TRAVEL DEMAND MODELING: ACTIVITY ANALYSIS FOR PERSON ALLOCATION AND INTERNET USE

By

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CHAPTER I

INTRODUCTION

1.1 Background

The limitations of trip-based approaches to travel demand modeling, especially its deficiencies with regard to dealing with dimensions such as trip-chaining, departure time, household interactions, etc. have been well-recognized. These shortcomings result from the fact that trip-based analysis does not explicitly account for the fact that the demand for travel is derived from the need for activity participation at different locations (Pas et al., (1996); Kurani et al., (1996); and Pendyala et al., (1996)). One consequence of these shortcomings is that trip-based models are not policy sensitive to changes in underlying activity patterns and associated behavior, and therefore are more correlational rather than causal in character. Given these limitations, there is growing interest in analyzing and representing individual traveler behavior together with the underlying activity patterns (Kitamura, (1996); Axhausen and Garling, (1992); and Bhat, (1997)). Recent developments such as increased computational power, availability of richer activity-episode level disaggregate data, and the development of more flexible statistical models are also supporting the analysis of interdependent, and more complex traveler decisions than ever before (Bhat, (1997); Bowman et al.,(1996); Revelt and Train, (1998); and Kitamura et al., (1996)).

Several behavioral dimensions that come under the scope of activity-based approaches (Kitamura, (1995)), but were not adequately captured in trip-based traditional four-step models, include:

- Constraints that affect activity and travel patterns (e.g., work start time, store hours, vehicle sharing, and parking cost)
- Scheduling of activities and trips over time and space: for instance, when to engage in what type of activities, in what sequence, and at what locations.
- Within-day variations in behavior and demand, as another special aspect of behavioral change (e.g., part-time carpooling, trip-chaining, task sharing),
- Trip-chaining: combining stops into a trip-chain,
- In-home/out-of-home activity substitution (e.g., going out for a movie vs. watching TV at home), which is directly related to trip generation,
- Inter-personal linkages, which may take on the form of task and resource assignment (e.g., vehicle allocation within a household) and resource sharing (e.g., carpooling by family members),

joint activity engagement (family dinner at a restaurant), and activity generation (e.g., a child's baseball/recreational activity generating the parent's activity of chauffeuring the child).

Capturing these richer and inter-related activity-travel dimensions poses several conceptual, measurements, data and modeling difficulties when compared to trip-based models. Despite these challenges, the activity-based framework offers the following advantages which more than offset its disadvantages (Kitamura, (1996)) as follows:

- *richer representation of time of day choices*: which enables predicting travel behavior more holistically;
- *more accurate evaluation of transportation control measures*: this framework is capable of realistically assessing the impact of congestion mitigation or other transportation control measures more accurately by considering impacts on daily travel, and by using the richer set of decision dimensions noted above.
- *more comprehensive view than trip-based models*: this framework treats a daily activity-travel pattern as a whole, thus avoiding the shortcomings of conventional trip-based methods;
- *increased realism*: since this approach explicitly includes effect of constraints such as vehicle ownership, household role, etc. , the approach facilitates more realistic prediction and scenario analyses;
- *more policy sensitive*: activity-based models provides planners with a richer range of tools since the approach can be used to influence activities directly rather than influencing trips indirectly. For instance, the approach can be used to analyze the effect of new activity opportunities (e.g. day-care facilities at work), change in activity patterns (increased work-duration or work flexibility) etc.

Due to these conceptual advantages of activity-models, a relatively large body of knowledge has started to emerge in relation to the various aspects of activity-based analysis of travel behavior and demand. In this context, studies have mostly focused on the following dimensions of analysis: i) activity generation including number of tours, and trips produced by a household, ii) activity scheduling including timing of activities, duration, and timing of trips, iii) activity allocation which pertains to allocation of activity episodes to different tours performed by individuals in the household. The research along these lines is briefly reviewed in Chapter 2. While most studies have focused on the first two of these dimensions, this thesis focuses on two dimensions of activity-travel behavior which have received comparatively less attention. This thesis aims to investigate activity allocation, particularly, the allocation of activities between household members, and the role of interactions between Internet and

Communications Technology (ICT) use, activity and travel patterns. The allocation between household members is important in the context of various aspects of travel demand including trip-chaining, vehicle ownership and use levels, and time-of-day decisions, with implications for congestion, air-quality, and others. The interest in ICT technologies on activity patterns stems from their potential to increase connectivity and access, as well as their potential to eliminate certain types of trips. Given their conflicting effects on travel demand, and the rapid growth in use of these technologies, a systematic examination of how ICT use affects activity patterns, and travel patterns is essential.

The rest of this chapter is organized as follows. Section two describes the motivation for this study from an empirical and practical perspective. The next section discusses the objectives and the scope of this thesis. The approach used in this study is also outlined in this section. The final section (Section 1.4) presents the structure of the thesis and provides a brief overview of the following chapters.

1.2 Motivation

This study aims to analyze activity-travel patterns of households in the context of travel demand analysis for transportation planning purposes. Specifically, the following two dimensions will be investigated:

1. Person allocation: allocation of activities among household members, and
2. the influence of Information and Communication Technologies (ICT's) on activity and travel patterns.

The main activity types under consideration in this study are discretionary and maintenance activities. In contrast, discretionary activities are those that can be performed at the discretion of the household or its members (for instance, recreational, social, games, community/civic activities, volunteer, etc.). For instance, a household may choose to participate in a few, if any, recreational activities on a certain day. In keeping with its flexible nature, the choice of location, and timing of discretionary activities is also flexible. Consequently, substitution across household members may be permissible in some discretionary activities. Maintenance activities, on the other hand, are those required for the maintenance of the household and include: shopping, banking, laundry, household and personal chores, appointments (medical etc.), eat meal, and pick-up/drop-off activities etc. There is a wide range of variation with regard to the flexibility in location, timing, and person participating in maintenance activities depending on the specific activity purpose. In this study, subsistence activities are not the focus of analysis since these activities tend to be personalized with limited potential for change of person, location or timing dimension. Unlike, maintenance and discretionary activities, subsistence activities are excluded from this study. Subsistence activities include activities pertaining to work, school, and others that are essential activities that must be performed at fixed locations/times for most individuals.

Furthermore, these are highly individualized activities that cannot be performed by others in the household.

The motivation for this study is two-fold: first, person allocation to activities is important from a behavioral perspective, since person allocation patterns can strongly influence vehicle occupancy levels, trip-chaining and mode choice and thus have significant implications for congestion, air-quality, and demand estimation for transit. For instance, how a household with one car allocates the activities and the vehicle across household members can determine the mode choice and timing of the various trips in the household. The allocation of several activities and trips to a single person (say the employed head of the household) may result in a greater degree of trip consolidation and trip-chaining, resulting in lower emissions rate, where several of these trips may be performed during the evening peak period or post-peak period. In contrast, in a household (with many adults and many vehicles), where the tasks may be delegated more evenly across members, more trips may result and may be staggered over time (possibly leading to lower congestion), resulting in fewer chained trips and worse environmental impact. In this respect, this study aims to explicitly analyze the allocation of maintenance and discretionary activities to household members.

From a practical standpoint, person allocation of activities has substantial practical implications in the context of: evaluation of vehicle occupancy based traffic management strategies such as: High Occupancy Vehicle (HOV) and High Occupancy Travel (HOT) lanes (person allocation may be used to determine the type of households and the conditions when activities are less likely to be flexible with regard to person occupancy - solo versus joint activities). Similarly, disregarding the constraints on trip-chaining and joint travel (that may arise due to household interaction and may favor one mode over another) can result in erroneous and misleading demand estimates while assessing the effectiveness of alternative transit improvement policies. For instance, the improvement of travel time or waiting time through more frequent services may prove to be ineffective and expensive, if there is a significant demand for trip-chaining on a route that may not be served by the transit. Furthermore, the person allocation patterns can also affect the departure time of trips which in turn affects the time-varying nature of congestion patterns on the network. Given these motivating considerations, there is a need for richer behavioral and policy sensitive representation of person allocation in activity-based microsimulation models of travel demand.

Second, recent advances in Information and Communication Technologies (ICT) make activities possible to conduct virtually, thus obviating the need for physical travel, at least for some types of activities. Activities that may be performed virtually include: online shopping, telecommuting, teleconferencing, information gathering, and maintenance activities (e.g. online banking). Further, as the prices of ICT products and services fall due to improved economies of scale, the adoption and use of these ICT devices (e.g. cell phones) continues to grow rapidly. These socio-technological developments offer individuals both the opportunity and the ability to substantially alter their activity and travel patterns. ICT use may contribute towards reducing urban congestion and air-quality problems (by replacing travel with virtual activities); on the other hand, they may also generate significant additional and induced travel due to the increased connectivity and access to resources that they provide. Thus, empirical insights on how the growing ICT use affects travel patterns and vice-versa has important implications for travel demand forecasting. While some researchers have investigated the effect of internet technologies on specific activities such as shopping or work trips, the interaction between ICT, activity, and travel patterns has not been adequately analyzed. Therefore, this paper investigates the linkages between ICT use, activity participation decisions, and travel patterns using recent empirical activity-diary data from the San-Francisco Bay Area (MTC, (2000); and Vaughn, (2003)).

ICT use can lead to a range of changes in activity travel patterns, including substitution, generation, and modification (Mokhtarian et al., (1997); and Krizek et al., (2003)). Substitution and modification of trips can have a significant impact on transportation system performance. For instance, the availability of virtual activities could result in fewer and/or more efficient trips in some cases. On the one hand, ICT use can promote more frequent yet more efficient trips, whereas, on the other hand ICTs can eliminate certain types of trips. Thus, ICTs can significantly affect mobility and travel demand, although the magnitude and nature of their impact is unclear as yet and requires more detailed analysis. The relative impacts on substitution, generation, and modification have important implications from a travel demand management perspective. The greater connectivity and mobility also indicates the potential for aggravation of urban congestion and air-quality problems with increasing connectivity and growing adoption of ICT systems.

1.3 Objectives and overview of approach

Based on the motivating considerations noted above, the following six objectives are considered in this study. The first three relate to person allocation models, and the last three are related to activity participation and ICT use:

1. To develop a methodology to model person allocation to activities that partially addresses the shortcomings of existing models.
2. Investigate the effect of socio-demographic, household role, and trip attributes on activity allocation and explore the role of constraints on time, vehicle availability, cost, and coordination on activity allocation among household members.

3. Analyze differences between households in allocation of persons to activities and the underlying factors.

4. Propose empirical models and analyze the ICT use patterns of individuals.

5. Investigate the linkages between ICT use and physical/virtual activity participation for discretionary and maintenance activities.

6. Analyze the interactions between observed daily travel patterns (represented by the dimensions of trip frequency and trip duration), ICT use and individual's activity attributes.

To achieve the first three objectives, this thesis proposes a series of disaggregate discrete choice models with suitable econometric specification for the analysis of person allocation of activities (i.e. to household members). The differences in allocation between maintenance and discretionary activities are analyzed explicitly by calibrating two sets of logit-based multinomial choice models. The analysis in this study is based on the disaggregate activity travel data from the Bay Area Travel Survey 1996, which contains rich data on activity episode records. This data was obtained using a two-day activity diary survey from 3,344 households. In this survey, data was collected on activity participation of individuals including details of each activity episode by each household member (more than 14 years of age). The activity data includes purpose, location, and duration of each activity, along with the associated travel attributes.

To address the objectives in relation to the ICT objectives (objectives 4-6), this study uses disaggregate activity travel data from the Bay Area Travel Survey 2000 (MTC, (2000)), since the earlier survey data did not contain ICT use information. In particular, a series of discrete and continuous statistical models are estimated using the rich and highly disaggregate activity diary from the San-Francisco Bay Area. With regard to ICT use and virtual activity participation, five binary discrete choice models are estimated. The first is a binary logit model for analyzing whether an individual used internet on a given day or not. The remaining four models investigate the use of internet (yes/no) for various activity types such as: subsistence, browsing, recreational and maintenance activities as defined by the discrete binary dependent variables. The second set of models analyzes the following dimensions: in-home versus out-of-home discretionary episode choice, in-home versus out-of-home maintenance activity participation (using binary logit models), and the durations of in-home and out-of-home episodes for these activities (using regression models). The third set of models focuses on two travel dimensions, namely, duration and frequency of daily trips by an individual. In this set of models, the effect of ICT use, individual and household attributes on daily travel decisions are investigated. The travel activities cover multiple modes including driving, walking, bus, and others. The duration analysis is conducted using a regression model, whereas, frequency analysis is performed using a Poisson regression model. Statistical significance tests are used to identify main factors affecting the relationship between key explanatory variables and dependent variables described above.

1.4 Structure of thesis

Chapter 1 describes the conceptual basis for pursuing activity-based travel demand modeling and its advantages. Further the objectives of this study and the motivation for investigating these objectives are also discussed. Chapter 2 reviews relevant literature on activity based analysis and highlights significant findings in existing literature in relation to the objectives of this study. This chapter also identifies some key limitations and gaps in existing studies with regard to the objectives of this study. In Chapter 3, a model is proposed for the analysis of activity allocation across household members. The key factors affecting the activity allocation decision are identified by estimating an empirical model using the 1996 San-Francisco Bay-Area activity survey data. The differences between households are compared based on the modeling results. The framework for modeling and analyzing the influence of ICT patterns on activity and travel behavior are presented in Chapter 4. The empirical effects of ICT use, socio demographic, household, person, and trip characteristics on travel are also presented and discussed. The final chapter summarizes the key findings from this study and proposes directions for future research.

CHAPTER II

BACKGROUND AND LITERATURE REVIEW

2.1 Introduction

The need for more accurate forecasting tools with richer analytical and theoretical basis than the conventional four step process is a primary motivation for activity-based demand modeling approaches. From a policy standpoint, the thrust towards intermodal transportation systems, requirement of congestion management systems for large urban areas (population >200000 people), and growing concern about air-quality are also providing strong impetus for the development of forecasting tools that can provide richer insights and greater accuracy (Goulias, (1996). The need for policy sensitive analysis of travel demand in turn necessitates a deeper and richer understanding of temporal, spatial, and behavioral elements underlying observed travel and associated activity patterns. Toward this end, activity based approaches propose a framework wherein travel is analyzed as daily or multi-day patterns of behavior, related to and derived from differences in life styles and activity participation among the population (Jones et al., (1990)).

As a research framework, activity-based analysis is concerned with the formation and execution of activity and travel patterns by households. The choice dimensions underlying these patterns include: creation of activity schedules, the mapping of activities in time and space, linkages within a household, activity type choice, and the resulting travel decisions including mode, timing, trip duration and distance of trips (Kurani, (1996)). The study of how these decisions are made requires a basic understanding of the activity scheduling mechanisms, linkages between the members of a household that perform the activities, the corresponding resource availability, feasibility constraints, and institutional regulations that may limit the patterns, and the supply side opportunities for activity participation.

The major conceptual differences between activity and trip-based approaches may be summarized as follows:

1. The activity-based frameworks explicitly recognize and seek to operationalize the notion that the demand for travel is derived from the need to participate in activities at geographically dispersed locations (Oi and Shuldiner, (1962)).

2. In contrast to the focus on individuals as the source/generators of travel, households are assumed to generate activities that result in observed travel patterns. This generation of activities is essential to fulfill subsistence roles (work, education), maintenance of the household (shopping etc.), and recreational needs of the household (entertainment, exercise etc.).

3. The focus is less on vehicle trips but more on household members' participation in activities. Given its stronger behavioral and psychological underpinnings than trip-based approaches, over the past decade several conceptual frameworks and operational activity-travel simulation systems have also been developed. Many modeling studies have been conducted into the various dimensions associated with activity-travel patterns especially over the last decade, leading to a large and rapidly growing body of knowledge. These developments have contributed significantly towards making an activity-based approach a vibrant area of continuing research.

This chapter discusses salient issues, insights and models of relevance from activity-based modeling approaches to travel demand analysis. The purpose of this review is two-fold. First, the review aims to describe the essential characteristics of the process under study, and outline the approaches adopted by various researchers while highlighting their salient advantages and limitations. Second, an attempt is made to synthesize current knowledge on activity-based analysis particularly in the context of the objectives of this study (presented in Chapter 1). Therefore, this review is not intended to be comprehensive in the related streams of research, which bear more detailed investigations. In view of the objectives of this study, this chapter focuses on the following three broad areas: modeling approaches, broad empirical findings and substantive insights in relation to activity based models, and review of literature on person allocation and ICT use on activity pattern and travel behavior.

Accordingly, first, the literature pertaining to conceptual and modeling frameworks is presented in Section 2.2. In Section 2.3, the classification of activities into various categories, and broad trends based on activity types reported in the literature are briefly discussed. Section 2.4 summarizes salient findings on intra-household interactions and inter-household differences in activity patterns. The following section presents a discussion of research on impacts of ICT (Information and Communication Technologies) and advanced technologies on activity and travel patterns. The chapter is concluded with a discussion of salient gaps and limitations of existing studies in relation to the objectives of this thesis.

2.2 Conceptual and modeling frameworks

Transportation planning agencies, nationwide, are engaged in collecting large amounts of highly disaggregate data on activity and travel patterns of households. Examples of such large activity-travel databases include the San Francisco Bay Area Activity-Travel Survey (1996) and the Puget Sound Transportation Panel (1987-1999) *[Metropolitan Transportation Commission, Vaughn et al., (1996); and Viswanathan et al., (2001)]*. These data are intended to convey a more accurate picture of travel-demand than trip-based models and provide a better basis for evaluating investments and assessing alternative transportation control measures, possibly using micro simulation approaches *[Jones et al. (1990); Kitamura et al. (1996); and Bhat et al. (2004)]*.

However, these activity travel databases are large and contain data on complex relationships between numerous inter-related activity and travel choice dimensions *[Pas (1996); Pendyala et al. (1996); and Bowman et al. (1996)]*. The size of the databases can be illustrated through the Bay Area Travel Survey that consists of records of 203,000 activities, and 64,000 trips (to be used in this study).

Activity travel data can be represented in the following form. Observed activity travel patterns (S_{itn}) for a given individual i, on day t, who undertakes n activities can be expressed as follows:

$$S_{itn} = \{ (T_1,A_1), (T_2,A_2),\ldots\ldots\ldots\ldots, (T_n,A_n)\} \qquad (1)$$

The vector of travel decisions T_r (for the r^{th} activity) consists of the decisions of travel mode, route, departure time, destination, and trip-time. The vector of activity decisions, A_r, is made up of the dimensions of activity purpose, duration, location, and others.

