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ON THE RELATIONSHIP OF INFORMATION AND (TELE)COMMUNICATION SYSTEMS WITH ACTIVITY PARTICIPATION AND TRAVEL

A Thesis in

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by

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ABSTRACT

During the last decade we have experienced the rapid advance and growing popularity of information and communications technology (ICT). It began to alter the way in which people conduct their everyday affairs and also the way in which businesses are conducted. Under these circumstances, our traditional concept of accessibility can no longer be valid. In fact, through ICT people can get virtual accessibility to a rapidly growing range of activities without the more traditional spatial and temporal limitations and constraints. Consequently, people have more flexibility to arrange their schedules, and eventually change their activity and travel patterns. These substantial impacts of ICT motivate the need for research on the present and future impacts of telecommunication on activity and travel behavior.

With the Puget Sound Transportation Panel (PSTP) data, especially the data collected in Wave7 (1997) and Wave 9 (2000), this study attempts to examine a variety of aspects of the relationships between ICT and activity and travel behaviors within comprehensive conceptual model systems examining correlation patterns. Several models have been developed, each of which focuses more on a specific aspect of the relationships.

First, technology choice models were developed to identify user groups for each ICT device. Multivariate multilevel categorical data models were used to account for a strong behavioral correlation among households and within household members as well as a high degree of people heterogeneity in technology adoption. The model revealed that decisions of ICT ownership and usage are most likely determined by joint decisions among members of the same household and there is heterogeneity in each type of ICT ownership and use among different situations.

Second, a comparative analysis of three different model systems, including a set of single-equation regression models, seeming unrelated regression models (SUR Model), and multivariate multilevel models, was conducted to examine the effect of ICT on activity and travel duration. Although the three different models produce very similar coefficient values, multivariate models are more advantageous over single-equation models. The multivariate models account for the correlation of the error terms across equations, and as a result, they produce smaller standard

errors of the coefficient estimates than those from single-equation models. Between the two multivariate models, the multilevel models are superior because they consider the hierarchy of level in the data and provide more information by estimating variance-covariance matrices and correlations for each of the multiple levels, offering additional insight on behavioral heterogeneity at each level.

Third, the joint models using a structural equation modeling technique are formulated for daily time allocation to various activities (subsistence, maintenance, and leisure) and travel, and mode frequency (driving alone, shared ride, transit, bike, walk, and others) as a function of cross-sectional and longitudinal information on personal and household socio-demographics and telecommunication technology ownership and usage. In this way, the impacts of information and communication technologies on daily time allocation to various activities and travel, and on modal split are assessed. At the same time, the complex relationships among different activities and travel time use indicators and their daily frequencies are explored. In addition, using longitudinal information on ICT, it is possible to check whether or not the changes in ICT ownership and usage have symmetric effects on time use for activity and travel behavior. From this model, it was found that the "technology" effect depends on the location and type of technology and that the majority of social, economic, and ICT changes have asymmetric effects on behavior.

Fourth, dynamic analysis of time use and frequency of activity and travel between Wave 7 and Wave 9 is conducted using latent class clustering and structural equation modeling. A fixed time budget is explicitly taken in account in these models, and existence of very strong substitutional and complementary relationships in time use among different activities and travel are examined. In addition, as a new approach to account for state dependence (past activity and travel behavior effects) in the model, relatively homogenous daily activity and travel behavior patterns in Wave 7 are first identified through latent class cluster analysis. Then time use for a specific activity (in-home activity, out-of-home subsistence activity, and out-of home non-subsistence activity) and traveling, and frequency of episodes by activity in Wave 9 are modeled as a function of cross-sectional and longitudinal information as well as activity and travel patterns in Wave 7. The model results showed that out-of-home activity duration and travel time have very large substitutional effects on in-home activity duration, while out-of-home activity duration has complementary effects on travel time. The model results also confirmed the existence of strong habit persistence in activity engagement and time use even in a relatively long period of time.

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CHAPTER 1
INTRODUCTION

The 1990s' explosive growth and continued proliferation in information and communications technology (ICT) (i.e., widespread use of computers, mobile phone, e-mail, the Internet, and e-commerce) began to alter the way in which people conduct their everyday affairs and also the way in which business is conducted. Under these circumstances, accessibility can no longer be measured only in terms of travel time, distance, or generalized travel costs (Golob, 2001; Golob and Regan, 2001). In fact, information technology gives individuals virtual accessibility to a rapidly growing range of activities without the more traditional spatial and temporal limitations and constraints. For example, ICT makes it possible for people to work at any place (telecommute) and to buy goods without a physical trip to the store (teleshopping or e-commerce). It therefore allows people more flexibility to arrange their schedules, and eventually changes their activity and travel patterns. In addition, access to technologies and knowledge about ICT are not uniform across the population. These substantial and differential impacts of ICT create the need for research on the present and future impacts of telecommunication on activity and travel behavior.

