simulate activities and trips one by one within each open period. This is shown in Figure 6. Table 2 shows the segments on which these models were developed in the Florida implementation of PCATS.

Table 2. Segmentation Adopted in Model Development

Models	Florida Case Study
Activity Type Choice Models	{Workers, Students, Others}
Destination-Mode Choice Models	{Work, Non-work} × {Workers, Students, Others}
Activity Duration Models	{Social/ Recreational, Shopping, Other Non-work} × {Workers, Students, Others}

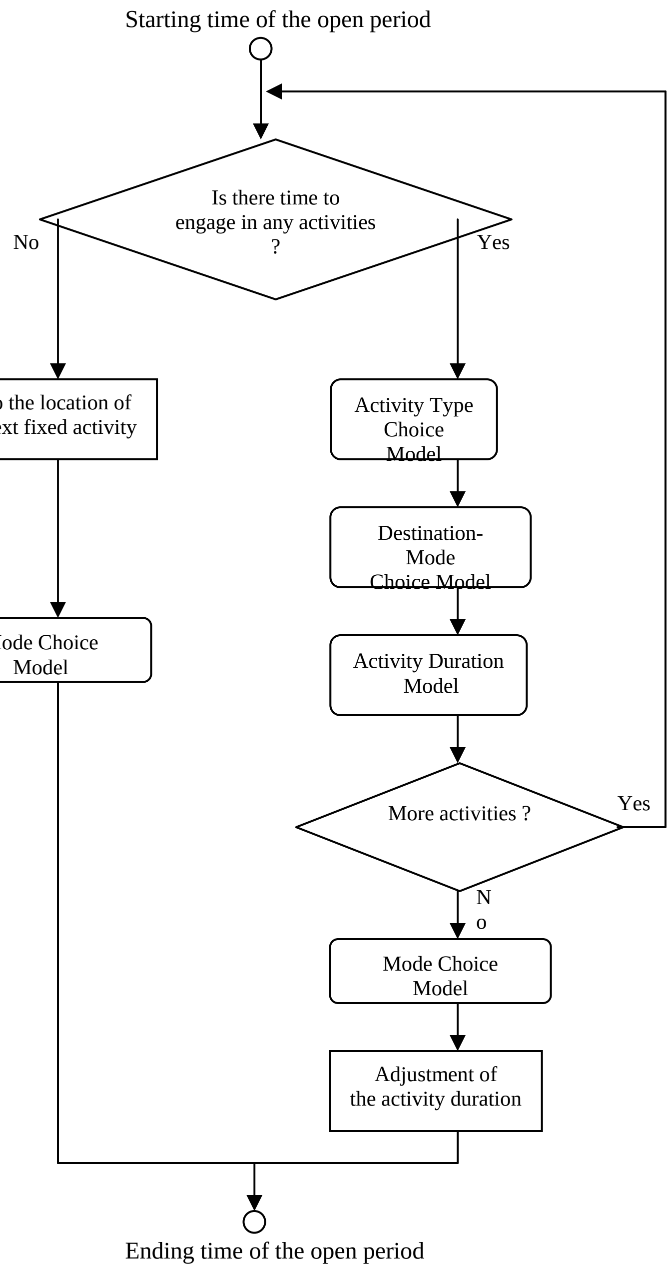

Figure 6. Structure of PCATS

2.3 Activity Type Choice Models

The activity type choice models are two-tier nested logit models. The upper tier comprises two categories of activity bundles: (A) in-home activities, and (B) out-of-home activities. The alternatives nested under (B) may include the following activity types: meal, social, grocery shopping, comparison shopping, hobbies and entertainment, and sports and recreation. These are defined in terms of the trip purposes as defined in the travel diary data used in the study.

The type of the first activity bundle in an open period is determined using an activity type choice model. In the models, the probability that a given activity type will be selected decreases as the time available in the prism becomes shorter relative to the distribution of activity durations for that type of activities. In other words, the models reflect the tendency that activities tend not to be pursued if there is not enough time for them. The time of day is another important factor that affects the choice of activity type. The explanatory variables used in the activity type choice models in the Florida implementation of PCATS are: age, sex, household auto ownership, household size, and the time of day. These models have been developed using the 1999 Southeast Florida survey data.

Given the activity type, a destination-mode pair is next determined using a destination and mode choice model. Following this, the duration of the activity at the destination is determined. At this point, the time of day when, and the location where, the next activity ends can be determined. The activity type choice model is applied again to simulate activity engagement in the remainder of the open period, using updated amount of time available. This process is repeated until all available time is exhausted in the open period.