Despite the deceptive simplicity of equation 1, the actual activity travel patterns are extremely complex *[Bhat et al. (1999)]*. The complexity arises due to: a) large number of multivariate (correlated), multinomial (many alternatives for each choice dimension such as departure time, activity sequencing decisions) decision dimensions, b) complex linkages over time and space, and c) significant heterogeneity (variations across different population segments) in activity participation and travel. These sources of complexity pose significant methodological and computational challenges in developing data mining and analysis methods for activity-travel data. These are illustrated below in the context of existing analyses methods.

Existing methods to analyze activity-travel behavior can be classified into three categories: extensions of trip-based methods, econometric frameworks to model joint choice decisions, and combinations of pattern matching and segmentation methods. Methods in the first category focus on the analysis of extended trip units such as trip-chains and usually model related choice dimensions jointly *[Bhat et al. (1997)]*. While this approach is more accurate than a trip-based model, the approach still retains many limitations of trip-based models including its inability to account for time-of-day and across-tour effects.

To overcome these limitations, the second class of models attempts to jointly model all relevant choice dimensions selected by an individual *[Bowman et al. (1996); and Kitamura et al. (1996)]*. This approach models the observed pattern of choices jointly by successively conditioning on the previous events in the day. Thus the likelihood of observing a sequence S_{itn} of activity and travel choices is given as:

$$P\{ S_{itn}\} = P[(T_1,A_1)]\, P[(T_2,A_2) \mid (T_1,A_1)]\ldots\, P[(T_n,A_n)\mid \{(T_1,A_1),., (T_{n-1},A_{n-1})\}] \qquad (2)$$

The choice dimensions within travel and activity vectors (T, A) are similarly decomposed. This approach is theoretically appealing, but computationally expensive due to the large dimensionality of models and parameters. There are practical parameter identification problems (in statistical models) due to the non-convexity of the likelihood function. Further the systems of models are susceptible to inconsistency and bias and error propagation if the choice sets or correlations are misspecified.

The third category of models uses a combination of clustering and discriminant analyses to analyze activity patterns *[Recker et al., (1986a&1986b); and Garling et al. (1994)]*. In these models patterns are represented by character strings, and are clustered based on heuristic dissimilarity measures. Factors influencing cluster membership is determined by discriminant analysis. This approach, though intuitively simple and computationally inexpensive, is behaviorally and methodologically limited in capturing interactions between correlated multiple dimensions.

A fourth category of models aims to analyze the scheduling of activities through the analogue of computerized production systems that comprise a set of rules in the form of condition-action (If-Then) pairs (See Garling et al., (1994)). Generally these approaches tend to separate out generation and scheduling activities, whereas, the joint modeling of generation and scheduling is likely to be more realistic due to the mutual interdependence of certain common factors (Bhat and Koppelman, (1999)). Computational Process Models are production systems models that are based on a set of rules in the form of condition-action pairs (Garling et al., (1994); and Miller et al., (2003)). Compared to the first two categories of models, which capture causal relationships using a system of equations and have a strong statistical foundation to test alternative hypotheses, the latter two approaches are based on heuristics and simulation-based approaches.

The common feature in all the approaches noted above is that they focus on the following decision dimensions in general: generation of activities at the household level, scheduling of activities over time and space, interactions between activity and travel decisions over the day/week/other time period of analysis, interactions between and within-households given the numerous spatial, temporal and interpersonal constraints that affect activity participation and travel choices. However, they differ from each other with respect to the primary decision variables, the temporal resolution of analysis (episode level, daily level, weekly level, choice set construction, econometric basis etc., computational complexity, and explicit or implicit nature of treatment of constraints.

The existing modeling frameworks may be summarized by the following observations. First, the sources of complexity highlighted earlier have been shown to be empirically significant and modeling methods must account for these relationships. Second, existing data analysis methods have significant shortcomings from computational, methodological, or behavioral perspectives. For instance, there are significant gaps in these approaches with regard to the treatment of choice set formation, sequencing, constraints, endogeneity, dynamics and correlations, and heterogeneity. More efficient and focused analysis methods are needed to address these shortcomings, particularly, in the context of emerging dimensions such as the role of advanced telecommunication technologies, or household interactions.

2.3 Activity-types and empirical analysis

Given the differences across activity patterns and constraints across different types of activities, typically activities are classified into the following three categories to classify activities: Subsistence, Maintenance and Discretionary or Leisure activities. The activities separated into these categories vary primarily in terms of their spatial and temporal characteristics. Subsistence activities refer to activities which are essential for the household such as work, education etc. and are typically non-home based and performed at fixed locations and often at fixed times (start and end-times) with little flexibility about these dimensions and are highly periodic in nature. In contrast, discretionary activities have substantial flexibility about whether or not they need to be performed, where, and when and therefore tend to be fairly the spectrum in terms of spatial and temporal flexibility and periodicity. These refer to activities such as groceries, filling gas, shopping, and others. which can be performed at not necessarily at fixed times, and possibly at different locations. In terms of periodicity, they may be cyclical (for e.g. regular grocery shopping, or irregular in frequency such as specialty or gift shopping). These differences in the nature of activity patterns are also reflected as differences in travel patterns, in terms of time-of-day, mode-choice, destination location etc. Therefore, segmenting activity and travel patterns based on activity purpose is essential.

Several studies have adopted this segmentation approach in analyzing activity and travel demand. There is a significant body of travel behavior literature on subsistence activities particularly focusing on work travel and commuting behavior. Numerous studies in this context (over the last three decades) have focused mainly on the dimensions of route, departure time, and mode choice of commuters, since destination choice is fixed. Factors influencing route choice include: travel time on alternate routes, habit, familiarity with the area, scenic nature, presence of congestion/accidents, availability and use of traffic information etc. Factors that affect departure time on the other hand are schedule delay (early and late), travel time, route-choice dimensions, travel time variability in the network, and others. Perhaps, the most extensively studied choice dimension in this regard is mode-choice which appears to be affected by: level-of-service attributes of modes such as travel time, waiting time, access time, transfer time across modes and on-time reliability, cost, convenience, and socio-demographic characteristics such as vehicle ownership, income, age, gender, and others. There is also a line of work that focuses on trip-chaining during the work commute. Along this line, some of the key factors that affect trip-chaining behavior are car-availability per worker in the household, license-holding, presence of children in household, income, joint activity participation, occupation, number of days to work, and car requirement for job etc. Recently, several studies have also investigated the influence of work activity on non-work travel and activities.

Activities such as grocery shopping, and irregular shopping are classified as maintenance activities in some studies, although there have been significant variation in this nomenclature across studies. Among these shopping behavior has begun to receive increasing attention for several reasons. First, the Nationwide Personal Transportation Survey (NPTS), 1995 (See FHWA and BTS, 1995) shows that 20.2 percent of total trips are shopping trips which is greater than the work trip percentage (17.7%). Second, there is significant flexibility associated with shopping trips for several reasons: i) they are spatially and temporally less rigid in character relative to work trips, ii) non-workers play an important role in performing shopping trips who have greater degree of time-flexibility, and iii) several avenues for e-shopping and e-commerce are recently emerging which may eliminate the need for travel associated with shopping in some cases. Further, observing workers trip-chaining commuting trips with shopping activities along the way which can strongly affect travel patterns (this trip-chaining may render particular modes unattractive for commute mode choice - e.g. bus due to the difficulty in carrying goods or grocery bags.). Several studies that have investigated shopping related activity and travel have noted the importance of the following factors: age, gender, time-constraints, income of household, ratio of workers/non-workers, presence and age of children, institutional timings (of shop and work), cost of activity, household role, land-use and supply opportunities on the duration of activity, location and distance of travel, and the mode chosen for travel. Recent studies are also examining the role of internet on electronic shopping behavior of consumers (Farag et al, (2003); and Casas et al., (2001)). For reasons noted above, non-work activity in general and shopping activity travel in particular has been receiving increasing attention in recent research studies (Bhat., (1998); Steed and Bhat, (2000b); Bhat and Steed, (2000)).

Discretionary activities include activities such as entertainment, hobbies, visiting, and exercise. Given the greatest degree of temporal and spatial flexibility in these activities, the elasticity to travel time is observed to be the least elastic (compared to the previous two types of activities) and the cost elasticity is perhaps the most. Studies focusing on discretionary activities have investigated the activity duration, location, mode, and timing of such activities, and the associated mode choice (Bhat and Lockwood, (2004)). For instance, Bhat and Lockwood, (2004) analyzed weekend day social-recreational activity episodes using 2000 San Francisco bay area travel survey. The authors formulated a mixed logit model for four choices: physically active recreational travel, physically active recreational activity, physically passive recreational travel and physically passive recreational activity. The authors found that senior adults (older than 65 years) are most likely to participate in physically active travel recreation compared to other recreation categories. Higher income households are less likely to pursue physically active travel episodes for recreation. The authors also noted a higher propensity to participate in physically active travel episodes on Sundays compared to Saturdays. Other major findings along this line of investigation include: (a) economic characteristics of the household play a strong role: income, car-availability, (b) highly elastic to price and inelastic to travel time, (c) personality related factors play an important role - health consciousness, variety seeking, and (d) household structure and life-cycle play an important role with greater participation is observed of younger and older respondents, for different reasons. The younger respondents were more likely to participate in recreational activities such as exercise, and physical fitness, whereas, older respondents have greater time-availability to pursue other discretionary activities.

2.4 Household role and within-household interactions

Subsistence activities are mostly personalized activities (such as work, or school) where substitution across household members is not possible. In contrast, task-sharing and delegation between different household members is possible for maintenance and discretionary activities. For this reason, this review primarily focuses on household role, and inter-person interaction mainly in the context of maintenance and discretionary activities. However, the role of work-related trips on such household interaction is also discussed. Jones et al., (1990) identify use of households as the decision-making unit and incorporation of inter-personal constraints as two important emerging features of activity analysis. Bhat and Koppelman, (1999) in their review of activity-based travel demand modeling noted that *"…efforts which accommodate inter-individual interactions in activity patterns with efforts that use a continuous time domain is likely to be a very fruitful area for further research."* In the past few years, this important feature in activity-travel analysis is gaining research attention. For instance, Gliebe and Koppelman (2001) remarked that joint activities tend to have a longer duration than non-work independent activities, and persons tend to stay out later and travel farther from home.

Several studies have examined the interaction between household members in the context of activity allocation to household members. Hagerstrand's (1970) pioneering work on activity-based frameworks in the early 70's identifies three such constraints influencing such interactions: coupling constraints, capability constraints and authority constraints. Coupling constraints relate to the need for coordination between household members' activities (for. e.g. due to joint activity participation). Capability constraints on the other hand refer to the limitations of an individual/household to undertake certain types of activities (e.g. lack of car/license). Authority constraints refer to institutional or other constraints which are imposed externally and are generally binding.

The interaction between workers and non-workers in a household in terms of activity allocation has been receiving increasing research attention. Along this line, Bhat and Mishra (2003) investigated the following decisions for non-workers: stop occurrence, stop type, and activity sequencing. They reported that non-workers in households with several employed individuals are less likely to leave home during the day. In contrast, individuals in a single-member and couple households, and in high income-earning households, are more likely to venture out-of-home to participate in activities. Goulias and Kim, (2001) analyzed activity and travel patterns at multi-level both at household level and person level. Activity patterns are classified into four groups of persons called worker-A, worker-B, Shopper and inactive individuals, based on the length and purpose of the trip. Similarly, travel patterns are also grouped into four groups of persons called non-motorized, car or carpool, public and immobile based on the mode of transportation. Explanatory variables that were significant in this study include person level, household level, time related, and accessibility characteristics.

Some researchers have focused on joint activity participation as a measure of household interaction. Joint travel by household members was modeled by Vovsha et al, (2003) at various stages: based on purpose of the activity, joint travel is classified based on the composition of participating members (such as joint tours with adults only, children only and adults with children). The primary conclusion in the study was that a significant percentage of household trips involved joint travel, and joint travel is common for school, maintenance and discretionary purposes. Balasubramanian and Goulias, (1999) presented a probit-model for the analysis of solo and joint trip making behavior. They found that life cycle stage has significant effect on joint trips such as trips made by multi-adult older household. Further, household with children are more likely to participate in joint trips. The authors also reported that persons classified as shoppers and car-poolers have a higher probability of making joint trips compared to others. In a similar study, Stopher and Metcalfe, (1999) observed that the time allocation of households to activites varied significantly based on life-cycle groups.

Other researchers have investigated household interaction and allocation based on gender, household role, and other factors. A recent study that examined individuals' participation in activities is by Bhat and Srinivasan, (2004). In this study, the authors evaluated the factors that affect the allocation of shopping activities in households with couples. A nested model is developed for generation and allocation of shopping activities (for male only, female only, both independently and both jointly) and a hazard duration model is estimated for duration of shopping (male, female and joint). The authors reported the following findings: 'the work duration of household heads negatively impacts the decision to undertake shopping during the day, a female non worker is more likely to be allocated the shopping responsibility compared to male non worker and both adults, on weekends, are found more likely to perform shopping activities jointly' (Bhat, (2004)). Along similar lines, Scott et al, (2002) performed empirical analysis on out-of-home activities of three types of households: couple, non-worker; couple, one worker; and couple, two worker households and reported the following findings. The presence of children in a couple, non-worker household result in more number of independent activities by males than females. More number of joint activities is found in households where children are present. Females who live in two worker and one vehicle households are more likely to participate in independent activities than females in multiple vehicle households. Other studies have also noted that joint activity between adult heads of households is significantly affected by the presence of children (Jones et al., (1990), Balasubramanian and Goulias, (1999); and Townsend (1987)). Simma and Axhausen, (2001) used structural equation models to capture the interactions between heads of the households with regard to participation in out-of-home activities. Dependent variables include number of cars, number of maintenance trips, number of leisure trips, and number of day distance trips by both males and females. Explanatory variables such as person characteristics, accessibility and activity related characteristics strongly affected the allocation of trips.

While the studies above analyze activity participation propensity, some researchers analyze the household role by examining time allocation patterns across household members. For instance, Goulias et al., (2001) found that males allocate more time to subsistence activities compared to females and non-workers allocate more time to maintenance activities compared to workers. Gliebe and Koppelman, (2001) estimated time allocation for different out-of-home activities by adult household members using proportional share model. Independent and joint activities are classified into subsistence, maintenance, leisure and home activities. The number of children, ages 0-17 years, had a significant positive effect on the time allocated to out-of-home independent maintenance activities by females relative to males. The variable, autos per person, was also found to have positive effect on time allocated to independent maintenance and leisure activities.

Golob and McNally, (1997) use a structural equations model to explain activity interactions and related travel between heads of households. Their analysis is limited to modeling activity participation and travel of couple households. By analyzing the durations of activities and travel for maintenance, discretionary and work activities, they reported significant interactions between members of household in their activity participations. However, they did not consider joint activity participation or joint travel in their analysis. Fujii et al., (1999) also used structural equation model system to study individuals' joint activity engagement. In this study, two models were presented: one for travel patterns and quality of life and the other for time allocation. They concluded that individuals prefer out-of-home solo activities to out-of-home joint activities with family members. They observed that a worker or a housewife is more likely to prefer spending time with family members at home.

Examining the reasons behind such inter-person interactions, Srinivasan and Bhat, (2003) suggest four factors which may lead to interdependencies among the activity-travel characteristics of household members: a) members of a household may share the responsibility in undertaking maintenance activities, leading to substitution effects among the members; b) companionship desires may motivate household members to undertake activities jointly; c) member of household acting as 'chauffeur' to enable other members participate in activities, e.g. chauffeuring children to school; and, d) compulsion to share the use of single car. The activity-travel behaviors of individuals, therefore, are dependent on those of other members of the household. Based on empirical analysis, Srinivasan and Bhat, (2003) found that gender, sharing the use of a single car, and presence of only one licensed driver in the household affect allocation of household shopping activities.

Townsend et al(1987) developed a conceptual framework for the analysis of multi-day activity patterns of households and their members, based on household utility maximization as weighted by the power of individual members. He showed evidence for the existence of three constructs related to intra-person and interpersonal time trade-offs in activity and travel patterns – efficiency, companionship and power/altruism. Efficiency was found in the case of single mothers who take specialized roles and link efficient linking of trips in tours. Companionship was observed while engaging adults without children in joint activities. Power is illustrated by individuals with more income, job status and education avoiding household maintenance activities, as contrasted with altruism in which more powerful individuals forgo free time to fulfill maintenance activities or help less powerful members of the household (children). He also found evidence of both substitution and complementary effects in husband-wife task allocation.

Scott and Kanorglou, (2002) also study interactions between household heads in the generation of daily household non-work, out-of-home activity episodes using a trivariate ordered probit model. These authors suggest two reasons for why household-level models may result in better demand forecasts than individual models: First, individual level models are incapable of handling complex responses to TDM measures, such as re-assignment of maintenance activities to a 'better' placed individual, and second, individual level models do not account for joint out-of-home activities. The modeling framework used by Scott, (2001) explicitly recognizes, a) membership identity within a household, b) the activity setting (independent or joint), and c) activity episodes as units of analysis.

The studies cited above analyze the activity participation patterns of household members in terms of couple households, life cycle groups, time allocation to various activities, joint activity engagement, and interactions among household individuals. These studies have presented empirical evidence, important insights and conceptual framework in relation to activity engagement of household members. However, above studies also have some limitations which cannot be ignored. For instance, differences across households in allocation patterns among head of the household, spouse, children, parent, and in-law have not been investigated. Similarly, specific person choice has not been considered in several studies (since the allocation is based on gender or employment characteristics). The lack of person specific identification of activity allocation may lead to misspecification because of correlated errors and will not distinguish activity participation by members with the same characteristics (e.g. between household non-workers). The current study addresses these shortcomings and investigates these aspects and significance of these aspects is discussed in sections 3.6.1, 3.6.2, and 3.6.3. Some other limitations of the above studies include: inadequate treatment of correlations between household members, variability within and between members, and neglect of a significant fraction of other trips which are performed by household members other than head of the household and spouse. The current study aims to address these limitations and presents empirical evidence that some of these factors are empirically significant.

2.5 Role of ICT and advanced technologies on activity allocation in the household

The advances in information and communication technologies in the form of internet, telephone, mobile phones etc. today offer three key capabilities that can significantly alter activity and travel patterns of users: a) greater connectivity to people and resources, b) greater selectivity through the ability to search and browse, and c) the ability to perform many activities which required out-of-home travel previously, using electronic means (virtual activities). Given the increasing diffusion of these ICT technologies, the activity patterns and household allocation, and associated travel patterns will also change. In this context, the review below discusses relevant literature from the following four research threads pertaining to the role of ICT on activity and travel patterns: i) Telecommuting - the role of ICT's on work activity participation, ii) E-shopping - the role of ICT's in shopping activities, iii) the effect of different types of ICT devices on overall travel and activity patterns and iv) findings from other studies in relation to substitution, modification of travel activities due to ICT use.