To date, a substantial amount of research on the relationship between ICT and transportation has been conducted, but most studies focused on the potential impacts of ICT on mobility, especially the degree of substitution and complementarity between transportation and telecommunication. In addition, many hypotheses have been empirically tested mostly in the telecommuting arena using data from one time point. There is still a gap in the literature on the effects of change in ICT availability and use and their effect on travel behavior, and very few studies exist to date on other broader aspects of ICT impacts on activity and travel behavior.

1.1 Research Objectives

The objectives of this research are to investigate relationships between ICT ownership and use and people's activity and travel behaviors from a variety of viewpoints using survey data instead of conceptual models and theoretical frameworks. Specifically using a variety of analytical methods the following hypotheses are tested:

- Examine if trends for each type of ICT ownership and use over time exist;
- Examine if there is heterogeneity in each type of ICT ownership and use among different situations in terms of age group, income, or occupation;
- Examine if there is a substitution or complementarity relationship between ICT and travel;
- Examine if the effects of ICT ownership and use on activity and travel behavior depend on the length of technology ownership and use; and
- Examine if there is symmetry in activity and travel behavior when people gain and lose ICT.

All these hypotheses, taken together, will provide a significant advancement in our knowledge about the interaction between ICT and activity and travel behavior by individuals. In all analyses a variety of other factors influencing the relationship between ICT, activity participation, and travel will also be controlled for.

To accomplish the research objectives, the Puget Sound Transportation Panel (PSTP) data are used, specifically the data collected in Wave 7 (1997) and Wave 9 (2000), within a more general and comprehensive conceptual model system shown in Figure 1. Due to the complexity of the model system, it is impossible to incorporate all the components in a single model. Therefore, several (sub)models have been developed, each of which focuses on a specific aspect of the relationships of Figure 1.

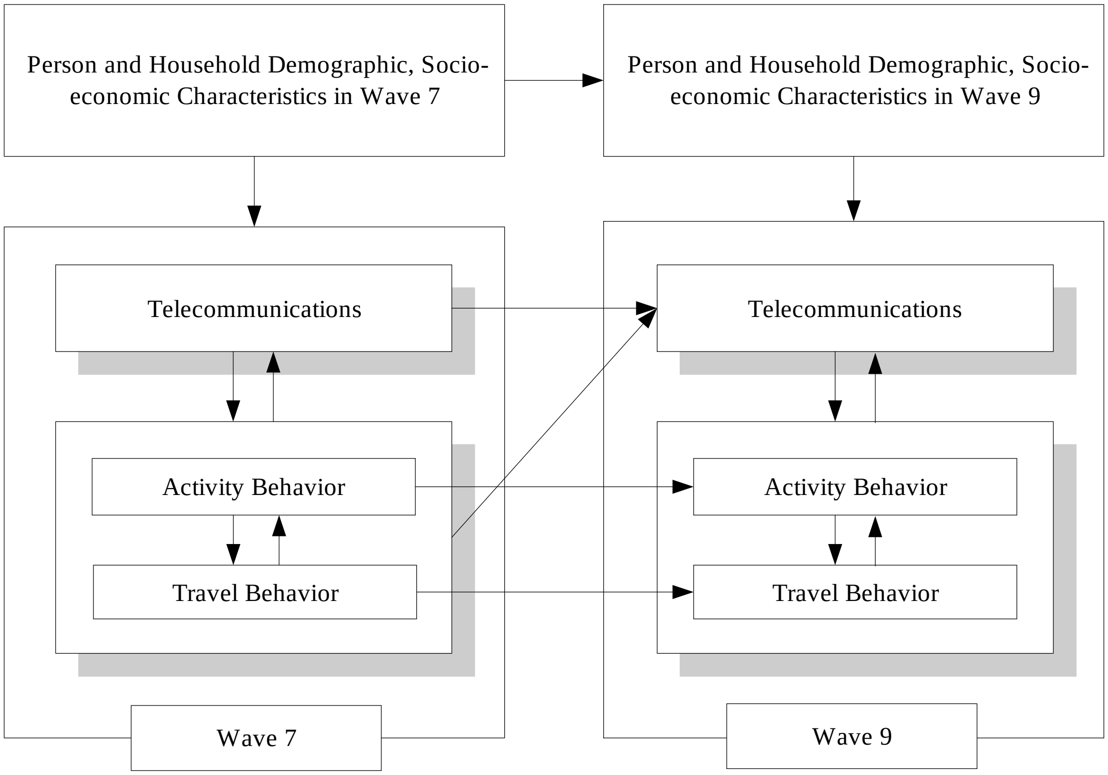


Figure 1-1 Comprehensive Conceptual Model

1.2 Organization of Thesis

Chapter 2 of this thesis is an overview of the past and current understanding on the relationships between telecommunication and transportation offered as background. The background contains the effects of telecommunication on the demand for and the supply of transportation.