2.4 Destination-Mode Choice Models

The destination and mode choice models are also nested logit models. Alternative destinations constitute the upper-level alternatives, and available travel modes are nested under each destination alternative. An example set of explanatory variables is presented in Table 3.

Table 3. Explanatory Variables of Destination-Mode Choice Model: For Workers, Non-work Activities

Zone Attributes
zone size
population density
number of commercial establishments
Household/Person Attributes
age
sex
auto ownership
Trip Attributes
travel cost
travel time
number of transfers
Activity Attributes
current time of day
location type of current activity
location type of next fixed activity

Geographical zones are used in the current version of PCATS to represent location.[6] As noted earlier, the geographical extension of the prism is evaluated for each travel mode, and destination-mode pairs are excluded from the choice set if they do not fall in the prism. The amount of time available at the destination is one of the determinants of the choice probability along with the attributes of the destination zone and the trip to the destination by respective travel modes. Travel modes are classified into auto drive alone, auto multi-occupant vehicle, public transit, and walk and bicycle.

Given a travel mode, PCATS evaluates travel time to the destination zone. If the automobile is used, a zone-to-zone travel time is obtained through dynamic network simulation using DEBNetS. If public transit is the travel mode, PCATS applies static mean zone-to-zone travel times that have been pre-calculated. Travel times by bicycle or walking are computed using an assumed mean speed of travel (12.0 mph for bicycle and 4.0 mph for walking) and the zone-to-zone distance. Given a travel time, the starting time of the activity at the destination is determined.

[6] Destination choice models that adopt a quasi-continuous coordinate system are being developed (Kikuchi, Yamamoto et al., 2000).

2.5 Activity Duration Models

Following these, the duration of the activity at the destination is determined using the activity duration model[7] corresponding to the activity type. The activity duration models in PCATS are hazard-based, split population survival models. In these models, the maximum possible activity duration is first determined based on the size of the prism, which is a function of the speed of travel, the location of the trip origin, the location of the current activity, and the location of the next fixed activity. Then, an individual is assumed to decide whether he allocates all the time within available in the current open period to a single activity, or to two or more activities. Binary logit models are developed to represent this binary choice.

If a person chooses the former option, the activity duration is the maximum possible activity duration in the current open period. If the person chooses the latter option, the duration of the next activity is determined using a hazard-based duration model. A set of hazard-based duration models is deployed in PCATS. A model is developed for each activity type, and the parameters of the distribution (the mean and a shape parameter) are formulated as functions of personal attributes and other explanatory variables. Weibull distributions are exclusively used in the current version of PCATS. The examples of explanatory variables used in the duration models are person and household attributes, time of day, time availability, location type indicator (see Table 4). The distribution as given by the duration model for the activity type is right truncated, i.e., a probability mass equaling to the probability that the activity duration will exceed the maximum available time is placed at the maximum. The resulting mix distribution is used to generate activity durations in the simulation. The two sub-models, the binary logit model and hazard-based duration model, are estimated simultaneously for each activity type.

[7] Hazard-based duration models are applied. In particular, split population survival models (Schmidt & Witte, 1989) are adopted.

Table 4. Explanatory Variables of Split Population Survival Models: For Workers, Shopping

Household/Person Attributes
age
sex
license
household size
car-ownership
Activity/Prism Attributes
current time of day
the possible maximum activity duration
location type of current activity
location type of next fixed activity

As noted earlier, once the attributes of an activity bundle are all determined, the procedure is repeated for the next activity bundle in the same prism. Activity and travel in each open period is thus simulated by recursively applying these model components, while considering the history of past activity engagement. Activity starting and ending times are determined based on simulated activity durations and travel times obtained from DEBNetS in case of auto trips, or pre-calculated in case of transit trips. The procedure is repeated until each open period is filled with activities.

2.6 Data Requirements

Estimating the components of PCATS and simulating an individual's activity-travel pattern in the target area, requires the following data:

- Household/person attributes (e.g., age, sex license, household size, car-ownership)
- Attributes of blocked periods (e.g., the beginning time, ending time, type, and location of each fixed activity within each blocked period)
- Level of service data by mode for each zone pair in the study area (e.g., travel time, travel cost, and number of transfers)
- Zone characteristics (e.g., area, population, population density, number of employees, and number of commercial establishments).

Validation results of HAGS and PCATS are provided in the FAMOS Users Guide accompanying the FAMOS software package.

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