2.5.1 Role of ICT's on telecommuting

In the context of telecommuting: Mokhtarian and Salomon, (1997) analyzed the influence of attitudinal factors while modeling the preference to telecommute. Their results highlighted the role of facilitating factors and constraints (e.g. job suitability) in telecommuting decisions, in addition to the effect of key travel related factors such as commute time, commute stress and personal benefits. Similarly, Mokhtarian and Meenakshisundaram, (1999) studied substitution and complementarity effects among the different modes of communication at the individual level. Structural equation models are used to analyze various factors involved in this context. Net generation of communication was found in a six-month period and complementarity is found across different modes of communication. These modes include phone, fax, e-mail, personal meeting and trips. Wells et al., (2001) presented case studies on the implications of telecommuting on travel behavior, based on surveys conducted in the twin cities of Minnesota. They found that telecommuters tend to have significantly longer commutes than non-telecommuters. Mokhtharian, (1989) reviewed and identified additional relationships between transportation and telecommunications in addition to present conceptual relationship. Two empirical examples based on video conference and telecommuting are presented, the former is an example of stimulation and the latter one could be considered as an example for reduction of travel.

2.5.2 Influence of ICT's on e-shopping behavior

The influence of ICT's on shopping behavior has also been receiving increasing attention recently. Farag et al., (2003) studied the impacts of e-shopping on personal travel behavior. Their findings suggest that electronic shopping can result in saving time for consumers. They also noted that the propensity for online shopping does not differ significantly across urban and rural areas. Middle-aged males are found to prefer online shopping activities to their female cohorts. Casas et al., (2001) also studied the impacts of online shopping on travel based on a one-day activity data. They concluded that the individuals who took part in Internet shopping do not make fewer 'physical' shopping trips.

2.5.3 Effect of different types of ICT devices on overall travel and activity patterns

Another interesting line of inquiry relates to the relationships between travel patterns and ICT use is evaluating the effects of ICT devices on travel. Along this line, Hjorthol, (2002) tried to explain the relation between daily travel and computer use at home, especially with regard to the degree of substitution. Access to information technology is found to have significant impact on travel activities. However, the author could not see any direct substitution effect of computer access at home on travel patterns. Bhat et al., (2003) focused on the effects of mobile phone and home computer usage on out-of-home non-maintenance shopping patterns. Their results show some evidence to substitution and complementary effects among different groups of individuals. For instance, mobile phone usage can result in a substitution effect on shopping trips for individuals, with certain educational and demographic characteristics. Senbil and Kitamura, (2003) investigated the effect of cellular and home phones on travel behavior. In this study frequency and duration of activities like home, work, discretionary and joint discretionary activities are modeled in relation to the number of phone-based communication activities. Poisson, Tobit regression and structural equation models are used to estimate these effects. The empirical findings suggested that the use of cell phones is positively correlated with work duration, and the frequency of joint discretionary activities. Classie and Rowe, (1992) investigated the interaction between telephone use and mobility. They found that two thirds of the total telephone traffic is related to an individual's mobility. Further they estimated seven percent increase in urban peak hour traffic due to hypothetical telephone network breakdown.

Viswanathan and Goulias, (2001) studied the impact of many types of ICT devices on total duration of travel and total duration of activities. They found that computer usage at work or school increases the daily activity durations but has no effect on travel duration. Internet users are found to spend less time on travel, whereas mobile phone user increases the duration of travel, but not the activity episodes. However, only aggregate travel durations in a day were modeled, and the influence on different activity purposes was not considered. Handy and Yantis, (1997) studied the impacts of telecommunications technologies on non-work travel behavior. Three specific activities are considered in this study: movie watching, shopping and banking based on in-home and out-of-home activity participation, based on a survey. They found that in-home entertainment activities (e.g. movie watching on television or video) correlated positively with an increase in travel. Home shopping (though Internet shopping was not considered) also results in an increase in travel by the shopper. ATM banking seems to be effective in reducing trips to the bank, while at the same time ATM banking increases the number of transactions (i.e. efficiency) of the bank.

2.5.4 Other ICT related studies

Some other studies explore and examine theoretical concepts and patterns behind the ICT use. In this regard, Golob and Regan, (2001) provide an extensive and thorough review of the range of potential impacts of information technology on personal travel and commercial vehicle operations by reviewing prior studies. The explanation of impacts of IT on personal travel behavior includes e-shopping, telecommuting, mobile working and so forth, and the need to collect ICT use related information in the context of activity diary data is emphasized. Marker and Goulias, (2000) focused on the possible benefits gained from trip replacement and load consolidation while presenting the analysis of online grocery shopping. In this context, they stated that benefits are likely to be small if trip-chaining is normally implemented during shopping trips. The authors also indicated that time savings from Internet activity may lead to more trips being generated. Kilpala et al, (2001) explore the implications of E-Commerce on transportation, particularly, the role of e-commerce on travel activities relating to the grocery industry. Krizek and Johnson, (2003) highlighted the role of trip substitution, modification, and generation, which resulted from ICT use and propose a conceptual and qualitative framework for the analysis of ICT's. This paper builds upon this theoretical framework using empirical models to analyze the relationships between ICT use, activity and travel patterns, and to obtain insights on potential substitution, modification, and generation effects. Another qualitative study is by Salomon, (1986), who reviewed literature related to the current topic, and explained the interactions between transport and various communication applications like remote work, teleconferencing, tele-services, mobile communications and electronic message transfer. He finally emphasized the necessity of empirical studies in this field and need to model behavioral changes and complex relationships. Selvanathan and Selvananthan, (1994) presented an empirical analysis of the demand for public transport, private transport and communication for two countries, the U.K and Australia. They concluded (by examining elasticities of use with cost) that in both countries, public transport is a necessity and private transport is a luxury, whereas transport and communication collectively as a group is a luxury.

2.5.5. Limitations of these studies

Some of the limitations of prior studies are presented in this section. The prior research studies have not investigated the interactions between ICT use, Activity pattern and Travel Pattern holistically, since the primary purpose in many studies has been to analyze ICT impact on a specific trip/activity purpose. Similarly, the purpose for ICT use in activity participation is not studied and whole day activity pattern are not analyzed. Furthermore, the influence of ICT use on inter-person interdependence within a household has not been sufficiently examined, and the effect of cross-substitution between different activity types and different ICT uses and travel needs to be investigated. For example, the effect cross-substitution of one virtual activity type on the other virtual activity and the effect of one virtual activity type on another physical activity is of interest for predicting travel demand. This study aims to overcome some of these shortcomings by investigating these research issues.

2.6 Summary

This chapter provides an overview of various aspects of activity episode analysis. The review of prior studies along this line indicate that activity based modeling approach provides a more powerful and versatile framework for travel demand modeling. However, this analysis is methodologically challenging because of the large number of inter-dependent dimensions of interest such as household relations, vehicle status, workers status, presence of children, cost constraints, time constraints, and location and situational constraints. Further, there is a growing body of empirical knowledge on activity travel behavior which has highlighted the importance of several key factors including person attributes, household attributes, socio demographic factors, trip related characteristics, household role, and cost, time and situational constraints.

However, several dimensions are not sufficiently investigated in the previous literature. These include: (a) interactions within households and differences between households, (b) the role of ICT's on activity based analysis rather trip based analysis, (c) interactions between physical and virtual activities, (d) need for more holistic patterns of analysis that take into account correlations of various sources, and treatment of all individuals in the household (some individuals are not considered in the prior studies), and (e) other dimensions such as sequencing of activities and associated dynamic methodologies.

Exploring some of these dimensions forms the main focus of this thesis. This thesis seeks to partially address the gaps noted above by developing two sets of models: models of person allocation to activities, and models of ICT use and its effect on activity travel patterns. The following chapter examines the person allocation in a household (without reference to presence of ICT's). The modeling frameworks and the specific objectives of this analysis are presented in the next chapter. A variety of statistical models are estimated using the Bay Area Travel Survey 1996 data. Chapter 4 investigates the role of ICT's on activity and travel patterns jointly using the Bay Area Travel Survey 2000 data. The modeling framework used for this analysis and the salient findings are also presented in this chapter.

CHAPTER III

PERSON ALLOCATION TO ACTIVITIES

3.1 Introduction

In this chapter, the allocation of household members for participation in discretionary and maintenance activities is investigated. Specifically, this chapter examines how individual household members are selected and assigned to participate in out-of-home discretionary and maintenance activities. In analyzing household person allocation to activities, the following dimensions will be considered: solo versus joint activities, within-household interactions, differences in activity allocation across households, and the role of constraints (e.g. time, cost, and vehicle availability).

The primary motivation for investigating person allocation to activities is two-fold: First, from a behavioral perspective, person allocation patterns can strongly influence vehicle occupancy levels, trip-chaining and mode choice and thus have significant implications for congestion, air-quality, and demand estimation for transit. For instance, how a household with one car allocates the activities and the vehicle across household members can determine the mode choice and timing of the various trips in the household. The allocation of several activities and trips to a single person (say the employed head of the household) may result in a greater degree of trip consolidation and trip-chaining, resulting in lower emission rate, with several of these trips being performed during the evening peak period or post-peak period. In contrast, in a household (with many adults and many vehicles), where the tasks may be delegated more evenly across members, more trips may result and may be staggered over time (possibly leading to lower congestion), resulting in fewer chained trips and worse environmental impact. The need for joint trips, trip-chaining (e.g. discretionary activities) or sequencing constraints of prior activity/vehicle allocation in the same day may render the transit mode relatively unattractive compared to the automobile in some cases. On the other hand, the activity and vehicle allocation in some households (e.g. one vehicle household) may necessitate the use of transit by other household members or postponement of trips to a later time.

Second, these behavioral issues also have substantial practical implications in the context of: evaluation of vehicle occupancy based traffic management strategies such as: High Occupancy Vehicle (HOV) and High Occupancy Travel (HOT) lanes. (person allocation may be used to determine conditions and households, and activities which are less likely to be elastic in terms of person occupancy - solo versus joint activities). Similarly, disregarding the constraints on trip-chaining and joint travel, that arises from person allocation to activities and within-household interactions can result in erroneous and misleading demand estimates while assessing the effectiveness of alternative transit improvement policies. For instance, the improvement of travel time or wait time through more frequent services may prove to be ineffective and expensive, if there is a significant need for trip-chaining on a route not served by the transit. Given these motivating considerations, there is a need for richer behavioral and policy sensitive representation of person allocation in activity-based microsimulation models of travel demand.

Given its significance in the context of activity-based demand analysis, the importance of representing and capturing the person allocation to activities has been recognized by several studies (Balasubramaniam and Goulias, (1999); Scott et al., (2002); Pendyala et al., (2002); Vovsha et al., (2003); and Bhat et al., (2004)). Research in this area can be classified along the following four broad lines of investigation:

a) Studies that model which person is selected for the activity (male versus female, head of household versus spouse, worker versus non-worker, and others (Vovsha et al., (2004))
b) Studies that examine whether an activity episode involved a solo trip or a joint trip (Fujii et al., (1999); and Vovsha et al., (2003))
c) Studies focusing on daily and episode level time allocation of household members to activities (Gliebe et al., (2001); and Bhat, Srinivasan and Axhausen (2004)) and
d) Comparative analyses of differences in task/activity participation among household members based on life cycle groups and role (Balasubramanian and Goulias, (1999); Stopher and Metcalfe, (1999); Simma et al, (2001); Scott, (2002); and Bhat et al., (2004)).

Investigations along these lines have provided valuable preliminary insights especially on within-household allocation of tasks, particularly between solo and joint trips. A more detailed review of these investigations and the associated findings are provided in Section 3.2. Given that research in this area is still in its initial stages, there are some methodological and definitional challenges that are not adequately addressed in current models of person allocation (these are discussed in Section 3.4.2 in detail). These shortcomings and issues can lead to biased or inconsistent parameter estimates, loss in efficiency and information in model due to aggregation, and forecast errors and inaccurate evaluation of policy impacts (could be found more discussion in section 3.4.2).

The objectives of this chapter are as follows:

1. Develop models to analyze the effect of socio-demographic, household role, and trip attributes on activity allocation among household members.
2. Investigate the role of constraints on time, vehicle availability, cost, and coordination on activity allocation among household members.

3. Analyze differences between households in terms of allocation of persons to activities and the underlying factors.

Addressing these substantive research objectives is likely to shed light towards the identification of behavioral basis underlying household allocation of activities among members. Furthermore, this analysis will also be valuable towards the development of richer activity-based micro-simulation models with implications for demand management, evaluation of transportation policy actions etc.

To achieve these objectives, this chapter proposes disaggregate discrete choice models for the analysis of allocation of activities to household members. The differences in allocation between maintenance and discretionary activities are analyzed explicitly. At the empirical level, the proposed work seeks to expand the existing body of knowledge from prior studies by explicitly investigating the following aspects of activity allocation to household members: a) within-household interactions, b) between household differences, c) the effect of situational constraints, and d) the influence of trip-related factors. From a modeling standpoint, the proposed approach provides an improved representation of activity allocation behavior than existing models by accounting for the: i) variable nature of choice set and alternatives across households, ii) inclusion of richer choice-related information by including solo participation by members other than the head or the spouse of the head of the household, iii) insights on within-day time-varying nature of activity allocation within a household, and iv) richer disaggregation and reduction in bias by analyzing allocation based on individuals instead of allocation based on gender or employment characteristics.

The remainder of this chapter is organized as follows. In Section 3.2, related prior literature on within-household interactions and person allocation of activities is reviewed. The activity-based data used in this study and the descriptive statistics of the associated variables of interest in this study are presented next, in Section 3.3. The modeling framework used to analyze person allocation to household maintenance and discretionary activities is described in Section 3.4, whereas, the hypotheses of interest are explained in Section 3.5, and modeling results are presented in Section 3.6, followed by Section 3.7 that discusses the model validation tasks conducted in this study. Finally, this chapter and its main results are summarized in Section 3.8.

3.2 Literature review related to person allocation

Some of the prior studies have sought to investigate activity participation of household members by classifying them into segments such as male or female, and worker or non-worker. For instance, Bhat and Srinivasan, (2004) examined the factors that affect the allocation of shopping activities in couple households. The authors used a nested model for the generation and allocation of shopping activities based on gender: for male only, female only, both independently and both jointly. A hazard duration model for the duration of shopping is also proposed based on gender: (for male, female and joint participation). They observed that a female non worker is more likely to be allocated to the shopping responsibility compared to male non-worker. Further, both the adults are found to be more likely to perform shopping activities jointly on weekends than weekdays. On the other hand, Vovsha, Petersen and Donnelly, (2004) developed a model for allocation of maintenance activities to the household members. The maintenance activities are classified as shopping, escorting, and other maintenance activities and then these activities are allocated to six categories of household individuals (fulltime worker, part-time worker, university student, non worker, pre driving child and driving child). In this study, zone-of-residence and available time window factors are evaluated in addition to household and person related factors. The authors concluded that the accessibility of retail attractions works in favor of more frequent individual maintenance tours and also, non-workers are found to perform maintenance activities most frequently.

In another stream of research work, the relationship between activity patterns and household role (head of the household and spouse) is investigated. For example, Simma and Axhausen, (2001) examined the allocation of activities between the head of the household and spouse. The authors used structural equation models to capture the interactions between heads of the households with regard to participation in out-of-home activities. Explanatory variables in this study include person, accessibility and activity related characteristics. Bhat and Srinivasan, (2004); and Vovsha, Petersen, and Donnelly, (2004) have also analyzed the factors that affect activity participation of the head of the household role. In this regard the former study concluded that work duration of household head negatively impacts the decision to undertake shopping during the day.

Balasubramanian and Goulias, (1999) presented a comparative analysis of solo and joint trip making behavior. A probit model was used for conducting a trip-by-trip analysis after classifying each trip as a solo or joint trip. They found that life cycle stage has a significant effect on joint trips by multi-adult household. Furthermore, households with children are more likely to participate in joint trips. Another finding is that persons classified as shoppers and carpoolers have a higher probability of making joint trips compared to others. Joint travel by household members was also modeled recently by Vovsha et al., (2003) at various levels. : Based on the purpose of the activity, joint travel is classified based on the participants present in the tour (e.g. joint tours with adults only, children only and adults with children, and person participation in fully joint tours). The primary conclusion in the study was that joint travel was more common for school, maintenance and discretionary purposes. Along similar lines, Fujii et al, (1999) study individuals' joint activity engagement using a structural equation model system. Two sets of models were presented: one for travel patterns and quality of life and the other for time allocation. Individuals' joint activity patterns were divided into four categories (HomeFamily, HomeOthers, OutFamily and

OutOthers) based on the location and companions in the joint activity. In addition, solo activities were also classified into two types: HomeAlone and OutAlone. They concluded that individuals prefer out-of -home solo activities to out-of-home joint activities with family members whereas workers and homemakers tend to spend more time with family members in-home.

Another aspect of activity related studies is the time allocation by individuals to various activities. Bhat, Srinivasan and Axhausen, (2004) examined the length between successive participations in several activity purposes over a multi-week period based on the data collected from German cities. The authors studied five different non-work activity purposes: recreation, social, personal business, maintenance shopping and non-maintenance shopping. They found that individuals who work longer are found to have longer interactivity duration than individuals who work shorter durations. Individuals who use a car as the primary mode to participate in shopping have higher inter-shopping duration than those who use other modes. Goulias, (2001) used multilevel models to examine individuals' choice of time allocation to subsistence, maintenance, discretionary and travel activities. Through the use of both longitudinal and cross sectional models, the authors found that males allocate more time to subsistence activities compared to females and non-workers allocate more time to maintenance activities compared to workers. Gliebe and Koppelman, (2001) estimated the time allocation for different out-of-home activities by adult household members using a proportional share model. Independent and joint activities are classified into subsistence, maintenance, leisure and home activities. The variable -autos per person was found to have positive effect on the time allocated to independent maintenance and leisure activities is traded off against the time spent in-home. The number of children (age < 17 years) had a significant positive effect on the time allocated to out-of-home independent maintenance activities by females.