Chapter 3 provides a general description of the Puget Sound Transportation Panel (PSTP) data that are used in this study.

Chapter 4 describes the analytical methods used in this study including the linear regression models, Seemingly Unrelated Regression models, Multilevel Regression models, Latent Class Cluster analysis, and Structural Equations Modeling.

Chapter 5 explains the development of technology choice models to identify user groups for each ICT device. Multivariate multilevel categorical data models are used to account for a strong correlation within household members as well as a high degree of people heterogeneity in technology adoption.

Chapter 6 describes the comparative evaluations of three different models (single-equation regression models, seeming unrelated regression models, and multivariate multilevel models) for the analysis of the impact of various telecommunication technologies on time use for out-of-home activity and travel.

Chapter 7 explores the complex inter-relationships among ICT ownership and use, time allocation to various activities and travel, and mode choice using structural equation modeling technique.

Chapter 8 provides a description of dynamic analysis of the impacts of ICT on time use and frequency of activity and travel using structural equation modeling technique. A new approach to take into account state dependence (past activity and travel behavior effects) is also demonstrated through Latent Class Cluster analysis.

Chapter 9 contains a summary of the research and a description of the need for further research to improve our current understanding of the relationships between ICT and activity and travel behavior.

CHAPTER 2
LITERATURE REVIEW

What is ICT? Cohen et al. (2002) defined: "(ICT is) *a family of electronic technologies and services used to process, store and disseminate information, facilitating the performance of information-related human activities, provided by, and serving the institutional and business sectors as well as the public-at-large.*"

The potential of ICT to affect travel behavior has been therefore perceived since the invention of a telephone. However, much of the initial research into the substitution potential of telecommunication for travel was not begun until the energy crisis in the 1970s. Subsequently, in the 1980s, the spread of computer and information technology in the workplace, coupled with policies directed toward reducing urban congestion and improving air quality, led to further studies of the potential impacts of telecommunication on transportation among transportation practitioners and academicians.

2.1 Different Impacts of ICT on Transportation

Because of the persistent attractiveness of reducing travel, which results in saving energy, decreasing congestion, and improving air quality, most research on the transportation demand side has concentrated on the 'substitution' aspect of telecommunication for travel. However, there exist other impacts of telecommunication on transportation. Salomon (1986) identified four different kinds of impacts of telecommunication on transportation:

- Substitution (telecommunication decreases travel);
- Enhancement (telecommunication stimulates travel);
- Operational efficiency (telecommunication improves travel by making the transportation system more efficient); and
- Indirect, long-term impacts (telecommunication may ultimately affect land use, which will affect travel).

While the substitution, enhancement, and indirect long-term impacts above are mainly the impacts of telecommunication on the demand for transportation, operational efficiency affects the supply of transportation.

Telecommunication and transportation share many common features, especially the fact that both are realizations of derived demand. Broadly speaking, transportation may take one or more of the three forms:

- Moving people, to participate in activities;
- Moving information goods, such as letters, books, newspapers, and so on; and/or
- Moving electronic impulses, either in the form of electrical current along wires, cable, or optical fiber, or in the form of radio waves through the air.

Therefore, telecommunication may be thought of as the transportation mode of information. However, Mokhtarian (1990, 2000) viewed these as three different alternate forms of communication. Furthermore, she identified several different relationships among these alternate modes: substitution (elimination, replacement), generation (stimulation, complementarity), modification, and neutrality. Based on Salomon’s (1986) hypothesis that communication increases exponentially, Mokhtarian (1990) argued that communication breeds communications. In other words, she claims if one form of communication increases, then it will result in the increase of all three forms of communications as a whole, namely, electronic transmission, information freight (e.g. letters, books, newspapers, etc), and personal travel. The relative shares of each of the three modes of communication may vary as one mode partially substitutes for another, but the absolute amounts of communication for each mode are likely to increase. Figure 2-1 shows this principle of simultaneous substitution and generation impacts. The combination of these two counteracting forces makes it very difficult to determine the net impact of telecommunication on transportation in any particular context. Her conceptual framework reflects the impacts of ICT on travel and contains the reverse causality of the effect of travel on ICT.

