A COMPARISON OF COMMUTER ACTIVITY SEQUENCING AND STOP-MAKING BEHAVIOR ACROSS GEOGRAPHICAL CONTEXTS

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ABSTRACT

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 paper 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.

Keywords: Activity schedule, stop organization, activity sequence, geographic comparison, commuter behavior, trip chaining

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 paper 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 paper 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 paper should be interpreted while keeping these possible interlinkages in mind.

In this paper, 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 paper. 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 paper 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 paper 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 paper, 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 paper 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 paper, 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 paper 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 paper, 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 paper, 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 a previous paper comparing commuter samples drawn from the same two survey data sets, Gangrade, et. al. (2000) show that overall activity durations and time allocation patterns (i.e., the time spent on each activity type) are very similar. They find that time use patterns and activity durations show greater similarities than activity and trip frequencies. In a following paper, Pendyala, et. al. (2001) show 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. 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 paper 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 paper sheds light on this question by comparing both stop making behavior and activity sequencing patterns across commuter samples. Within the context of this paper, 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 paper.

There are potentially several other types of analyses about activity sequencing and activity scheduling that merit investigation. These are beyond the scope of this paper, 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 paper 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 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 paper, 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.

COMPARISON OF 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 paper.

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.

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.

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.

COMPARISON OF 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 paper 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 paper 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.

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. 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.

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.

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 paper 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 paper 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 papers, 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 paper 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.

ACKNOWLEDGMENT

The authors owe a debt of gratitude to Ryuichi Kitamura and Toshiyuki Yamamoto of Kyoto University who provided the initial ideas for this analysis. The authors thank the Florida Department of Transportation for providing funding for the research described in this paper. The authors are extremely grateful to Ken Vaughn and Chuck Purvis of the San Francisco Bay Area Metropolitan Transportation Commission for providing the data used in this study and taking the time to answer many questions. The contents of this paper reflect the views of the authors who are responsible for the facts and the accuracy of the information presented herein. The contents do not necessarily reflect the official views or policies of the Florida Department of Transportation.

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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

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

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

TABLE 4 Comparison of Out of Home 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

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

TABLE 6 Comparison of Out of Home Activity Sequencing Before Work

Sequence	San Francisco		Miami	
	% Valid* N=706	% Total N=4331	% Valid* N=152	% 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

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

Sequence	San Francisco		Miami	
	% 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

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

Sequence	San Francisco		Miami	
	% Valid* N=993	% Total N=4331	% Valid* N=318	% 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

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

Sequence	San Francisco		Miami	
	% Valid* N=727	% Total N=4331	% Valid* N=55	% 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

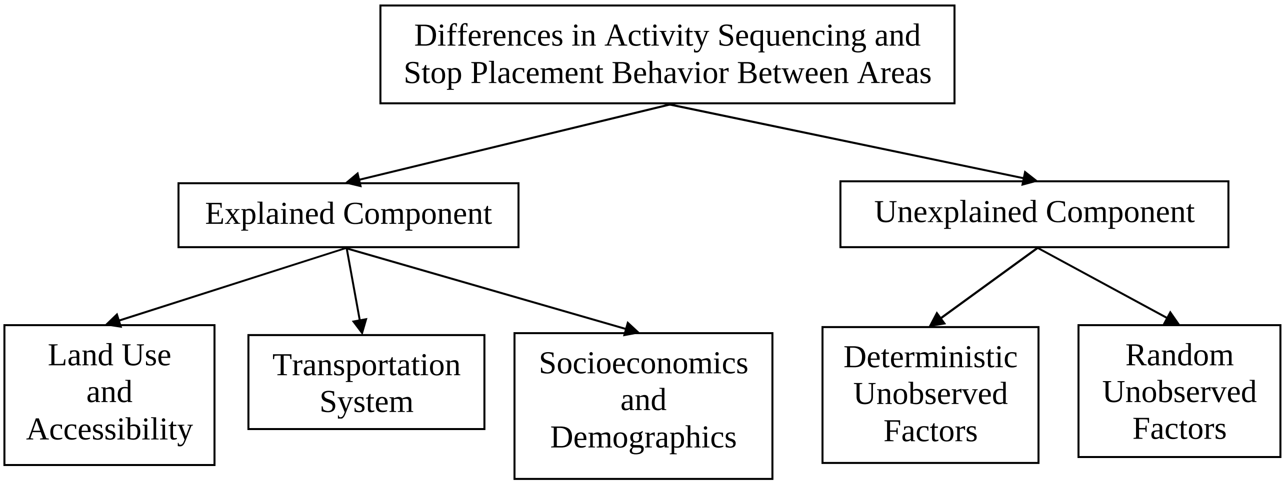

FIGURE 1 Framework for Analyzing Differences in Activity Patterns Between Geographic Areas