Life cycle analysis was presented by Scott, (2001); and Stopher and Metcalfe, (1999) to assess the influence of household role on activity participation. Scott, (2001) performed an empirical analysis of out-of-home activities across three types of households: non-worker couple; couple with a single worker; and two-worker couple families. They noted that the presence of children in a non-worker couple household resulted in increased male participation in independent activities. In contrast, joint activity participation is found to increase in one-worker couple families when children are present. Females who live in two worker couple households owning only one vehicle are more likely to participate in independent activities compared to females from multi-vehicle households. Stopher and Metcalfe, (1999) performed statistical analysis to infer the role of household composition and structure on activity participation. They found that there exist significant differences between different life cycle groups. The influence of gender and worker's employment status were also tested. Gender was not a significant factor whereas employment status is reported as a significant variable.

Most of the researchers were interested in the primary couple (i.e. the head of the household and spouse) in a household (Simma et al., (2001); Vovsha et al., (2004); and Bhat et al, (2004)) where as the authors in this study have also analyzed the activity patterns of other individuals. Empirical data used in this study shows that the solo activity participation of other individuals is also significant (20% of solo discretionary trips are performed by other than head of the household and spouse). In fact, Table 3.3, shows that in some segments of the population, the probability of selecting other household member can be as high as 52.9%. Analysis of activity patterns based on life cycle groups was done by many researchers. However the current study investigates between-household differences based on life-cycle groups.

3.3 Data and descriptive statistics

To address the objectives discussed earlier, this study uses disaggregate activity travel data from the Bay Area Travel Survey 1996, which contains rich data at the activity episode level. This data was obtained using a two-day activity diary survey from 3,344 households. In this survey, data was collected on activity participation of individuals including details of activity episode participation by each household member (14 years or older in age). The activity data includes the purpose, location, and duration of each activity, along with the associated travel attributes. The trip attribute information obtained includes: timing and duration of trip, origin and destination, mode of travel, trip-chaining, and co-passengers present. The dataset also contained detailed information on household and individual attributes of all survey respondents.

In this study, the activity travel data is used from 17500 activity episode records corresponding to a sample size of 1174 households, collected on the first day. The current analysis focuses on the allocation of tasks to persons only for out-of-home activities since these activities directly involve travel. A rigorous data screening process is carried out to consider only those records with consistent and complete data in the analysis. For instance, all activities performed by single person households are excluded from the analysis, as the question of allocation of activities among members does not arise in this context. Activities performed by individuals younger than 14 years of age are also excluded from the analysis due to legal restrictions on their mobility. All records that have missing information regarding key explanatory variables (worker status, job type, number of household individuals and cars, gender, age and so forth) are also excluded from the analysis. However, household income values are imputed as per the distribution of income in the remaining data. This analysis focuses only on out-of-home discretionary and maintenance activities. Subsistence activities (such as work and school) were not considered since they are individual specific and cannot be reallocated across household members. Maintenance activities include episodes involving household business, household maintenance / chores, shopping, and pick up and drop off activities. In contrast, discretionary activities include activities such as recreational, entertainment, visiting, hobbies and so forth.

After this screening process, a total of 2518 valid maintenance records are used in the analysis. Among these 2200 records are solo activities and 318 episodes consist of joint activities. Similarly among the 1079 valid discretionary activities, there were 950 solo activities and 129 joint activities. Thus, the major part of activities is performed as solo activities. Table 3.1 illustrates the distribution of socio-demographic, household, and individual characteristics across the sample. The mean household size in the sample is about 2.87. Nearly 35% of the households are single person households and were not considered for further analysis. Among the sample households, nearly 53%, 22%, and 26% of households consisted of 2, 3, and 4+ members respectively. The sample is nearly evenly distributed among males and females with 49% males and 51 % females. In relation to number of workers in a household: 13% of the households do not have any workers, 25 % are one-worker households, 52% are two-worker households, and the remaining 10% are three or more worker households. Ten percent households are classified into low-income (<$30,000) category, 33% medium-income ($30,000-$59,000), 44% are high-income (>$59,000), and 12% households in the sample did not provide their household income information. Interestingly, 18% of the households have 0-5 year old kids and a similar fraction of households has 6-10 year old kids.

The number of valid individual members in the sample are 2692 and among them 22% are younger individuals (14-30 years), 45 % are middle-aged (31-50 years), 24% are upper middle-aged (51-70 years), and 9% are older individuals (>70 years). Nearly 67% of individuals in the sample were employed, and a majority of these individuals are employed full-time (83% of employed individuals were full-time workers). In this regard, non-worker is defined as a person who is not employed and hence, students and retired individuals are also considered as non-workers. With regard to the distribution of household role in the sample, 44% of individuals are head of the households, 36% are spouses, 4% are parents / in-laws, 12% are children, and the remaining 4% individuals correspond to other household role (sibling, grandparent, aunt/uncle). As expected most of the eligible individuals (about 88% of the sample) hold a driver's license and the remaining 12% don't. This data was compared against the socio-demographic profile of other activity based surveys to verify whether the sample is reasonably representative of the population and the characteristics noted above found to be similar to those reported in the other data sets: 2000 Bay Area Travel Survey (Srinivasan and Athuru, (2004)), and 1998 Miami-Dade County Area Survey.

3.4 Modeling framework and calibration procedure

Two inter-related decisions are of interest in this set of person allocation models: (i) whether the given activity episode is performed individually (solo) or jointly, and (ii) if the activity is a solo activity, to which household member is the activity allocated? In modeling these choice dimensions, the following two-stage nested model depicted in Figure 3.1 is used.

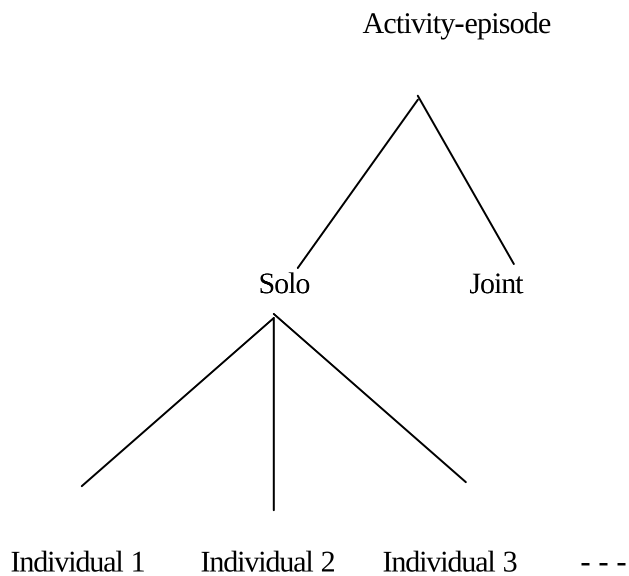

Figure 3.1 Activity episode allocation to individuals

3.4.1 Behavioral framework

Both decisions are modeled based on the random utility maximization framework described below. The first stage decision of solo or joint activity participation is modeled using a binary utility structure. According to this framework, a joint activity is selected if and only if the utility of joint participation exceeds the utility of solo participation.

Conditional on the first stage decision to participate in a solo activity, a multinomial utility structure is used to analyze the allocation of activity to eligible household members. An eligible member is defined in this study as the person who is at least 15 years or older and stays with at least one other person who also should be 15 years or older in a household. In this stage, the individual, whose selection yields the largest conditional utility of activity participation (given that the utility is a solo activity), is selected as per the utility maximization framework.

3.4.2 Special features of this framework

Although, both stages involve discrete unordered choices, the following distinct features of this problem context require some significant extensions of the standard discrete choice models for its analysis. First, this framework represents a discrete choice context where the choice set is variable in dimension across households. For instance, the number of eligible persons who may participate in a solo activity can vary from one household to the other, and must be appropriately modeled. More interestingly, not only is the choice set variable in size but also variable in terms of alternatives. In contrast to standard discrete choice models, where at least some (if not all) alternatives are common across many (if not all observations), in this case no alternative is common across two observational units (since each eligible individual belongs to and can be selected by one and only one household). As a result, the alternative specific constants are not directly meaningful, as the alternatives (persons selected) vary from household to household. Third, unlike the standard discrete choice models where the decision-maker is typically an individual, in this case the decision-making entity corresponds to a household, which allocates activities to members. Consequently, household attributes (e.g. number of workers), which are invariant across household members, must be carefully specified in order to infer inter-household differences. Finally, several sources of potential correlations must be accounted for in the model specification. These include: unobserved shared terms across members from the same household, correlation between decisions made across different episodes performed by the same individual, and correlations induced across conditional solo person utility terms, due to the shared errors associated with household solo utility term. The following model is used to capture these features of the person allocation problem context.

3.4.3 Model specification

Notations:

Let h denote the index for household h = 1,…H,

Let i_h denote individual i from household h, and

Let I_h={i_h = 1,2,…, number of members in household h} represent the set of household members in household h.

Let k_h represent the index of trips made by household h (subscript is dropped in what follows for ease of notation) and K_{hmax} represent the maximum number of trips made by household h on the given day

Let U_{hksolo} represent the utility of a solo activity relative to a joint activity for household h for activity k ($U_{hkjoint}$ is taken as 0 with no loss of generality).

Let U_{hki} =conditional utility of selecting individual i belonging to household h for participating in the kth household activity for the day given that the activity is a solo activity.

Let $\delta_{hksolo} = 1$ if activity k performed by household h is a solo activity

= 0 otherwise

$\delta_{hkjoint}$ = 1 if the activity k performed by household h is performed jointly

= 0 otherwise

δ_{hki} = 1 if individual i from household h is selected for the kth activity and that the activity is a solo activity

= 0 otherwise

Random Utility Maximizing Behavioral Framework:

Utility maximization for Person Selection:

$\delta_{hksolo} = 1$ if $U_{hksolo} \geq 0$

$\delta_{hksolo} = 0$ otherwise.

$\delta_{hkjoint} = 1 - \delta_{hksolo}$

Utility maximization for Person Selection:

$\delta_{hki} = 1$ if $U_{hki} > U_{hkj}$ for all $j \neq i$ and

j and i are eligible members in household h for performing activity k.

Utility Specifications:

Utility solo: $U_{hksolo} = X_{1hk}\beta_1 + \varepsilon_{1h} + \varepsilon_{1hk} + ?_{1hk}$

Conditional Utility of Selecting Person i for the kth activity given that it is a Solo activity:

$U_{hki} = X_{2hki}\,\beta_2 + \varepsilon_{2h} + \varepsilon_{2hk} + \varepsilon_{2hi} + ?_{2hki}$

$U_{hki*} = 0$ (for baseline person, head of the household)

For ease of convenience, the normal errors, which contribute to the two utilities, are represented as $?_{1hk}$ and $?_{2hki}$ respectively.

$$U_{hksolo} = X_{1hk}\beta_1 + ?_{1hk} + ?_{1hk} \qquad (1a)$$

$$U_{hki} = X_{2hki}\,\beta_2 + ?_{2hki} + ?_{2hki} \qquad (1b)$$

Systematic Utility Specification:

β_1 = vector of parameters associated with the solo utility

β_2 = vector of parameters associated with the conditional person allocation utility given that the activity is a solo activity.

X_{1hk} = vector of explanatory attributes affecting solo utility for household h, and activity k (e.g. license holding, household income etc.).

X_{2hki} = explanatory attributes affecting conditional person allocation utility for individual i from household h, for activity k (e.g. age, gender etc.).

Specification of Random Error Terms:

ε_{1h} = persistent error of solo utility across various activities performed by household h and ~ N(0, ? $_{?h}{}^{2}$)

ε_{1hk} = correlated component of the time-varying error of the utility that varies across different activities k of household h ~ N(0, ? $_{?hk}{}^{2}$)

? $_{1hk}$ = independent component of the time-varying error of the utility that varies across different activities k of household h and ~ IID Gumbel(0, ? ^{2}/6)

ε_{2h} = shared error that is common to conditional solo utility of all individuals from household h for all trips k and ~ N(0, ? $_{?h}{}^{2}$)

ε_{2hk} = shared unobservable error that is common to the conditional solo utility of all individuals for activity k of household h and ~ N(0, ? $_{?hk}{}^{2}$)

ε_{2hki} = correlated part of the person and trip-specific random component of conditional solo utility for individual i from household h for activity k, and ~ N(0, ? $_{?hki}{}^{2}$)

? $_{2hki}$ = independent part of the person and trip-specific random component of conditional solo utility for individual i from household h for activity k, and ~ IID Gumbel(0, ? ^{2}/6)

where the ? ^{2} represent the suitable variances corresponding to the error-terms with the specified subscripts. It is assumed that the covariance structure involves the following non-zero correlations as follows:

$$\mathrm{Cov}(\varepsilon_{1hk'}, \varepsilon_{1hk}) = ?_{1hkk'} \text{ for } k' \neq k \quad (2a)$$

$$\mathrm{Cov}(\varepsilon_{2hk'}, \varepsilon_{2hk}) = ?_{2hkk'} \text{ for } k' \neq k \quad (2b)$$

$$\mathrm{Cov}(\varepsilon_{2hki'}, \varepsilon_{2hki}) = ?_{2hkii'} \text{ for } i' \neq i \quad (2c)$$

$$\mathrm{Cov}(\varepsilon_{1hk'}, \varepsilon_{2hk}) = ?_{1hk2hk'} \text{ for } k' \neq k \quad (2d)$$

All other cross correlations within a given household are assumed to be zero. Furthermore, all error terms are independent across households. For convenience of analysis and interpretation, all cross-correlations are assumed as zero to focus on the effect of systematic explanatory variables rather than the random error terms. Nevertheless, the general formulation presented above can be used to capture the effect of various sources of correlations.

Log-likelihood formulation:

Given the normal error vectors ? $_{1.}$ and ? $_{2.}$, note that the utilities U_{hksolo}, and U_{hki} become mutually independent across individuals in the household, and activities of the household. This property is exploited in formulating the likelihood as a mixed logit as follows:

Pr(Activity k by household h is a solo activity | ? $_{1.}$ and ? $_{2}$)

$$= P_{1hk|\eta_{1.},\eta_{2.}} = \frac{e^{X_{1hk}\beta_1 + \eta_{1hk}}}{(e^{X_{1hk}\beta_1 + \eta_{1hk}} + 1)} \tag{3a}$$

Pr(Activity k by household h is performed by individual i as a solo activity | ? $_{1.}$ and ? $_{2}$)

$$= P_{2hki|\eta_{1.},\eta_{2.}} = \frac{e^{X_{2hki}\beta_2 + \eta_{2hki}}}{\sum_{i'\in I_h} (e^{X_{2hki'}\beta_2 + \eta_{2hki'}})} \tag{3b}$$

The joint choice of solo activity and the allocation of person i to the kth activity can then be obtained by unconditioning over the vectors ? $_{1.}$ and ? $_{2.}$, and is expressed as the following integral:

$P_{hksolo,i}$ = Pr(hk solo and ith person is selected) =

$$\iint_{\eta_{1.},\eta_{2.}} P_{1hk|\eta_{1.},\eta_{2.}} . P_{2hki|\eta_{1.},\eta_{2.}} . d\eta_{1.} . d\eta_{2.} =$$

$$\iint_{\eta_{1.},\eta_{2.}} \frac{e^{X_{2hki}\beta_2 + \eta_{2hki}}}{\sum_{i'\in I_h} (e^{X_{2hki'}\beta_2 + \eta_{2hki'}})} \frac{e^{X_{1hk}\beta_1 + \eta_{1hk}}}{(e^{X_{1hk}\beta_1 + \eta_{1hk}} + 1)} d\eta_{1.} . d\eta_{2.} \tag{3c}$$

The expression for $P_{hkjoint}$ can be written similarly.

Likelihood of activity participation for household h is given by:

$$L(h) = \prod_{k_h \in K_{h,max}} [P_{hkjoint}]^{\delta_{hkjoint}} \{ \prod_{i' \in I_h} [P_{hki'}]^{\delta_{hksolo} * \delta_{hki'}} \} \tag{3d}$$

The Log-likelihood is written assuming independence across households h:

Log-Likelihood of sample = ? $_{h}$ log L(h) and is estimated using Simulated Maximum Likelihood Estimation Technique (Revelt and Train, (1998)).

3.4.4 Modeling modifications to accommodate these features

1. Variable Choice Set Problem:

To address the issue of varying number of alternatives across households, the choice set dimension was set to a large constant for all households I_{max} (maximum household size). As far as the model is concerned, all households have I_{max} members in order to have a constant choice set dimension across households but members after I_{hmax} are treated as virtual and ineligible members who are never allocated to any activity. The person-level utility for ineligible members (e.g. children < 15 years of age or virtual members) is set as a large negative number to preclude their choice for household activities.

2. Alternatives are variable across household:

The members in each household h are classified as person 1, person 2, person 3, … person I_{hmax}. Thus, strictly speaking none of the alternatives are common across households. This problem can be dealt with by treating each household as a sample and the associated activities as repeated observations for the purpose of calibration. While the advantage of the variable alternatives across household is that household specific parameters can be estimated but the disadvantage is the inefficiency of estimates because the coefficients will then be based on too few observations. To overcome this problem, it is possible to specify the alternatives in such a way that they are common across households based on household role as head-of-the-household, spouse-of-the-head, spouse's father, spouse's mother, eldest child, second eldest child and siblings. However, such a specification of alternatives directly based on household role is likely to result in endogeneity bias, resulting in inconsistent coefficient estimates. This endogeneity bias is the result of common unobserved terms that could simultaneously effect of household role on task allocation to members, and the effect of household role on explanatory variables.

To illustrate, consider for example, a three-person household consisting of the head, the spouse and a small child (say 3 years old). Assume that the baseline is the head of the household. The conditional utility of solo participation for the spouse relative to the head may be given as:

Uspouse = b0 + b1*female + b2*presence of children 0-5 + b3*hhincome + b4*worker + error (4a)

If the household income is high, the household may engage a care-taker for the children. A working spouse due to time constraints may be less likely to be chosen to participate in household activities. Due to the unobserved time constraint effects and greater discretionary household income, such a spouse may engage the services of child-care service provider. This interaction, in turn, affects the propensity of task allocation to the spouse and can result in an endogeneity bias during estimation.