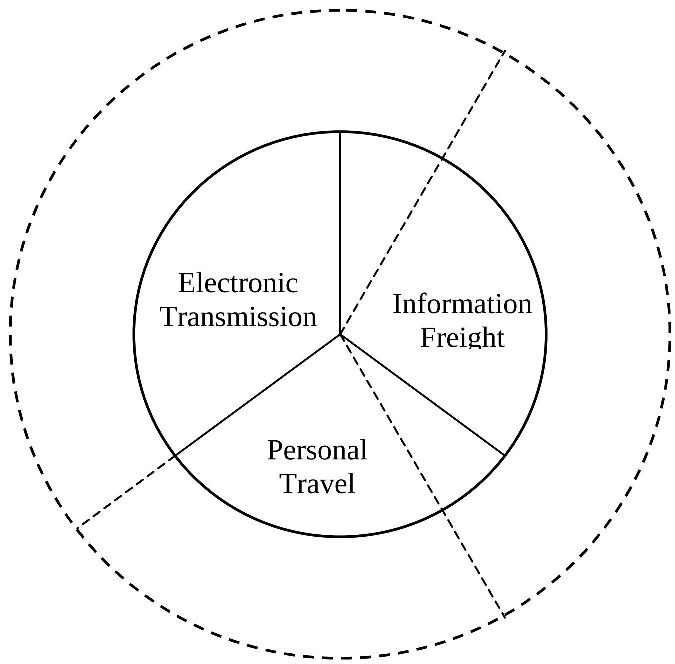


Figure 2-1 Simultaneous Substitution and Generation Impacts among Communications (Mokhtarian, 1990).

In one of the most recent summaries about this interaction, Krizek and Johnson (2003) map the terrain of research recognizing the many complexities of interaction. In fact, they agree with Mokhtarian (1990) that the four relationships discussed in Salomon (1986) are only a simplification. Krizek and Johnson (2003) expand the Salomon-Mokhtarian framework one step further considering a triad of dimensions that are: a) the effect of ICT on travel (using the four Salomon effects); b) nature of the activity pursued using ICT (borrowing the categorization of subsistence, maintenance, and leisure from activity analysis in travel behavior); and c) the effect of “subtasks” when pursuing an ICT action.

2.2 The Impact of Telecommunication on the Demand for Transportation

In many cases, transportation can accomplish the same purpose as telecommunication. Thus, telecommunication and transportation can either be competing modes of communication (substitute), or they can synergistically support each other in increasing all forms of communications (complement). The impact of telecommunication on the demand for transportation can be classified into two types: substitution and stimulation. However, the most important feature of telecommunication is that it permits a great deal of flexibility in whether, when, where, and how to travel. Telecommunication relaxes the constraint of having to be at a certain place at a certain time.

2.2.1 Substitution

As the availability of telecommunication technologies expands to allow more applications at reduced cost, the need to travel will decrease, because telecommunication will be used instead. Therefore, in many ways, telecommunication technologies can substitute trip making. Many conceptual (Salomon, 1985; Mokhtarian, 1990) and empirical (Nilles, 1988; Mokhtarian, 1991; Mokhtarian, *et al.*, 1995) studies on the impacts of telecommunication on travel have been conducted over the past two decades. However, most of the empirical research has focused on telecommuting, probably because (1) it has been feasible for longer than most other tele-applications due to data availability, (2) it has the advantage of eliminating or reducing the peak-period commute trip, which is especially attractive, and (3) it addresses some policy issues, such as the family friendly workplace and employment opportunities for mobility-limited sectors of the labor force (Mokharian, 1998).

A list of some currently practiced substitution applications includes the following:

- *Telecommuting*: It refers to working at a home or other remote location with telecommunication technologies, such as home computing, the Internet, email, fax machine and express delivery, to central office. Information and Communication Technology (ICT) has made possible the flexible working arrangements between employers and their employees. Advantages of telecommuting include more flexibility in activity scheduling and sharing of activities with household members, more opportunities for quality time with family members, and saved commuting time. From the perspective of travel behavior, it is argued that telecommuting participation might increase non-commuting trips and also influence residential and employment location choices, which in turn affect travel demand (Niles, 1991; Pendyala, et al., 1991). However, Mokhtarian and Salomon (1996, 1997) report that the effect of telecommuting on non-commuting trips is statistically insignificant in most studies, and that no significant impact on mode choice or residential choice has been observed. Furthermore, ICT can influence the type of employment (increase in self-employed, contingent, or part-time workers). In order to cut costs and increase flexibility in rapidly changing marketplaces, businesses have tended to increase the percentage of contingent and part-time workers or increase subcontracting and other types of outsourcing, which in turn encourages self-employment (Manser and Picot, 1999). Giuliano (1998) reports on important differences between full-time, part-time, and self-employed workers in terms of their commuting patterns and residential and work locations. In addition, due to mobile phone and portable computer and fax devices, many people carry out even mobile working. This type of employment and work would be impossible without information technologies.