To circumvent the endogeneity issue, in this study the alternatives are not classified based on household role but instead are labeled as person 1, person 2, … person k in each household. This labeling is done in such a way that there is no direct linkage between this ordering and household role (in other words, person 1 is not the head of the household in all households). To capture generic effects across households due to the household role and life-cycle group, indicator variables are defined for each household and member (e.g. $y_{person1,head}$ = 1 if person 1 is the head of the household and is zero otherwise;

other indicators for spouse etc. are similarly defined). These indicator variables (except one, which is left out as a baseline - indicator for head), are added to the conditional solo utility specification for each person for each activity.

$$\text{Uperson1} = \text{b0} + \text{b1}^* \, y_{\text{person1,spouse}} + \text{b2}^* y_{\text{person1,child}} + \text{b3}^* y_{\text{person1,parentofhead}} + \text{error} \qquad (4b)$$

The treatment of household-role as an explanatory variable instead of its treatment as a dependent variable can reduce the potential for endogeneity bias. This specification enables capturing both non-role specific person attributes and role-specific factors that affect person allocation, whereas, the role-specific attributes and person-choice are confounded when alternatives are defined based on household-role in equation Y.

3. Specification and Interpretation of ASC, ASV, and generic variables

Note that for the specification above where the alternatives are labeled person 1, person 2, explicit capturing of an alternative specific constant that is robust across households may not be possible, since no alternatives are common across households. Consequently, the coefficients corresponding to the indicators can be interpreted as alternative specific constants that reflect the intrinsic propensity of a household to select the spouse, parent/in-laws, and children etc. For the same reason, specification of alternative specific variables is not possible (parameter values corresponding to the same attribute whose influence changes across alternatives). Therefore, all variables in the model are captured as generic variables in the specification, except in the case of interaction terms. In other words, the effect of gender (say a male) remains unchanged for all males in the household. However, to account for differences within people of the same gender, interaction terms are specified by combining two or more indicator variables (e.g. female*presence of children in household) that account for person-specific or situational characteristics.

4. Specification of Inter-household differences and modeling inter household differences

Between household differences are modeled at two levels. The first level is through the specification of explanatory variables such as (1) the presence of 6-15 year old kids*part-time worker presence, and (2) household with 0-5 kids*female) that reflect differences between households. The household level attributes (number of cars, number of workers etc.) remains unchanged across all persons/alternatives considered. Therefore, direct estimation of these differences is not possible, if these terms are included in the utility of all eligible persons. Consequently, to capture inter-household differences, the household attributes are interacted with person-level indicators and applied to the utility of all but one of the eligible members in the model. While this approach is useful, in many cases incorporating the interaction between two or more indicator variables is essential to capture this effect, and the interpretation can become somewhat difficult and non-intuitive (for instance whether the same effect is seen for females with older kids or for males with 0-5 year kids is not immediately obvious for the variable 2 noted above). The other difficulty in this approach arises from the presence of similar and correlated variables together with multiple interaction terms which makes the interpretation of the first order effect such as gender less straight-forward.

To overcome this difficulty, another approach is proposed here which combines the statistical model developed previously with exogenous segmentation based on categorical-type analysis is used for analyzing inter-household differences. To analyze these differences, the individual probabilities are estimated by using the calibrated model for each household member and each activity. These probabilities are then aggregated to obtain the average probability of estimation for the head of the household, spouse of the head, other solo, and joint activity participation for each household. The sample is then divided into mutually exclusive and homogeneous exogenously defined segments (for e.g. based on number of cars, income etc., see Section 3.6.5 or Table 3.3), and the average probabilities for each segment and associated standard deviations are obtained. The differences across these segments (allocation of tasks to 0, 1, 2+ cars to head, spouse, joint, and other solo) are analyzed using Bonferroni confidence intervals that permit multiple comparisons. Only statistically significant differences in task allocation across segments are reported.

5. Treatment of Correlations and Nesting

Correlation terms in equation 2a and 2b reflect within-household correlations for solo activity and conditional solo utility respectively. In contrast, terms given in equations 2c denote within activity correlation across members of the same household, whereas equations 2d represent nesting effects between solo and conditional person allocation utilities.

3.5 Hypothesis

In this section specific research questions that have guided the systematic variable specification are presented and are classified into the following five different categories.

i) *Household role*: In this category, the role of different household members in performing household activities is analyzed. The specific factors considered include the role of head of the household, spouse, child, parent/in-law, effect of prior activity performance by males etc.

ii) *Person characteristics*: gender differences, age, possession of license, disability status, race of household members are analyzed as part of the person related characteristics while allocating household individuals to out-of-home maintenance and discretionary activities. Further, the interaction between trip duration and gender on activity participation is also estimated.

iii) *Role of Constraints*: In general, various constraints limit / enhance the activity participation. For example, fewer vehicles (vehicle constraint) in a household limit solo activities where as vehicle constraint enhances joint activities, cost constraint (either gas cost or parking cost) can increase transit use, and time constraints can limit activity participation and / or increase trip-chaining. Other constraints including the presence of children may result in more joint maintenance activity participation and perhaps lower levels of participation by female household members (when the kids are young). Other constraints include coordination constraints which apply to activities that require coordination among multiple people and synchronization of time. Location-based constraints are related to the proximity of activity Origin-Destination from work or home, and may result in trip-chains.

iv) *Within-household variability*: Variability in activity participation within a given day for each individual is estimated by considering the previous history of activity performance of that individual.

v) *Between-household variability*: The primary interest of this aspect is to explore the differences in activity participation of head of the household, spouse and the other individuals belonging to various types of households (classified based on household composition, structure, or socio-economic characteristics). In this context, questions such as whether differences exist across households that have male as a head of the household as opposed to female head are of interest. Similarly, differences across zero-car, one-car and two or more car households, variations across zero-non-worker, one-non-worker, two or more non-worker households are also relevant. Activity participation differences across various households are also analyzed in terms of age groups of couples, vehicle-adult combinations and household income.

3.6 Model results and discussion

3.6.1 Household role effects

The results provide significant evidence of the effect of life-cycle and household role on person allocation to activities. The head of the household is generally more likely to participate in both maintenance and discretionary activities than the spouse of the head of the household. In addition to reflecting a greater degree of household responsibility (for the head), this may also be the result of car-availability and sharing in some households. However, this decision is affected by the relative extent of time constraints on the head and the spouse. Children in the household are significantly less likely to perform maintenance activities (in part due to lack of mobility resulting from driving age restrictions). These results are also corroborated by findings from other studies (Simma et al., (2001); Bhat et al., (2004); and Vovsha et al., (2004)).

As the number of household members who are employed increases, participation in joint activities decreases significantly for maintenance activities (shown at the bottom of Table 3.2). This effect may be attributed to greater income and mobility resources, and greater delegation of activities across working adults (as there are fewer if any non-workers). Furthermore, the participation in discretionary activities drops to an even greater extent with increasing number of workers. In addition, to the reasons cited above, the flexible nature and timing of the discretionary activities suggest that the need and/or ability to synchronize or coordinate joint trips diminish with increasing number of workers.

A similar employment related effect pertains to the role of female workers in the household. As the fraction of female workers in the household increases, joint participation in discretionary activities decreases, due to the added work-related time constraints on both male and female workers in the household. Two other contrasting within-household interactions were also found in the data. In households, where males perform most of the prior maintenance activities, the likelihood of female performing current maintenance activities was lower (suggesting a gender-based allocation of tasks, perhaps due to child care obligations of female household members). On the other hand, in case of maintenance activities, if the head of the household performed several prior activities, the propensity to participate in a current maintenance activity increases for the spouse, suggesting a delegative or greater participatory role of the spouse in such a case.

The alternative specific constant for joint trip-making is negative, indicating that most activities involve solo driving, a common trend in many U.S cities. Lower income households are more likely to participate in joint maintenance activities than their medium and high-income counterparts, whereas, no significant differences are seen for discretionary activities. Similarly, a greater degree of joint activity participation was found in households with related members than households with unrelated individuals (e.g. co-residents). This finding may be explained due to greater synergistic resource sharing (e.g. vehicle) and activity delegation in related households.

3.6.2 Person characteristics

The attributes of household members also play a significant role in allocation. In this regard, with increasing age the propensity of participating in a maintenance activity increased, which can be expected due to greater household responsibility for middle aged respondents, and relatively more free time in the case of retired individuals. In contrast, a greater propensity to participate in discretionary activities is found as age decreases, which is also along expected lines. Data also suggest that females are more likely to participate in maintenance activities than males, which may be partly due to the greater degree of responsibility for shopping activities by female members in the household (also consistent with several other studies Simma et al., (2001); Gliebe et al., (2001); Scott, (2001); and Stopher and Metcalfe, (1999)). However, it was observed that females are more likely to participate in shorter duration trips than males, suggesting that the destinations for maintenance activities are likely to be closer to anchor points (home or work) for females than males. License holding is positively correlated with maintenance activity participation, whereas, individuals with disability have a lower discretionary activity participation propensity. These two observations highlight the role of mobility constraints on activity participation and resulting travel.

3.6.3 Role of constraints

The results reveal that constraints play a substantial role in determining person allocation to activities. Cost, time, coordination, and location/proximity factors play a key role in determining person allocation propensity. In terms of cost, the presence of parking charges inhibited the participation of individuals employed in the financial, educational, and health care sectors in maintenance activities. The following findings highlight the role of time constraints. Workers are more likely to participate in discretionary activities over the weekends compared to weekdays. Further, as the duration of work activity increases, the propensity for participating in maintenance and discretionary activities for full-time workers decreases. On the other hand, workers with two or more jobs were observed to be more likely to participate in discretionary activities (possibly due to the availability of free time between jobs).

Not only in the case of workers, but also more generally joint maintenance activities are more likely in the weekends than weekdays, suggesting the inhibitive effect of work and related time constraints on coordination between household members. Joint activity participation (both discretionary and maintenance) was also lower in households with 0-5 year old kids due to child-care requirements. It is seen that female members are more likely to fulfill this responsibility, as their maintenance participation propensity appears to reduce significantly when small children (0-5 years) are present. These observations highlight the role of coordination and in-home activity responsibilities on joint out-of-home activities, thus underscoring the need to jointly analyze in-home and out-of-home activity patterns.

Location and proximity factors from home and work-place also appear to influence person allocation. For instance, full-time workers are less likely to be selected for home-based maintenance trips, suggesting that a significant number of maintenance activities are performed en-route to and from work locations whereas, non-workers are more likely to participate in home-based tours. Given the time constrained nature of the former trips (due to institutional and work timings), these differences have significant implications for VMT, duration of activity and trip, and location of activity and analysis of transportation planning policies. Users without license are observed to participate in a significant amount of non-home based activities, possibly due to their use of transit modes (requiring) with transfer from intermediate non-home based points. The data also suggest that females are less likely to be selected for home-based maintenance activities (than females for non-home based activities), whereas, younger respondents are less likely to participate in home-based discretionary activities than older respondents.

3.6.4 Within-household differences in activity allocation across different episodes

Note that most of the factors discussed above pertain to how life-cycle, household and personal attributes (head of the household, spouse, income and number of workers, age, gender, and license holding) influence person allocation. However, these factors are essentially static within a given household over the several different episodes during the study period (of two consecutive days). Nevertheless, the activity participation propensity varies across episodes and over time even within a given household. To capture these effects, the following variables are employed in the specification. Reflecting the significance of state-dependence effects, the results indicate that individuals with greater level of participation in prior discretionary activities are more likely to be chosen to participate in current maintenance activities but the converse does not appear to hold. This dynamic influence may be the result of greater access to household vehicles (especially if number of vehicles is limited), and/or greater intrinsic trip-making or activity participation propensity of the selected individuals in the household. Note that state dependence refers to the influence of past activity decisions on current choice outcomes.

3.6.5 Between-Household Differences

While allocating individuals to activities, between household differences have been analyzed up to a certain extent in the joint activity model. However, to examine these differences in detail, this analysis examines differences in probability of selecting the head of the household, the spouse, other individuals, and joint participation across various types of market segments. These segments are based on gender of the household head, number of workers, number of vehicles, number of children, and the employment status of the primary couple (head and the spouse). Using the episode level model discussed previously, the probabilities of selecting each individual in each household are first computed. These probabilities are then aggregated and averaged across different types of market segments mentioned above and the associated standard deviations are also computed. The mean probabilities of activity allocation for the four levels above are then compared across different market segments. Only statistically significant differences are reported below. The results reveal significant differences between households in relation to socio-demographic attributes.

Gender of head of the household:

For instance, the gender of head of the household (hhh) affects the person allocation process for both maintenance and discretionary activities. Households with female heads are more likely to choose the head of the household for maintenance activities (53.6% probability, spouse = 23.6% probability) than if the head of the household is male (39.1% for the head). In households with a male head of the household, the participation between head and his spouse is nearly equal, whereas, maintenance appears to be the primary responsibility of the head, if the head of the household is a female. A similar trend is also seen for discretionary activities (hhh female 44% whereas hhh male 39%). However, no differences are seen for joint activities based on the gender of the head of the household.

Effect of Number of cars in HHH:

In zero car households, the primary maintenance role is allocated to the head of the household (hhh - 49%, spouse of hhh - 20.3%, others 19.6%), whereas joint participation is low (10.8%) due to the difficulty in coordination/activity sharing with transit mode. In one car households also, the primary role is for the head (51.7%), and can be attributed to the greater access to the vehicle for the head of the household. However, in this case, the spouse of the head is more likely to participate in maintenance activities (24.3%) and the probability of joint activities also increase (13.9%) due to car availability and sharing. In contrast, the role of the other individuals in the household drops quite significantly (9.9%). However, as the number of cars increases (from one to two or three cars), the primary role of the head reduces significantly (from 51.7% to 42.8% for 3+ cars) and the spouse's role increases (24.5% to between 29 and 33%), indicating a greater redistribution of activities. The joint participation decreases understandably from 13.9% to 11.8% indicating a greater delegative effect and more staggering of trips. The differences across households based on car-ownership levels are virtually along the same lines for discretionary activities. The major difference pertains to the pre-eminent role in discretionary activities for the head of the household in zero car households (65% for hhh, spouse 18%, other 9 %, joint 8%). Therefore, the reduction in head's participation with increasing number of cars is also more substantial (nearly 20% reduction in 1 car household). As the number of cars increases, the primary role of the head reduces more drastically (it nearly halves from 65.1% for 0 cars to 35.7% for 3 cars); the spouse's role increases (nearly doubles 18 to 25-33%), and the participation of other household members also nearly doubles. The joint discretionary activity propensity is at a maximum for a one-car household (13%) due to possibly car-sharing constraints, and decreases as the number of cars (10% for 3+ cars) increases. Note that the absence of household vehicles is also not conducive to joint discretionary activity participation (joint activity participation = 7.6 %).

These results are also confirmed by differences based on number of vehicles available per driver. As the number of vehicles per driver increases, a greater participation of other individuals (neither the head nor the spouse) is observed. This increases from 7 to 30.3% for maintenance activities, and is even larger for discretionary activities (ranging from 12 to 53%!). As expected the role of the head decreases (48 to 40% for maintenance, and 44 to 23% for discretionary activities). A similar reduction (nearly 50% drop) is also seen in spouse's activity participation probabilities (32 to 17% maintenance, and 32 to 13% for discretionary activities).

Household income:

Interesting differences in activity allocation are observed across different income groups. In households with higher income, the maintenance allocation between head and spouse is more equitable (hhh = 44%, and spouse = 36%). In contrast, in households with lower income the head of the household plays a primary role in maintenance activities (head = 49%, spouse = 26%). A similar trend is also seen in discretionary activities (high income: head - 41%, spouse - 35%, whereas in low income households: head - 43%, spouse - 27%). These differences may be attributable to the greater availability of disposable income and vehicles in higher income households, and possibly a greater value of travel time for the head of the household in these cases. Evidence of this conjecture is also seen in the joint activity participation. While only 11% of activities involve joint participation in high income households, nearly 16% of maintenance and 13% of discretionary activities in lower income households involve joint activity participation.

Presence of Kids:

The head of the household is more likely to participate in maintenance activities in households with small children compared to those households with no kids (51 versus 46%). A similar effect is also seen for discretionary activities (50 and 42% respectively). Interestingly, the role of the spouse (of hhh) is also increased (36 % with kids, and 30% without children for maintenance; whereas, the corresponding probabilities are 38% versus 29% for discretionary activities). The increase above is compensated by a reduction in joint participation, which drops drastically with the presence of small children. The joint activity participation probabilities average about 4% (5%), 10% (9%) and 15% (14%) respectively for maintenance (discretionary) activities in households with 0-5 year old children, 6-15 year old children, and no children. The solo participation of other individuals is also high in households with school going children (6-15), with 24% (nearly a fourth of household activities) in discretionary activities and around 10% for maintenance activities. Thus, modeling activities and trips by these individuals (not just hhh and spouse) at least for selected segments of the population is essential, possibly due to the non-motorized nature of such trips, and significant contribution to household trip-making.

Employment Status of the Couple (HHH and Spouse):

To examine the role of employment status of head and spouse, the activity propensities are compared for three groups of respondents: i) the head is full-time employed but the spouse is a non-worker, ii) both the head and spouse are full-time workers, and iii) only the spouse is full-time employed, the head is a non-worker. Interestingly, when both are working the participation of the head and spouse are both higher compared to the case when the spouse is not working. For instance, the participation propensities for maintenance were 45, and 38% respectively for the head and spouse respectively in households where both individuals are employed, whereas, the rates were lower at 41% and 30 % respectively. A similar trend is also observed for discretionary activity (both employed: 41, 36% probabilities for the head and spouse respectively, whereas, the probabilities drop to 37 and 25% for households where only the head is employed).

The overall increase for both partners is indicative of a greater level of mobility when both hhh and spouse are employed, whereas, the increase in spouse's participation indicates a greater degree of activity sharing due to work-related time constraints when both members are full-time workers. While the lower participation rate of a spouse of the head when the spouse is not a full-time worker may appear counter-intuitive given the lack of time-constraints, this may be attributable possibly to a reduced level of access to vehicles to non-workers in households with limited number of cars. In contrast, in households where the spouse is a full-time worker, but the head is not employed, the head of the household plays a key role in maintenance and discretionary activities (maintenance probabilities are: 57% head, 26% spouse, whereas, for discretionary activities the probabilities are: 47% head and 28% spouse) highlighting the role of spouse's work-related time-constraints and greater time-availability with the head of the household (possibly retired). These results emphasize the trade-off between vehicle availability and time-availability on person allocation to activities. Note that the nature and extent of trade-off varies across households depending on the employment status of the head of the household and his/her spouse.

Age of couple:

Differences in person allocation are also observed based on age of the couple, which is partially reflective of life-cycle differences. In younger couples (when both hhh and spouse are less than 30 years of age), a greater distribution of activities is observed. The probability of participation is 46% (48%) for the head, and 43% (41%) for the spouse for maintenance (discretionary) activities, whereas joint activity propensity is about 9%. When both partners are middle aged (30-50 years old), the head plays a slightly more active role (hhh - 46%, spouse - 38% for maintenance; hhh - 40%, spouse - 36% for discretionary), partly due to additional child-care responsibilities for the spouse in many cases, and the joint activity level remains unchanged at around 10%. In contrast, when both the hhh and spouse belong to the older age category (> 50 years), the joint activity participation increases between 15-17% for both maintenance and discretionary activity. This increase may be partly attributed to the reduced time constraints possible after retirement. The primary participant in these households is also its head (47% maintenance, 41% discretionary), and the spouse's role is also nearly the same as middle-aged couple (34% and 35% respectively). Note that the participation of other individuals (solo) is the maximum (15%) for couple in the age range 31-50 years, and may coincide with the presence of 6-15 year old children and their participation in recreational activities. In contrast, the participation of other individuals is much lower 4-6% for couples in other age ranges. The lower participation in younger age couples is due to lack of children or presence of small children (0-5 years), whereas, for older couples, children are older than 18 year and are unlikely to stay with their parents.

3.7 Assumptions and validation

In this study, all records pertaining to one person household and single parents are excluded from analysis, as the person allocation to activities is obvious. Further, this study also only focuses on person allocation conditional on activity generation, but does not investigate the interactions between generation and allocation. The justification for these simplifying assumptions is three-fold: First, given the large number of models and decision variables, the simpler model choice is dictated by computational tractability, and the ease of specification and interpretation of the assumptions. These can be relaxed in a straightforward manner using more sophisticated models specifications as per the formulation shown in equations (3d) analyze the decision dimensions jointly, though at considerable computational expense in further research. Future research will also consider: dynamics and variability in person allocation across activities within the same household, influence of vehicle availability and person location jointly with person allocation, and the allocation of persons who participate in a joint activity.

Validation: The models presented above are validated using different data records of the same BATS 1996 data set. For validating the models, 14,518 activity records were used that were not used for calibration. The results are found to be robust across the two data sets for most variables, in terms of signs, significance and magnitudes. The goodness of fit across the two samples was also comparable (ρ^2 = 0.27 for maintenance, ρ^2 = 0.24 for discretionary activity models in the predicted data set as opposed to ρ^2 = 0.31 for maintenance and ρ^2 = 0.28 for discretionary for the calibration data set). In addition, the aggregate sample market shares are reported for three cases in Table 3.4: i) calibrated model applied to prediction data set, ii) actual observations prediction data set and iii) calibrated model on calibration data set (for comparison). It is noteworthy that the calibrated model performs quite well in predicting aggregate market shares on the predicted data set, with errors of <1.2% for maintenance activities, and <0.3% for discretionary activities. Thus, despite the simplifying assumptions noted above, the model appears to provide intuitive and fairly robust insights on the role of various explanatory factors on activity allocation to household members.

3.8 Summary

This paper investigates the allocation of household individuals to out-of-home maintenance and discretionary activities using the rich activity-travel diary data from the San Francisco Bay Area (cite BATS, 96). In particular, a series of models are used to (i) explore the effect of household role, person characteristics, and trip attributes on activity allocation (ii) investigate the role of constraints on time, vehicle availability, cost, and coordination on activity allocation among household members (iii) analyze the differences between households in allocation of persons to activities.

The results provide significant evidence of the effect of life-cycle and household role on person allocation to activities: the head of the household is generally more likely to participate in both maintenance and discretionary activities than the spouse of the head of the household. As the number of household members who are employed increases, participation in joint activities is observed to be decreasing significantly for maintenance activities. The results also suggested a strong role of gender on the allocation of tasks: in households, where most of the prior maintenance activities are performed by males, the likelihood of female performing future maintenance activities was lower. Household income is also found to have significant in activity participation patterns of household members. For instance, lower income households are more likely to participate in joint activities than their medium and high income counterparts.

Location and proximity factors from home and work place also appear to influence person allocation (full time workers are less likely to participate in home-based maintenance trips, non-licensed individuals more likely to perform non-home based trips). The results also suggest a significant drop in non-motorized travel from 0 cars to 1 car households, a greater participation of other household individuals occurs with an increase in the number vehicles available per driver. The analysis reveals: i) a more equitable maintenance activity allocation between the head and the spouse in higher income households, ii) existence of a trade-off between vehicle allocation decisions and time availability on person allocation to activities, and iii) a greater level of activity participation by females in maintenance activities than males. Further, various results emphasized the importance of explicitly considering the activity participation of other household individuals (i.e., other than the head and the spouse).

The proposed person allocation models can be further enhanced to investigate the following research directions in the future:

1) the use of more sophisticated error-structure to capture various sources of correlations (for e.g. within-person, within-household etc.)
2) variables that explicitly account for the time-varying nature of household vehicle allocation decisions and vehicle availability on person allocation decisions.

Other directions for future research are also presented in the next chapter.

Table 3.1: Household and person attribute descriptive statistics

Sample Size: 1174 Households		
Household size	(mean)	2.87
	2 person households	53 %
	3 person households	22 %
	4+ person households	26 %
Number of workers	(mean)	1.63
	0 worker households	13 %
	1 worker households	25 %
	2 worker households	52 %
	3+ worker households	10 %
Income:	Low(<30k)	10 %
	Medium (30k-59.99k)	33 %
	High(>=60k)	44 %
	No information	12 %
Children:	0-5 year old kids households	18 %
	6-10 year old kids households	18 %
Person attributes		
Number of persons in sample (>=14 years)		2692
Gender:	Males	49 %
	Females	51 %
Age:	Young (14-30years)	22 %
	Middle age (31-50years)	45 %
	Upper middle age (51-70years)	24 %
	Older	9 %
Employed		67 %
Unemployed		33 %
Worker status:	Full time	83 %
	Part-time	17 %
License:	With license	88 %
	Without license	12 %
HH Role:	Head of the household (hhh)	44 %
	Spouse of hhh	36 %
	Parent/ in-law of hhh	4 %
	Child of hhh	12 %
	Others	4 %

Table 3.2 Results of both maintenance and discretionary activities, within household differences

Variable Name	Maintenance		Discretionary	
	Coefficient	t-stat	Coefficient	t-stat
Household role				
Spouse of head of the household	-0.261	-4.446	-0.141	-1.581
Child of head of the household	-0.577	-2.873	---	---
# prior activities by all males*female	-0.194	-2.819	---	---
# prior activities by all hhh*spouse	0.354	5.066	---	---
Person Characteristics				
Young (14-30 years)	---	---	1.598	3.153
Mid age (31-50 years)	0.851	4.064	0.998	2.282
Upper mid age (51-70 years)	1.112	6.042	0.616	1.572
Male	-0.396	-3.589	---	---
[Trip duration <=15 min indicator]*female	0.245	2.365	---	---
License	1.410	7.403	---	---
Disability	---	---	-0.619	-2.118
Role of Constraints				
Paid parking * educational, health, bank worker	-1.639	-2.009	---	---
Weekend * full time worker	---	---	0.441	1.469
Work duration	-0.050	-4.514	-0.069	-4.064
Worker with two or more jobs	---	---	0.477	1.810
Household with 0-5 year old kids*female	-0.272	-1.875	---	---
Home-based trip*full time worker	-0.439	-3.425	---	---
Non-home-based trip* no-license	0.568	1.991	0.530	1.890
Home-based trip*female	-0.284	-2.745	---	---
Home-based trip*young	---	---	-0.826	-2.964
Presence of 6-15 year kids*part-time worker	0.309	1.770	---	---
Fraction of part-time workers	-0.503	-1.833	---	---
Within household differences				
# of prior discretionary activity by that person	0.140	1.890	---	---
Joint activities				
Constant	-2.074	-15.300	-2.447	-16.435
# of workers in household	-0.084	-1.582	-0.319	-3.027
Fraction of female workers	---	---	-0.762	-1.869
Low income hh	0.853	4.764	---	---
All persons in hh are related	0.362	4.920	1.232	15.436
Weekend end	0.732	4.451	---	---
Presence of 0-5 year kids in hh	-1.514	-4.668	-1.028	-2.527
Valid observations	2518		1079	
Initial log likely hood value	-3570.75		-1547.63	
Final log likely hood value	-2481.49		-1118.41	
Model fit (ρ^2)	0.31		0.28	

Table 3.3 Mean probabilities of household individuals to evaluate across household differences

	MAINTENACE ACTIVITIES				DISCRETIONARY ACTIVITIES			
Variable	Head of the household	Spouse	Other individual	Joint	Head of the household	Spouse	Other individual	Joint
HHH is male	0.391	0.381	0.106	0.123	0.388	0.315	0.181	0.116
HHH is female	0.537	0.246	0.092	0.125	0.440	0.275	0.167	0.118
Zero Car household	0.493	0.203	0.196	0.108	0.651	0.181	0.092	0.076
One car household	0.517	0.245	0.099	0.139	0.467	0.234	0.170	0.129
Two car household	0.479	0.333	0.065	0.123	0.425	0.330	0.127	0.118
Three or more car household	0.428	0.293	0.160	0.118	0.357	0.257	0.278	0.108
(eligible drivers - vehicles)>=2	0.481	0.322	0.075	0.123	0.441	0.324	0.117	0.118
(eligible drivers - vehicles)==1	0.447	0.282	0.142	0.128	0.375	0.233	0.276	0.117
(eligible drivers – vehicles)<=0	0.397	0.173	0.303	0.127	0.233	0.133	0.529	0.106
Low income hh (<40K)	0.486	0.264	0.092	0.158	0.426	0.262	0.183	0.130
Medium income hh (40-74k)	0.475	0.295	0.115	0.115	0.411	0.272	0.201	0.117
High income hh (>=75k)	0.441	0.362	0.084	0.113	0.405	0.347	0.146	0.103
Zero kid household	0.458	0.299	0.097	0.146	0.425	0.294	0.138	0.143
Presence of 0-5 yrs kids	0.546	0.362	0.054	0.038	0.504	0.379	0.069	0.048
Presence of 6-15 yrs kids	0.480	0.329	0.086	0.105	0.383	0.289	0.242	0.086
HHH is full time but not Spouse	0.412	0.295	0.177	0.116	0.367	0.254	0.279	0.100
Spouse is full time but not HHH	0.573	0.267	0.049	0.110	0.474	0.281	0.148	0.097
HHH and Spouse are full time	0.454	0.381	0.057	0.108	0.412	0.367	0.131	0.090
Couple <=30 yrs	0.458	0.425	0.029	0.088	0.480	0.407	0.041	0.073
Couple 31-50 years	0.460	0.383	0.054	0.102	0.404	0.356	0.152	0.088
Couple >=51 years	0.468	0.343	0.034	0.156	0.414	0.350	0.062	0.174
Zero non-worker household	0.482	0.322	0.084	0.111	0.434	0.312	0.164	0.090
One non-worker household	0.465	0.303	0.108	0.124	0.422	0.286	0.170	0.122
Two or more non-worker hh	0.444	0.273	0.110	0.173	0.375	0.285	0.139	0.202

Table 3.4 Model validation: estimation of calibration model for predicted dataset and calibrated dataset

Variable	Maintenance Activities			Discretionary Activities		
	Actual Prob.	Estimated mean prob.	% prediction discrepancy	Actual Prob.	Estimated mean prob.	% prediction discrepancy
Calibrated model on predicted data set						
Head of the household	0.472	0.468	0.41	0.401	0.399	0.23
Spouse	0.286	0.280	0.65	0.251	0.254	0.27
Other (non-hhh, non-spouse)	0.088	0.099	1.10	0.185	0.186	0.10
Joint activity	0.153	0.153	0.03	0.163	0.162	0.14
Calibrated model on calibrated data set						
Head of the household	0.463	0.458	0.57	0.406	0.402	0.36
Spouse	0.315	0.311	0.35	0.281	0.283	0.21
Other (non-hhh, non-spouse)	0.096	0.106	1.05	0.194	0.197	0.29
Joint activity	0.126	0.125	0.13	0.120	0.118	0.14

CHAPTER IV

PHYSICAL/VIRTUAL ACTIVITY PARTICIPATION

4.1 Introduction

Recent advances in Information and Communication Technologies (ICT) make possible to conduct activities virtually, thus obviating the need for physical travel, at least for some types of activities. Activities that may be performed virtually include: online shopping, telecommuting, teleconferencing, information gathering, and maintenance activities (such as online banking and bill payment). Further, as the prices of ICT products and services fall due to improved economies of scale (for example, cell phone use is growing rapidly), the adoption and use of ICTs continues to grow rapidly. These socio-technological developments offer individuals both the opportunity and the ability to substantially alter their activity and travel patterns. ICT use may contribute towards reducing urban congestion and air-quality problems (by replacing travel with virtual activities); on the other hand, they may also generate significant additional and induced travel due to increased connectivity and access to resources. Thus, empirical insights on how the growing ICT use affects travel patterns and vice-versa have important implications for planning, travel demand forecasting, and urban facility location decisions. Given these motivating considerations, this chapter investigates the linkages between ICT use, activity participation decisions, and travel patterns using recent empirical activity-diary data from the San-Francisco Bay Area (MTC, (2000); and Vaughn, (2003)).

ICT use can lead to a range of changes in activity travel patterns, including substitution, generation, and modification (Mokhtarian et al., (1997); and Krizek et al., (2003)). Substitution and modification of trips can have a significant impact on transportation system performance. For instance, the availability of virtual activities could result in fewer and more efficient trips. To illustrate, consider an example where a customer seeks to purchase a product from a physical store location. For this activity, he/she will make two trips. However, if the product is purchased online, only one trip may be needed for delivering the product. Further, since the producer may be delivering goods to more than one customer, these trips can be planned and executed more efficiently. In contrast, the availability of new technologies could actually generate additional trips. Part of the trip time saved by more efficient trip patterns may be used towards additional or longer trips. Furthermore, easy access to information and resources through browsing and increased interpersonal communications using ICT devices, may lead to additional trips. ICT use may also lead to a modification in current trip patterns. For instance, a user may change his destination for shopping activities in response to price promotions found through ICT use (e.g., by browsing). Although ICTs have an important impact on mobility and travel demand, the magnitude and nature of their impact is unclear as yet.

In order to explore the linkages between ICT, travel and mobility patterns of users, this chapter investigates three objectives. The first objective aims to analyze ICT use patterns of individuals. The second objective investigates the linkages between ICT use and physical/virtual activity participation for discretionary and maintenance activities. The role of ICT use attributes and the virtual activity propensity on these decision dimensions are explicitly modeled in this objective. The final objective aims to investigate the linkages between observed daily travel patterns (represented by the dimensions of trip frequency and trip duration), ICT use and individual's activity attributes. In particular, this objective focuses on analyzing the relationship between virtual activity participation, physical activity participation, Internet use patterns, and observed travel dimensions.

To achieve these objectives, a series of thirteen discrete and continuous econometric models are estimated using the rich and highly disaggregate activity diary from the San-Francisco Bay Area *(BATS 2000)*. This dataset provides three key advantages (for this analysis) compared to other datasets containing Internet use data: i) availability of disaggregate data on physical activities, virtual activities and travel patterns (at episode and daily levels), ii) data provides a more holistic representation of ICT use and various virtual activities, in contrast to focused studies where interest is centered on ICT use for tele-work or tele-shopping etc. and iii) the availability of a large real-world database (with 390,000 records per day for two days) permits the development of richer multi-level models to explore the relationship between ICT use, activity patterns, and travel decisions. The empirical models developed in this study reveal evidence of significant linkages between ICT use, activity participation, and travel patterns, with implications for developing demand management measures, promoting ICT use to reduce congestion/air-quality problems, and forecasting future travel patterns.

The rest of this chapter is organized as follows. Section 4.2 presents the descriptive statistics of the data that is used in this study. The model structure used in this study and assumptions and exceptions related to models are described in Section 4.3. Model results and analysis are presented in the next section. The final section summarizes major findings, limitations of the study and proposes some directions for future work.

4.2 Data description and descriptive statistics

To address the objectives discussed earlier, this study uses disaggregate activity travel data from the Bay Area Travel Survey 2000 *(BATS 2000)*, which contains data on 780,000 activity episode records from 15,064 households obtained using a two day activity diary survey. In this survey, data was collected on activity participation of individuals. Further data was also obtained on daily and episode level ICT use variables such as: web access at home, Internet use for work, Internet use for non work purpose, number of faxes and phones. The dataset also contained detailed information on household and individual attributes of all survey respondents. However, information on the presence of computers at home and number of cell phones is not available directly.

From these records, this study uses 50,055 first day activity records, and corresponding 4,214 respondents. A rigorous screening procedure was used to eliminate records and observations with implausible or incomplete data. For instance, missing information on Internet usage and outliers in activity duration was treated as missing. Further, records of children of age less than 14 years were excluded from the usable sample given that their decisions are most likely to be dependent on other adults in the household. A total number of 2,381 usable person records were obtained after the screening procedure.

Analysis of descriptive statistics of the sample used in this study revealed that the sample profile matched reasonably closely in terms of activity and travel characteristics with the 1996 SF activity data and the 1998 Miami survey data. The following respondent characteristics were observed in the sample with 1,793 households and 4,214 persons. Household variables include income, vehicle status, phones, faxes and Internet access. The sample consisted of 58% households with income >= $60,000, 34% of households had an income in the range $25,000-$59,999, whereas, 8% of the households had an annual income of less than $25,000. Nearly 31% of households had one car, and 65% had two or more cars, but 4% had zero cars. Nearly three-fourths of the sample (72%) had one phone in their household, whereas, 28% had two or more phones). Only 31% of the households in the sample had access to a fax at home, whereas, 73% of the sample had access to the Internet from home.

Among individual attributes, the sample consisted of 48% males, and nearly 69% of the respondents were workers. The age distribution consisted of 23% young (14-30), 42% middle aged (31-50), 27% upper middle aged (51-70), and 8% elderly respondents (>70). The mean daily trip frequency was 4.2 trips (std. deviation = 2.74 trips), and the mean trip duration was 93 minutes (std. Deviation was 73 minutes). In terms of ICT use, nearly 35% of respondents used Internet on the first survey day. The proportion of in-home maintenance and discretionary activities (in terms of respective total maintenance and discretionary activities) were 26 and 24% respectively.

4.3 Modeling structure

Three different types of dependent variables are of interest in the set of 13 models noted above. Discrete binary decisions are of interest in relation to decisions such as Internet use/not, Internet use for maintenance/not, in-home or out-of-home discretionary activities etc. Continuous decision dimensions relate to durations of interest such as duration of in-home and out-of-home activity episodes, or total travel duration in a day. The third decision variable pertains to discrete trip frequencies. These three sets of dependent variables are analyzed using the binary logit model, linear regression model and the Poisson regression model respectively and the model results are presented in Section 4.0. The three sets of models and their interactions are schematically illustrated in Figure 4.1 and a brief overview of the model structure for each of these categories is provided below.