- *Teleconferencing*: It refers to meeting at multiple locations with audio, video, and/or data links among sites.

- *Teleshopping*: It refers to Internet- or TV-based services to obtain information about products, and to sometimes purchase them. The recent growth in applications of teleshopping, especially e-commerce on the Internet, has been phenomenal. In 1999, it is estimated that 7 million households in the United States made their first online purchases. It is also estimated that more than 17 million U.S. households shopped online by the end of 1999, and the forecast is that 49 million American households will shop on line by 2004 (Forrester, 2000). Currently, the major sectors of consumer e-commerce are books, travel, software, music, hardware, clothing, and electronics (Cyber Dialogue, 2000). Despite this growth, it is hardly believable that online shopping will replace a large portion of traditional shopping in the foreseeable future, because shopping is often linked with other activities and there are many other reasons for shopping besides the purchase of goods (Gould, 1998). Shopping also involves recreation, social contact, search for new opportunities and enjoyment of being outside. However, it is estimated that in 1995 shopping trips comprised 20 percent of person trips and 14 percent of person miles traveled in the United States (NPTS, 2000). Thus, although only a few shopping trips per person are replaced by e-commerce, the total number of trips affected in the United States can be large. Much of the travel behavior research has recently concentrated on on-line grocery shopping because household replenishment trips occupy a large portion of all shopping trips. On-line shopping for groceries and household goods can be particularly important for activity and travel behavior, because this activity is much more repetitive than other types of shopping.

- *Telebanking*: using a computer with modem and a touch-tone telephone to perform banking transactions. Automated teller machines (ATMs) may also be considered as a form of telebanking, in that they are found in convenient places not requiring a separate trip to access the facility. European systems in Portugal (the Multibanco system) and Finland allow a wider range of transactions in which a person can perform the entire range of payments from telephone and electricity bill payments to more complex bank transfers around the world.

- *Tele-entertainment*: It refers to the use of telecommunication to transmit a cultural, athletic, or other entertainment activity to multiple locations. Televised live events and TV movies are good examples of Tele-entertainment.

- *Tele-education*: Distance learning involves using Internet, satellite, or cable TV systems to transmit classroom instruction to one or more remote locations. It allows off-campus study for full-time and extension students at colleges, vocational school, and other institutions. The Penn State World campus is one such example.

- *Telemedicine (or online medical services)*: Video and data links make it possible for health professionals to transmit video images, X-rays, and other information to a specialist and receive a diagnosis and treatment regimen without a trip for the patient. The Internet provides a way of extending medical services to people who are unable or unwilling to visit traditional office and hospital sites for treatment and diagnosis. It can be particularly important for remote emergency situations as well as for the dispensing of drugs and other pharmaceutical products. In addition, according to Cyber Dialogue (2000), 33.5 million adults in the United States will use the Internet to find health and medical information in 2000, searching from more than 15,000 Internet health sites. Although telemedicine will probably have only sparse effects on the activity patterns of most people, it could have profound effects on the activity patterns and transportation needs of some elderly and chronically ill people.

- *Telejustice*: Videoconferencing links between the courthouse and the prison to do routine functions such as depositions and arraignments. This capability eliminates the costs and hazards of transporting prisoners back and forth.

These applications primarily replace passenger transportation by telecommunication. However, telecommunication can also substitute freight transportation. For example, electronic data transmission using modems can substitute for physical shipment of information products. Many documents now transmitted by facsimile would have been sent by overnight or conventional mail. Even market shares of fax transmissions are currently taken by another telecommunication service, e-mail.

2.2.2 Stimulation

In spite of extensive list of trip substitution applications, telecommunication can also stimulate travel in several ways. Due to telecommunication, information about people and activities is much more accessible than otherwise. This information may create the opportunities and desire to travel to participate in those activities and interact with those people. In addition, the time saved by telecommunication substitution for travel may be used to make other trips. In the long-term, telecommunication infrastructure and services may lead to change in land-use patterns that may in turn result in longer trips or more travel in general.

In addition, telecommunication technologies make some transportation services attractive. For example, telecommunication can affect public transit operations. Through ITS applications, improvements in transit service with real-time route and schedule information might stimulate people's transit usage, and enhanced information systems about ridesharing can promote carpooling thereby increasing both ridesharing demand and supply.