4.3.1 Logit model structure

The logit model is specified using the random utility maximization framework, where the utilities are given by:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad (1a)$$

Where

Uij = utility of alternative i for person j

Vij = deterministic component of utility of alternative i for person j

ε_{ij} = random component of utility of alternative i for person j

ε_{ij} ~ IID Gumbel distribution

Under these assumptions, let Prob(ij) = represents the probability that person j chooses alternative i. Then this probability can be expressed as:

$$\text{Prob}(ij) = \frac{e^{Vij}}{1+e^{Vij}} \quad (1b)$$

Linear regression model:

This model is applied to analyze the durations of activity episodes.

$$Y_i = ß\, X_i + \varepsilon_i \quad (1c)$$

Where

Y_i = continuous dependent variable for individual i (e.g. total trip duration in a day)

ε_i = error term & $\varepsilon_i \sim N(0,s^2)$ (i.e. errors are normally distributed with a standard deviation s)

X_i = Vector of independent factors or socio demographic variables for individual i

Poisson regression model:

This model is used to analyze the discrete trip frequency for each individual i. This model can be written as:

$$\text{Prob}(Y_i = k) = \frac{e^{-li}\, l_i^{\,k}}{k!} \quad (1d)$$

Where

Y_i is the observed frequency of travel activities by person i

$?_i = ßX_i$ is the mean trip frequency for individual I given the socio-demographic factors X.

X_i = vector of independent variables

4.3.2 Assumptions and exceptions

Several simplifying assumptions have been made in selecting the models above to analyze the decision dimensions of interest. For instance, the use of the binary logit model assumes that Internet use decisions across different virtual purposes are mutually independent. Similarly, the decisions of activity episode durations and in-home and out-of-home activities are not modeled jointly although they are likely to be correlated. Further, relationships and correlation between members from the same household are not explicitly modeled. The justification for these simplifying assumptions is three-fold: First, given the large number of models and decision variables, the simpler model choice is dictated by computational tractability, and ease of specification and interpretation. Therefore, the initial focus in this study is on systematic utility rather than unobserved errors. Second, since the models are presented as marginal choice probabilities, due to these sources of misspecification, the model coefficients are likely to be inefficient (variance of the estimator will be high, leading to less sharp inferences), but the coefficients themselves are not subject to inconsistency or bias. Besides, given the large sample size, it is reasonable to expect that the inefficiency issue is less severe than potential bias/inconsistency. Finally, the assumptions above can be relaxed in a straightforward manner using more sophisticated models such as mixed logit or MNP models to analyze the decision dimensions jointly, though at considerable computational expense.

All models are estimated using the Maximum Likelihood Estimation technique. This technique finds the likelihood of data and maximizes this likelihood to estimate required parameters. The factors considered in this study include: ICT, person, worker, household related variables and also time of day and day of week related information. The estimated model coefficients are shown in Tables 4.1 through 4.4 and the discussion on the coefficients is presented in the following section.

4.4 Results and Discussion

The modeling results (coefficients are shown in Tables 4.1-4.4) reveal a better fit for the discrete choice dimensions than continuous decision dimensions (goodness of fit ρ^2 ranges from 0.2-0.8, with two exceptions, browsing and overall Internet use models had goodness of fit measures of 0.06 and 0.135 respectively). The model fit for duration decisions are generally poorer (suggesting a greater degree of unaccounted variability) than the discrete decisions, and have low ρ^2 values in the range of 0.04-0.07.

4.4.1 Models of ICT use patterns:

Role of access to communication devices

Increasing access to communication devices appears to increase the propensity of Internet use as expected. For example, with increasing numbers of phones available to a household, the Internet use propensity also increases. Individuals with multiple phone lines, but who live alone, are more likely to perform maintenance activities through Internet. The presence of faxes in a household has a positive effect on both Internet usage and performing work-related activities online. Access to the worldwide web from home also increases the probability of Internet use for recreational purposes.

Effect of work-related attributes

As with physical activities, the types of activities performed virtually via the internet also vary based on work-related characteristics. The availability and the need for ICT resources at work and/or home may encourage the substitution of physical activities with virtual activities. The results show that employees working in computer and semiconductor industries, educational or entertainment sectors are more likely to use Internet than workers in other industries. Further, executives are found to display a greater propensity for performing maintenance activities virtually (online), possibly due time constraints.

Workers particularly, in construction, business, or health industries tend to perform maintenance activities online more than respondents in other professions. Workers holding multiple jobs (presumably part-time) were found to have a greater propensity for Internet-related subsistence activities than those with only one full-time job. With increasing income, the probability of Internet use and online maintenance activity participation increases (possibly a reflection of access to ICT resources) a trend also noted by Farag et al, (2003), whereas, the likelihood of recreational use of internet decreases.

Cross-substitution among virtual activities

Not only is there possible substitution between travel and virtual activities, there also appears to be some degree of cross-substitution among virtual activities themselves. Individuals that use the Internet for recreational activities are less likely to perform subsistence, browsing and maintenance activities online.

Relationship between mobility and connectivity

A strong positive relationship is observed between mobility and connectivity (internet use) needs of users. For instance, individuals with licenses are more likely to use Internet than those without licenses. Younger and middle aged individuals are more likely to use the Internet than older individuals, also consistent with their increased mobility levels (see Section 4.3).

The results indicate that Internet use can also generate additional travel. For example, individuals who make more trips are more likely to use the Internet, also supporting the hypothesis that mobility and connectivity are strongly positively correlated. However, individuals with longer duration of daily travel are less likely to use the internet than individuals with shorter daily travel duration. Both these results may be attributed to the fact that Internet use may partially offset physical travel for some types of trips (possible substitution of travel by internet activities), thus reducing overall travel-times, which in turn may form the basis for increased travel frequency for Internet users. This hypothesis is further corroborated in the travel pattern model reported later in Section 4.3. However, the causality of whether connectivity affects drivers' mobility or vice-versa cannot be ascertained from this model, and needs further investigation.

With the increasing number of vehicles in a household, a greater propensity of Internet use for browsing and recreational activities is observed. This suggests that such browsing and recreational virtual activities may contribute to additional travel by making users aware of new activity participation opportunities (both physical and virtual). The awareness of additional discretionary activities (online) and the availability of vehicles provide these households with the ability to pursue additional travel. Thus, promoting virtual activities may in some cases be counterproductive in terms of trip-reduction, and air-quality improvement measures, if this promotion leads to the pursuit of additional physical travel opportunities.

Socio-demographic differences

There appear to be significant differences in ICT use patterns across various socio-demographic segments of users. Individuals with African-American or Hispanic ethnicity are less likely to use the Internet than people of other races. Males are more likely to use the Internet in general than females, though females are more likely to perform subsistence and recreational activities online. A greater probability of Internet use is also found among students, non-workers and occasional workers, individuals from small households, and respondents living in rented apartments, compared to other socio-demographic segments.

4.4.2 Relationship between physical and virtual activity participation

To study the relationship between physical and virtual activity participation patterns, this section focuses on two types of activities: discretionary and maintenance. These two activity types have been selected since there is significant opportunity to participate in virtual activities for these two purposes.

4.4.2.1 Relative propensity of in-home and out-of-home participation for discretionary and maintenance activities

Effect of work-related attributes

Among worker-related attributes, respondents with flexible work times (possibly due to tele-work arrangements) display a greater propensity for out-of-home maintenance activity participation than those with fixed work times. Thus, flexible work policies can lead to additional trips, which may offset some of the benefits obtained by staggering of work trips away from the peak-period. Furthermore, the additional trips are likely to worsen air-quality problems.

Professionals and executives are more likely to pursue in-home maintenance activities than other user groups, suggesting the substitution of some maintenance-related travel with virtual activities. This result also corroborates the greater online maintenance activity participation of this group of users, noted based on the models of ICT use (Section 4.1). Compared to non-workers, full-time workers are also more likely to perform in-home discretionary activities. Given the larger propensity of non-workers to perform physical maintenance and discretionary activities, greater degree of temporal and spatial flexibility, and their lower virtual activity participation, demand-reduction measures aimed at non-workers, (especially through the promotion of virtual activity participation) can lead to significant potential benefits in terms of trip substitution.

While substitution effects noted above can lead to demand reduction for particular types of trips, the data shows also evidence of generation of other trip types that tends to increase demand for travel. For instance, professionals and executives, particularly workers in the health care and service sectors who are more likely to participate in online and in-home maintenance activities also display a greater propensity for out-of-home discretionary activities compared to non-workers and workers in other industries. The implication of this finding is that it is essential to consider virtual and physical activity participation in all activity types jointly (rather than one virtual activity type such as telecommute or teleshop) in order to obtain accurate forecasts of the net impact of ICT's on travel demand.

Effect of mobility and income

Among household characteristics, both car-ownership and income play an important role in determining physical or virtual activity participation. Households with fewer vehicles are more likely to participate in in-home discretionary activities. Thus, virtual activity access and connectivity can at least partially offset mobility restrictions. On the other hand, the substitution of physical activity with virtual activity is also higher for high-income households for maintenance activities. The likelihood of out-of-home maintenance activity decreases, while at the same time, the propensity for online maintenance activities increases (noted in Section 4.1).

Timing effects

The results also provide evidence that time-of-day and day-of-week affect the choice of physical and virtual activity participation. Maintenance and discretionary activities requiring travel are more likely to be conducted during morning (peak or pre-peak), and afternoon periods (possibly by non-workers), whereas, the propensity for in-home discretionary activities increases during evening peak or night times. Thus, there may be a differential impact of substitution of physical and virtual activities between morning and evening peak periods, with a larger demand reduction potential during the latter. Further, physical travel for both purposes is more likely during the weekends than the weekdays.

Socio-demographic differences

Socio-demographic patterns such as age, gender, and ethnicity affect the decision on physical and virtual activity participation, in a manner that is consistent with their ICT use patterns discussed in Section 4.1. Hispanic and African American respondents display a greater preference for out-of-home maintenance activities than other ethnic groups, which is consistent with the lower internet use rate among these groups. Respondents in the age group 31-50 years are more likely to perform discretionary activities in-home compared to younger and older individuals, a trend consistent with the greater internet use and online maintenance activity participation among full-time workers (a majority of which belong to this age-group) noted previously.

4.4.2.2 Duration of in-home and out-of-home episodes for discretionary and maintenance activities

Substitution and generation effects

ICT use patterns also affect the episode duration of in-home and out-of-home activities. Users who are more likely to use Internet for recreational purposes (obtained from models in section 4.1) are also likely to spend less time on out-of-home discretionary activities. These results suggest that travel becomes more efficient (either by elimination of certain physical trips or trips may be destined to nearby locations), thus providing evidence of substitution or modification effects. In contrast, the data also reveals a generative influence of ICT use on travel behavior, in terms of longer travel duration in the following cases. Shorter in-home discretionary activity duration is observed for households with access to the Internet. Similarly, the presence of fax devices at home correlates positively with longer out-of-home discretionary activities.

Effect of work-related attributes

Work-characteristics strongly affect the duration of in-home and out-of-home maintenance activities. Full time workers and executives spend less time on out-of-home activities than non-workers, which is also corroborated by the greater internet use, especially for online maintenance activities, observed for this user segment. This finding can be attributed to the tighter time constraints on workers and the greater role of household maintenance activities for non-workers. However, there was no discernible effect of work-related variables on discretionary activity duration.

Effect of mobility-related factors

Mobility-related factors affect the durations of physical and virtual activity episodes. Individuals without a driver's license tend to have larger out-of-home maintenance duration, possibly due to the longer transfer, waiting and access times associated with alternative modes. Further, the in-home maintenance duration is also larger for users in this group than for individuals with a license, suggesting the potential to substitute physical activity access with virtual activity access to offset mobility restrictions. As expected, the number and type of vehicles in the household also affect out-of-home discretionary duration. Longer trips are observed in households with more cars, and shorter trips are noted for households with bicycles.

Timing effects

As expected out-of-home discretionary activities are longer during the weekends than weekdays, afternoons and evening peak than early morning or night times. The duration of out-of-home maintenance activity of workers during weekends is longer than on weekdays. This suggests that although ICTs may be effective in substituting travel with virtual activities under time constraints for certain class of users (such as full-time workers in the weekdays), the increase in travel during weekends may partially offset if not negate benefits that may be obtained during weekdays. Ignoring these temporal effects (increase in weekends) could lead to serious errors of overestimating ICT impacts on demand reduction, and policy consequences (modification can be misinterpreted as substitution effects). Thus, the findings suggest that obtaining longitudinal data and models to jointly capture the effects of ICT use on virtual activity and physical travel patterns is important. Not only should the bngitudinal data capture activity participation across different activity types on a given day (see cross-substitution effects in Section 4.1), but the trends over a longer time-frame that includes week-days and weekends also needs to be analyzed.

Socio-demographic effects

Age significantly affects in-home and out-of-home activity duration. Upper middle age and old age individuals spend more time on out-of-home maintenance activities than younger and middle aged individuals, supporting the hypothesis in Section 4.1 that older respondents prefer to participate in physical rather than virtual activities.

4.4.3 Interactions between travel, activity pattern, and ICT use

Table 4.4 presents the results from the analysis of daily trip frequency and total travel duration. The probability of performing online maintenance activities correlates positively with increasing trip frequency. This increase may be the result of time saved in virtual activities relative to physical activity performance and supports the generation hypothesis noted in Section 4.1.

Along similar lines, some of the work-related attributes that increase the propensity to use the Internet, particularly for maintenance activities also significantly increase the frequency and duration of daily travel. For example, professionals, executives, technicians and service related workers tend to make more trips than other kinds of employees. Respondents with flexible work hours (possibly due to tele-work arrangements) are likely to make longer and more frequent trips than workers with fixed work hours. Full time workers, however, tend to make fewer trips than non-workers, but spend more time on travel, possibly a reflection of travel under congested conditions by these individuals.

Socio-demographic factors that affect ICT use such as age, gender and disability also lead to significant differences in trip patterns. Males make fewer trips than females overall, though the travel durations are not significantly different. Younger, middle aged and upper middle-aged individuals tend to make more trips than older respondents, but users with disability tend to make fewer trips. As expected, individuals holding a driver's license make more frequent and longer trips. Larger households are seen to produce shorter but more frequent trips, possibly a reflection of delegation of responsibilities across household members. In contrast, with increasing number of vehicles, the frequency of individual person trips reduces.

Finally, the trip-frequency increases during the weekday relative to the weekend due to the need for subsistence related trips such as work/school. However, as noted in the previous section, workers tend to spend more time on out-of-home maintenance activities on weekends than weekday.

4.5 Summary and Conclusions

This chapter investigates the relationship between ICT use, virtual activity participation, and travel patterns of individuals using a rich activity-travel diary data from the San Francisco Bay Area. In particular, a series of models used to analyze i) ICT use and virtual activity participation patterns ii) relationship between in-home and out-of-home participation in maintenance and discretionary activities (iii) models of travel pattern represented by the dimensions of aggregate trip frequency and trip duration in a day across all activities. The linkages across models are also modeled using ICT related variables, common socio-demographic factors, and through the use of predicted estimates from one model as explanatory variables in other models.

The results provide considerable evidence in support of substitution and generation of trips due to ICT (particularly Internet) use. Both technological familiarity and time constraints appear to significantly affect relative propensity for physical or virtual activity participation for maintenance and discretionary activities and their duration. The results suggest a strong positive relationship between mobility needs and connectivity needs. Work-related characteristics, socio-demographic attributes, not only strongly affect whether Internet is used, but also for what virtual activity purposes. The results also suggest that Internet use for maintenance activities especially by workers, leads to more frequent but shorter trips. However, whether such ICT use actually translates into additional travel depends on the supply of activity opportunities (urban locations), as well as availability of resources to pursue these opportunities (number of vehicles, and time availability for workers etc.). The results also suggest that substitution impacts of ICT's may be limited for certain classes of users (executives, retired or elderly respondents) and for particular travel periods (weekends). These results have important implications for travel demand estimation and forecasting in the context of increasing ICT adoption and use among various segments of the population.

Given the growing adoption and rapid change in the ICT use trends, the impacts on travel demand and patterns presented here must be viewed as corresponding to a snapshot in time and exploratory in nature. Therefore, there is a need to include the dynamics of ICT adoption into this modeling framework in future work, to provide more realistic and accurate forecasts of activity travel patterns in the future. Other promising research directions include the analysis of household level interactions on the dimensions considered here, and the impact of other types of communication transactions including mobile phones, pagers, phones, and other ICT devices on activity travel patterns.