2.3 The Impact of Telecommunication on the Supply of Transportation

This impact is of more interest to the transportation professionals and system managers. Telecommunication can increase the effective level of service of a transportation system by supporting more efficient use of existing networks. In other words, it promotes more efficient use of existing capacity and decreases delays while inhibiting the need to construct expensive new infrastructure. One great example is Advanced Traveler Information Systems (ATIS). With new Internet technology travelers will be provided information on traffic conditions and near-term forecasts as well as real-time information on hazards and incidents. Furthermore, travelers will be recommended alternative trip routing and timing. Handheld Internet devices will allow travelers to access web pages and receive reports from agents at sites away from home. Other examples of telecommunication-based control or feedback systems supporting goods and people movement include (but are not limited to):

- Highway emergency call boxes, permitting quicker removal of accidents;
- Changeable message signs to route traffic around major incidents;
- CB radios, permitting prompt accident reporting and route diversion;
- Freeway ramp metering;
- Remote video surveillance of freeway ramps and high-occupancy vehicle lanes, permitting more effective enforcement and incident management abilities;
- In-vehicle navigation devices;
- Automated vehicle and guideway technologies;
- Radio determination satellite (RDSS), permitting tracking and control of cargo at any point in the shipment;
- Electronic document transfer among shippers, customers, and customs officials;
- Voice mail systems for truckers, reducing the difficulty of communication between dispatchers and drivers on the road; and
- Microwave landing systems for aircraft.

Figure 2-2 summarizes the interrelations among ICT, transportation demand and supply, and land use pattern. The impact of ICT on transportation is direct and relatively in short-term, while its impact on land use pattern occurs in indirect and long-term ways.

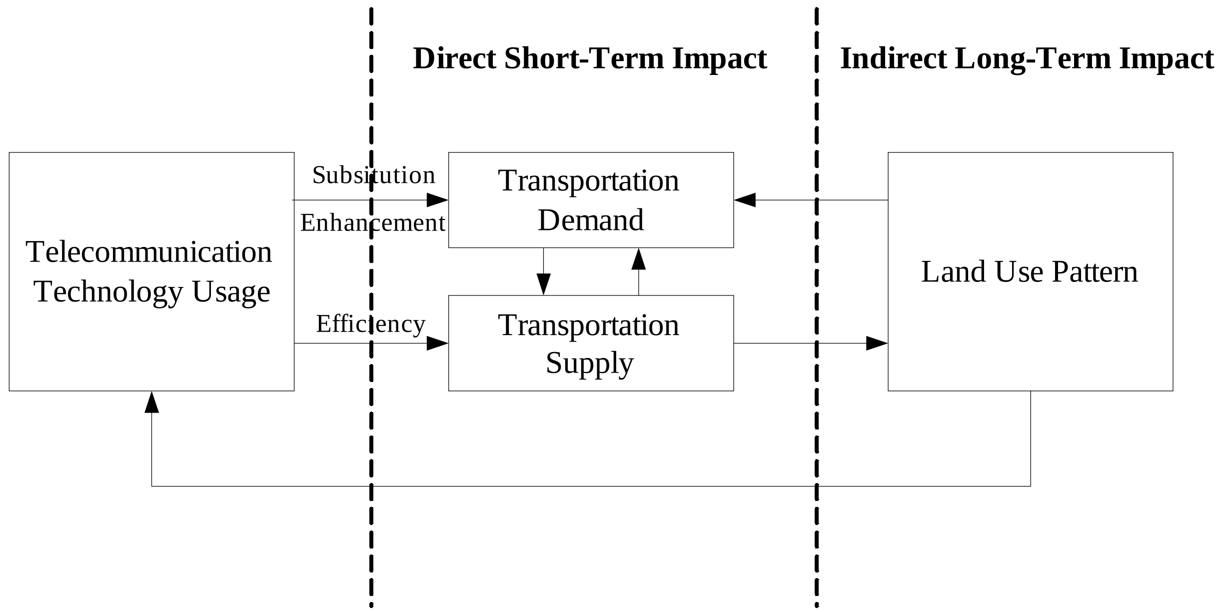


Figure 2-2 Interrelationships between Telecommunication and Transportation

2.4 Telecommunication and Time Allocation for Activity and Travel

What are the relationships between ICT and people's time allocation for activity and travel? Do people with ICT spend more time at home? Are they having longer leisure activity?