Table 4.1 Logit models for internet use and internet-related activity participation at person level

Dep. Variable (→)	Internet use	Subsistence	Browsing	Recreational	Maintenance
Ind variable (↓)	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	-1.512	---	1.256	---	---
ICT related					
Prob-recreational	---	-5.693	-2.285	---	-2.525
Nphone	0.136	---	---	---	---
Hhfax (0/1)	0.227	*0.834*	---	---	---
Hhweb (0/1)	---	---	---	0.660	---
Hh1size*nphone	---	---	---	---	*0.314*
Travel related					
Ntravel activities	0.093	---	---	---	---
Travel duration	-0.002	---	---	---	---
Worker related					
One job holder	---	-1.072	---	---	---
Executive	---	---	---	---	0.459
Full/ part time wrk	-0.682	---	---	---	---
Occasional worker	*1.027*	---	---	---	---
Comp/semicond	0.446	---	---	---	---
Edu/enter/prof(b)	0.309	---	*0.454*	---	---
Exec staying alone	---	---	---	*2.005*	---
Transp(b) /const	---	---	*-0.968*	---	0.649
Business/Health	---	---	---	---	0.856
Person related					
License	0.523	---	---	---	---
Younger	0.574	---	*0.387*	---	---
Midage	0.419	---	---	---	---
Male	0.457	-1.918	---	-0.677	---
Student	*0.262*	---	---	---	---
High sch/ college	---	---	---	1.207	---
Post college student	---	---	---	-1.280	---
Afri-ame/ Hispanic	-1.015	---	---	---	---
Household					
Num of vehicles	---	---	0.188	0.215	---
Urban	---	---	*0.261*	---	---
Lowincomehh	-0.796	---	---	1.894	---
Highincomehh	0.314	---	---	-0.410	---
Income40Kup	---	---	---	---	0.614
Hhsize	-0.191	---	---	---	---
Two vehicle hh	---	---	---	---	0.433
Rented hh	0.261	---	---	---	---
Valid observations	2381	753	753	753	753
$?^2$ value	0.136	0.824	0.04	0.256	0.338

Note: Normal size are significant at 5% or better, Italicized are significant at 10%
--- indicates insignificant at 10%

Table 4.2 Logit models for out-of-home versus in-home maintenance and discretionary activities

Dep. Variable (→)	Out-of-home maintenance	Out-of-home discretionary
Ind variable name (↓)	Coefficient	Coefficient
Constant	*0.193*	1.980
ICT related		
Hhfax (0/1)	0.136	---
Worker related		
Flexibility	0.266	---
Prof/exec	-0.111	0.463
Fulltime worker	-0.311	-0.662
Part time worker	-0.439	-0.400
Service (pri/protect)	---	0.799
Health industry	0.220	---
Person related		
Younger (14-30)	---	-0.543
Mid age (31-50)	*-0.127*	-0.434
Uppermidage (51-70)	---	-0.453
Afri-Ame/ Hispanic	*0.165*	---
Household related		
Income40Kup	-0.175	---
Hhsize	-0.053	---
0 veh/ 1 veh	---	-0.202
Start time of activity		
Early morning (–6.30)	3.653	---
Morning peak(6.30-10.30)	2.388	0.758
Afternoon (10.30-4)	0.711	---
Evening peak (4-7.30)	---	-0.445
Night (7.30-)	---	-0.531
Day of week		
Weekend	0.549	*0.197*
Valid observations	11864	3068
$?^2$ value	0.373	0.246

Note: Normal size are significant at 5% or better

Italicized are significant at 10%

--- indicates insignificant at 10%

Table 4.3 Regression models for duration of in-home and out-of-home maintenance and discretionary activities

Dep. Variable (→)	Dur .of OHM	Dur. Of IHM	Dur. of OHD	Dur. of IHD
Ind variable name (↓)	Coefficient	Coefficient	Coefficient	Coefficient
Constant	61.671	204.896	93.369	168.592
ICT related				
Prob-recreational	---	---	-8.592	---
Non work Internet use	---	---	---	-28.886
Hhfax (0/1)	*2.616*	---	10.554	---
Hhweb (0/1)	---	---	---	-26.040
Worker related				
Full time worker	-15.863	---	---	---
Part time worker	-6.630	---	---	---
Non worker	---	20.664	---	---
Executive	*-3.270*	---	---	---
Government employ	---	-22.494	---	---
Person related				
Younger	-8.212	---	---	---
Mid age	-8.670	24.843	---	---
Upper mid age	---	30.519	---	---
Old age	---	46.733	---	---
Spouse	5.081	---	---	---
High school student	-12.875	---	---	---
License	-4.690	-50.875	---	---
Male	---	---	7.541	*18.359*
Household related				
Income40Kup	---	---	-14.107	---
Hhsize	---	---	---	*-7.377*
Onepersonhh	6.425	---	---	---
Nveh	---	---	*3.185*	---
Bicyclehh (0/1)	---	---	-7.309	---
Mcyclehh (0/1)	---	---	*12.913*	---
Rentedhh	---	-23.307	---	---
Start time of activity				
Morning peak	---	-37.792	19.588	---
Afternoon	15.651	41.631	21.959	---
Evening peak	24.869	74.994	35.713	---
Nighttime	22.912	---	---	---
Mornpeak*fultimewr	30.953	---	---	---
Pmpeak*nonwrkr	---	---	12.957	*34.150*
Day of week				
Weekend	---	---	21.840	---
Weekend*worker	9.303	---	---	---
Valid observations	8402	2987	2270	717
?^{2} value	0.06	0.061	0.065	0.043

Note: Normal size are significant at 5% or better, Italicized are significant at 10%, --- indicates insignificant at 10%

OHM: Out-of-home Maintenance; IHM: In-home Maintenance;

OHD: Out-of-home Discretionary; IHD: In-home Discretionary.

Table 4.4 Poisson model for number of travel activities and regression model for duration of travel per person

Dep. Variable (→)	Number of travel activities in a day	Total duration of travel in a day
Ind variable name (↓)	Coefficient	Coefficient
Constant	1.162	62.268
ICT related		
Prob-maintenance	0.450	---
Worker related		
Professional	0.156	---
Executive	0.113	---
Tech/sales/adm	0.094	---
Service (pri/protect)	0.137	---
Flexibility	0.071	8.391
Full time worker	-0.109	11.426
Part time worker	---	15.161
Occasional worker	-0.497	---
Person related		
Male	-0.102	---
Younger	*0.090*	---
Mid age	0.121	---
Upper mid age	*0.093*	---
License	0.222	22.089
Disability	-0.326	---
Household related		
Hhsize	0.023	*-2.274*
Nveh	-0.059	---
Bicyclehh (0/1)	*0.039*	*5.261*
Mcyclehh (0/1)	-0.094	*-9.799*
Rentedhh	---	*5.934*
Day of week		
Weekend	-0.288	-23.325
Valid observations	2318	2347
$?^2$ value	0.457	0.051

Note: Normal size are significant at 5% or better
Italicized are significant at 10%
--- indicates insignificant at 10%

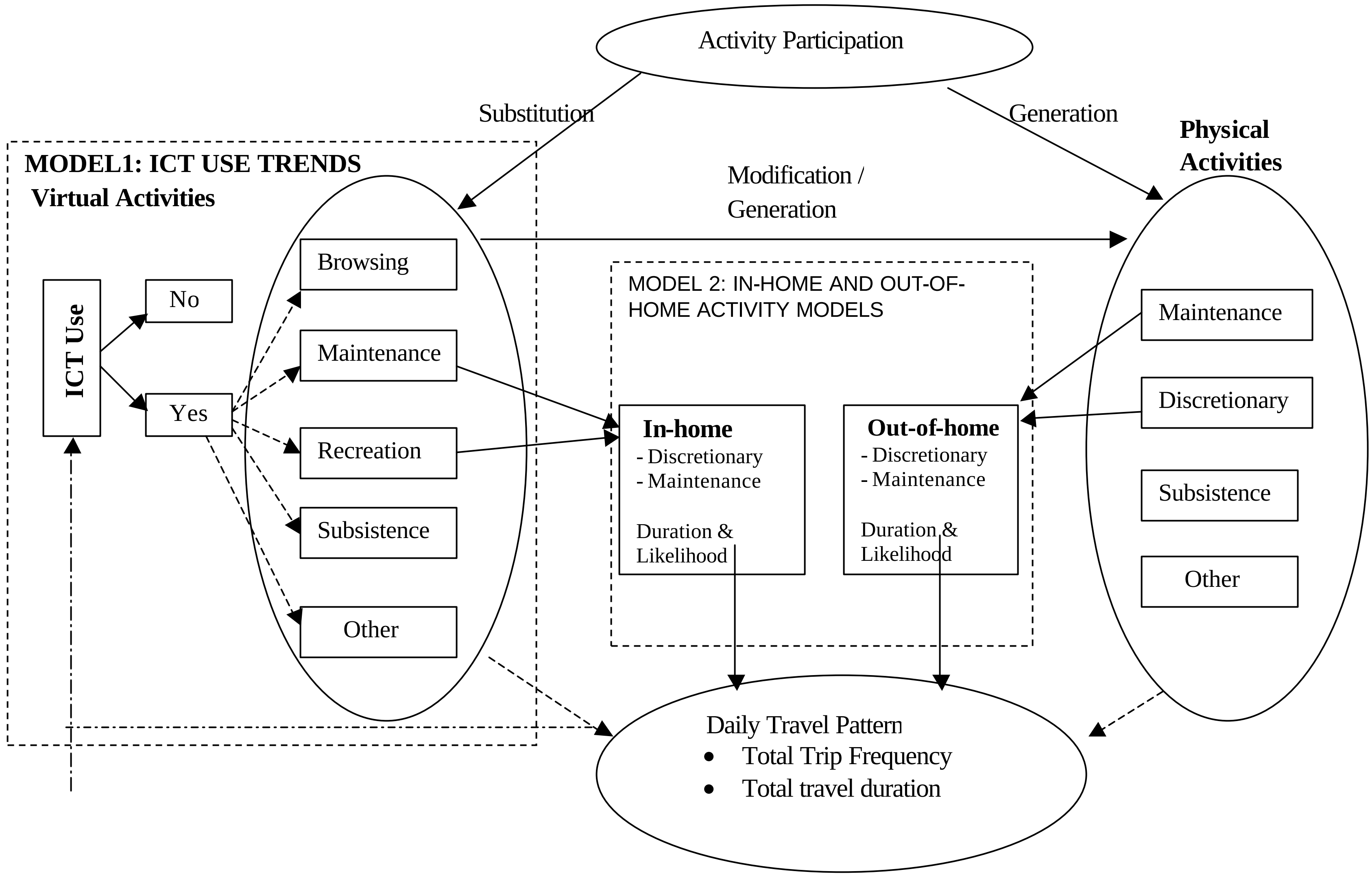

Figure 4.1: Schematic representation of interactions between physical and virtual activity participation and ICT use trends
Note: Physical activities can be performed in-home and virtual activities may be performed out-of-home, but are not modeled in this study due to lack of disaggregate data.

CHAPTER V

CONCLUSIONS

5.1 Overview

This study investigated two activity-related decision dimensions: i) allocation of household members to activities for discretionary and maintenance activities, and ii) the analysis of relationship among Information Communication Technology (ICT) use, activity patterns and travel behavior at the household level. These two tasks were achieved by performing activity episode analysis using San Francisco Bay Area Travel Survey Data (1996 and 2000). In this process, the author developed and estimated a series of econometric models, and performed extensive statistical analysis to achieve the primary objectives of the study.

In the first task, this study investigates person allocation to activities by pursuing the following research issues. In the first objective, household role, within-household differences, socio-demographic, and trip attributes on activity allocation were explored. In this regard, the role of household structure and life-cycle differences between household members, namely, the head of the household, spouse, children, parent / in-law, and siblings were analyzed. The effect of prior activity performance history on the probability of performing current activity was also considered as part of within household differences. Furthermore, the influence of trip related attributes include origin and destination of travel activities, mode, and trip-chaining characteristics on person allocation was also studied. Also, under this task, the role of constraints on time, vehicle availability, cost, and coordination on activity allocation among household members was examined. In addition, the influence of employment status, type of industry, parking costs, and differences by time-of-day were assessed. Finally, in this task, the differences between households in terms of the allocation of persons to activities were investigated. The between household comparison revealed significant difference in person allocation based on the gender of head of the households, number of vehicles, presence of children, vehicles per driver, income, and age differences of a couple. In this process of investigating these objectives, a methodology was developed to model person allocation to activities that partially addresses the shortcomings of existing models.

The second major task in this study was to explore the linkages between ICT use, travel, and activity patterns of households. This analysis pursued the following three research objectives by developing a series of statistical models. The first objective under the second task was to analyze the ICT use patterns of users particularly, the dimensions of whether or not internet was used, and the purpose for which it was used (subsistence, browsing, maintenance, and recreational). The explanatory factors influencing these decisions were analyzed. The second objective in this task explored the linkages between ICT use and physical/virtual activity participation for discretionary and maintenance activities. Toward this end, the propensity to participate in out-of-home maintenance and discretionary activities, and durations of out-of-home and in-home maintenance and discretionary activities were analyzed by studying the role of person, household and activity attributes. In the third objective, this study also investigated the linkages between observed daily travel patterns (represented by the dimensions of trip frequency and trip duration), ICT use and individual's activity attributes. In particular, the relationship between virtual activity participation, physical activity participation, internet use patterns, and observed travel dimensions were analyzed. The salient findings from the two sets of tasks are discussed in the following section.

5.2 Salient findings and their significance

5.2.1 Person allocation patterns

The salient findings based on the person allocation models are presented below:

- The results provide significant evidence of the effect of life-cycle and household role on person allocation to activities. The head of the household is generally more likely to participate in both maintenance and discretionary activities than the spouse of the head of the household.
- With an increase in number of household members who are employed, participation in joint activities decreases significantly for maintenance and discretionary activities.
- As the fraction of female workers in the household increases, joint participation in discretionary activities decreases, due to the added work-related time constraints on both male and female workers in the household.
- It was observed that females are more likely to participate in shorter duration trips than males, suggesting that the destinations for maintenance activities are likely to be closer to anchor points (home or work) for females than males.
- In terms of cost, the presence of parking charges inhibited the participation of individuals employed in the financial, educational, and health care sectors in maintenance activities. Several other findings are also presented that highlight the role of time constraints on activity participation.

Location and proximity factors from home and work-place also appear to influence person allocation. For instance, full-time workers are less likely to be selected for home-based maintenance trips, suggesting that a significant number of maintenance activities are performed en-route to and from work locations whereas, non-workers are more likely to participate in home-based tours. Given the time constrained nature of the former trips (due to institutional and work timings), these differences have significant implications for mobility levels (measured by VMT), duration of activity and travel episodes, and the evaluation of transportation planning policies.

The results indicate that individuals with a greater level of participation in prior maintenance (discretionary) activities are more likely to be chosen to participate in current discretionary (maintenance) activities. This dynamic influence may be the result of greater access to household vehicles (especially if number of vehicles is limited), and/or greater intrinsic trip-making or activity participation propensity of the selected individuals in the household.

Interesting differences in activity allocation were observed across different income groups. In households with higher income, the maintenance allocation between head and spouse is more equitable (hhh = 44%, and spouse = 36%). In contrast, in households with lower income the head of the household plays a primary role in maintenance activities (49%, spouse=26%). These differences may be attributable to the greater availability of disposable income and vehicles in higher income household, and possibly greater value of travel time for the head of the household in these cases.

The solo participation of other individuals is also high in households with school going children (6-15), with 24% (nearly a fourth of household activities) in discretionary activities and around 10% for maintenance activities. Thus, modeling activities and trips by these individuals is essential (not just the head of the household and spouse) at least for selected segments of the population, possibly due to the non-motorized nature of such trips, and significant contribution to household trip-making.

5.2.2 ICT use patterns

The main conclusion from these diverse threads of related results is that the relationship between telecommunications and transportation is multi-directional and multi-dimensional in nature. There is strong evidence to support each of the hypothesized interactions of ICT use, activity pattern, and travel behavior: substitution, generation and modification.

The following salient findings are noteworthy and distinct from prior research on ICT use:

- The data suggests considerable heterogeneity across user groups in terms of the degree of substitution between ICT use and physical activities. Executives are more likely to perform maintenance activities online (compared to physical activities) and spend less time on out-of-home maintenance activities. Males are less likely to perform recreational activities online, but spend more time on out-of-home discretionary activities than females.
- Internet use can generate increased travel frequency, but may result in reduced travel duration. In this regard, internet use is correlated positively with larger trip frequency but shorter travel durations.

- ICT use can also lead to substitution across virtual activities, in addition to substitution between physical and virtual activities. For instance, individuals using Internet for recreational activities are less likely to perform subsistence, maintenance and browsing activities online.
- Not only are there trade-offs between physical and virtual activities in a given day, but there could also be trade-offs between physical and virtual activities over days (weekdays and weekends).

The findings from this study have the following important policy and data analysis implications:

Flexible work arrangements, made possible through ICT use, can lead to increased demand for mobility and travel (more out-of-home maintenance activities, longer and more frequent trips are seen), which may reduce if not negate the positive impacts of work-trip reduction. Unless the additional trips are staggered away from peak periods and flexible work arrangements are carefully designed, congestion and air-quality may actually become worse due to the increased demand.

Time constraints and familiarity with newer technologies tend to increase ICT use and virtual activity participation (workers, professionals etc.). However, the extent of travel demand reduction from such virtual activity participation may at least be partially offset by increased travel during weekends by these respondents. These results underscore the need for data and analyses on linkages between ICT use, physical and virtual activity participation, and travel on a given day, but also across days of the week.

ICT use can promote more frequent yet more efficient trips (more frequency-higher internet usage, more duration-lesser internet usage). This result suggests that the impact of ICT may not be uniformly beneficial from a travel demand management (TDM) standpoint. On the one hand, ICT use may reduce congestion (due to more efficient trips). However, travel pattern changes due to ICT use can also make air-quality worse in some cases due to induced and additional trips. The positive correlation between connectivity and mobility also indicates the potential for aggravation of urban congestion and air-quality problems with increasing connectivity and growing adoption of ICT systems. The strong interactions between mobility and connectivity suggest the need to account for the trip-generative influence of connectivity explicitly, in addition to the current focus on activity demand.

Promoting ICT use and virtual activity propensity may lead to travel demand reduction, but only among certain classes of users and trip purposes (for instance, males in the context of recreational activities, and low income households etc.). Thus, to successfully achieve travel demand reduction through increased ICT use, tailoring these programs to users with both considerable amount of travel activities and time constraints is essential. Though time constraints appear to encourage virtual participation, the tangible substitution effects of such virtual activities may be less than anticipated.

5.3 Directions for future research

The proposed person allocation models can be further enhanced to investigate the following research directions in the future:

3) the use of more sophisticated error-structure to capture various sources of correlations (for e.g. within-person, within-household etc.)
4) variables that explicitly account for the time-varying nature of household vehicle allocation decisions and vehicle availability on person allocation decisions.
5) analysis of individuals who participated in joint trips, whereas, the current study only focuses on whether or not a given activity episode involved joint participation. Specifically, the household members participating in the joint episode are not considered here.
6) this study mainly focuses on person allocation given the generation of discretionary and maintenance activities. The joint analysis of generation and allocation is a promising and computationally more intensive direction for future research.

Given the growing adoption and rapid change in the ICT use trends, the impacts on travel demand and patterns presented here must be viewed as corresponding to a snapshot in time and exploratory in nature. Therefore, there is a need to include the dynamics of ICT adoption into this modeling framework in future work, to provide more realistic and accurate forecasts of activity travel patterns in the future. Other promising research directions include the analysis of household level interactions on the dimensions considered here, and the impact of other types of communication transactions including mobile phones, pagers, phones etc on activity travel patterns. In this study, an implicit assumption is that the virtual activity participation takes place at home. However, in the more general case, the modeling framework above could be expanded by including additional choice dimensions that distinguish between in-home and out-of-home virtual activities. Similarly, this study does not differentiate between physical and virtual activity participation for in-home activities due to data availability issues. Therefore, the findings from this study need to be validated from other studies when further disaggregate data on virtual activity participation location (in-home or out-of-home) and type of in-home activities (physical or virtual) become available.

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