In terms of the relationship between ICT and subsistence activity, the majority of ICT studies have focused on telecommuting due to its potential benefit of relieving peak-hour traffic congestion and creating more flexible working arrangements. Telecommuting generally leads to spending more time at home and less time on out-of–home subsistence activity, but prior studies yielded somewhat conflicting findings regarding the number of trips and distance traveled on net travel resulting from telecommuting. Some have found that telecommuters reduce their number of trips and distance traveled on telecommuting days (Pendyala, et al., 1991; Wells, et al., 2001), while other studies have provided empirical evidence of travel stimulation or generation (Mokhtarian and Salomon, 1997; Salomon, 1986). The actual impact of telecommuting may depend on the level of telecommuting. For example, those who are full time workers at home tend to have the most changed travel behavior, while those who telecommute a few days a week at home tend to have pre-telework behavior (Wells, et al., 2001). Senbil and Kitamura (2003) found that the use of cellular phones is accompanied by longer work duration.

In terms of maintenance activity, most of existing maintenance-related studies focus on home shopping and e-commerce. Gould (1998) and Gould and Golob (1997) provided an overview of the transportation implications emerging from home shopping and e-commerce. Marker and Goulias (2000) provided a conceptual framework of on-line grocery shopping and explored some issues related to its likely effects on traffic, delivery forms, and modeling methods. Handy and Yantis (1997) examined the potential substitutability of non-grocery shopping and banking by the use of ICT using household survey data collected in three different cities, and concluded that out-of-home shopping and on-line shopping may not be mutual substitutes because the former offer qualities that are not duplicated by the latter. This is confirmed by Casas, et al. (2001) observing that individuals who participated in on-line shopping do not make fewer physical shopping trips. But it is found that on-line banking seems to reduce physical trips to the bank. In addition, Handy and Yantis (1997) found that in-home entertainment activities and home shopping are positively accompanied by an increase in travel. Farag, et al. (2003), however, studied the impacts of on-line shopping on personal travel behavior and reported that on-line shopping saves time for consumers. Decision on whether or not people purchase products on-line depends on the type of the products. Book, music and movies, home electronics, computer hardware and software, and travel and theatre tickets are the most convenient items to shop for on-line, while clothing is the least (Bhatnagar, et al., 2000; Underhill, 1999).

In terms of leisure activity, the use of ICT hardly replaces people’s out-of-home leisure activity. For example, socializing with others and human contact are important parts of peoples’ lives, and this need cannot be adequately served electronically. In addition, a very limited amount of other leisure activity can be replicated electronically. For instance, renting a movie is not a substitute for going to the theatre because the two are usually not considered to be equivalent services. Handy and Yantis (1997) explored a possible substitution of home movie rental or television for theatre visits and concluded that the in-home activity is not likely to be viable substitute for out-of-home and physical versions, because home movie rental or television can not fulfill the main reasons for going to the theatre, such as bigger screen size, better sound, newer movies, getting out of the house, and going out with friends. Although leisure activity may not be replicated by ICT, it is more likely affected by time allocation to subsistence and maintenance activity. As Salomon (1985) implies, ICT has an indirect effect on leisure activity through subsistence and maintenance activity. In other words, ICT makes subsistence and maintenance activity more efficient, so people will have more leisure time and consequently travel more often.

2.5 Panel Analysis

Different people have different activity and travel patterns. In addition, people's activity and travel behavior is constantly evolving. This is due to continuous changes in factors affecting people's behavior, such as different life cycle patterns resulting from transitions from one life cycle stage to next, technological innovation, migration of jobs and population to the suburbs, changes in transportation network and policies, etc. These heterogeneity and dynamic changes in activity and travel behavior can be more effectively captured by repeated measurements on the same individuals and households (that are called panel surveys) over time than by conventional cross-sectional surveys. Kitamura (1990) provided an overview of transportation panels and their technical issues and claimed that panel analysis is the most effective, sometimes the only, way in which dynamics of travel behavior can be investigated.

Panel surveys are advantageous in many ways over traditional cross-sectional travel surveys that are the most common travel surveys in the United States. A panel survey also provides a unique opportunity to measure changes in travel behavior of individuals over time in response to other factors. As summarized in Table 2-1, there are four different types of survey designs. One-time cross-sectional designs provide a snapshot of travel behavior at the time of survey and measure variation among the members of a population (cross-sectional variation), but they do not provide information on how travel behavior changes over time (longitudinal variation). Like one-time cross-sectional surveys, repeated cross-sectional designs can measure cross-sectional variation. In addition, they can monitor changes in travel behavior of the population over time, but they can not measure changes at the individual level because they use distinct samples for each survey. On the other hand, panel surveys permit to measure cross-sectional variation as well as longitudinal variation at the level of individual by asking the same questions to the same persons over time, and they thus detect individual changes. In other words, they provide information on how the travel behavior of individual sample members changes over time in response to changes in the travel environment, household background characteristics, or other factors. This advantage of panel surveys is very useful in the following situations:

- To develop travel demand models and forecast future demand;
- To measure and understand trends in population behavior;
- To conduct behavioral analyses; and
- To assess the impact of a change in transportation policy or a change in the transportation systems (Tourangeau, Zimowski, and Ghadialy, 1997).

Murakami and Ulberg (1997) found that regional travel forecasts based on cross-sectional surveys had seriously underestimated actual demand and argued that a panel would offer a more realistic and cost-effective tool for planning and forecasting.

Table 2-1 Features of Four Types of Survey Designs

Approach	Design	Number of Tome Points	Number of Measurements Per Sample Units	Type of Variation Measured		
				Variation Among Sample Units (Cross-sectional Variation)	Variation Within Sample Units (Longitudinal Variation)	Variation in the Population Across Time
Cross-sectional	One–time Cross-sectional Designs	One	One	Yes	No	No
	Repeated Cross-sectional Designs	Two or More	One	Yes	No	Yes
Panel (Longitudinal)	Longitudinal Panel Designs (PSTP)	Two or More	Two or More	Yes	Yes	Usually No
	Rotated Panel Designs	Two or More	Two or More	Yes	Yes	Yes

Source: Tourangeau, Zimowski, and Ghadialy, 1997

CHAPTER 3
PUGET SOUND TRANSPORTATION PANEL

The Puget Sound Transportation Panel (PSTP) is the primary database used in this dissertation. It is the first general purpose, urban household panel survey in the United States (Murakami and Watterson, 1990) designed for transportation analysis. As Murakami and Ulberg (1997) state, the three major objectives of PSTP are to:

- Track changes in employment, work characteristics, household composition, and vehicle availability;
- Monitor changes in travel behavior and responses to changes in the transportation environment; and
- Examine the effects of changes in attitudes and values on mode choice and travel behavior.

The PSTP was initiated in the four counties (King, Kitsap, Pierce, and Snohomish) of the Puget Sound region including Seattle in the fall of 1989 by the Puget Sound Regional Council (PSRC, then the Puget Sound Council of Governments) in partnership with transit agencies in the region, and continues until today. Unlike traditional cross-sectional surveys, the PSTP is a panel or longitudinal survey in which similar measurements are made repeatedly on the same households and persons within the households over time. A survey conducted at each point in time is called a wave. Each wave of the PSTP collects three groups of data that are household demographics, person's social economic information, and reported travel behavior. Trip information was collected using a travel diary. In the travel diary, to capture driving age individual behavior, each person in the recruited household that is 15 years of age or older was required to report every trip made during two consecutive weekdays, which remained approximately the same throughout the panel years. Each trip contains information about trip purpose, type, mode, starting and ending time, origin and destination, and distance. Based on the hypothesis that travel is derived from a person's desire to participate in activity, the purpose of a trip is to engage in a certain type of activity, and the trip destination is the place where the activity is pursued.

Therefore, the durations of activities are computed by the difference between the start time of the next trip and the end time of the current trip giving the sojourn time at an activity location.

These behavioral data are supplemented by periodic surveys of travel attitudes, perceptions and needs. So far, there are 10 waves of PSTP travel data collected (1989, 1990, 1992, 1993, 1994, 1996, 1997, 1999, 2000, and 2002) and seven attitudes and values surveys (1990, 1992, 1993, 1996, 1997, 1999, 2000, and 2002). The length and depth of this panel make it the richest and longest record of individual and household social, demographic, and economic changes and associated travel behavior.

PSTP is a choice-based survey of households, with stratification based on usual mode of travel to work. Therefore the PSTP consists of three distinct household populations:

- SOV households (in which all household members make less than four one-way work trips by carpool or transit on a weekly basis);
- Transit households (in which at least one person makes at least four one-way work trips by transit on a weekly basis); and
- Carpool households (in which at least one person makes at least four one-way work trips by carpool on a weekly basis).

Tables 3-1 and 3-2 show the number of households and persons for each travel-mode group for each wave. Each wave of PSTP contained approximately 1800 households and 3500 persons. The transit households and carpool households comprised about 20 percent and 10 percent of the sample, respectively. It indicates that transit households were particularly oversampled. In addition to the stratification on the travel modes, each sample of the three household populations is further stratified by county of residence (King, Kitsap, Pierce, and Snohomish). The main reason of this double sample stratification is to increase the sample size of transit users for acceptable statistical analysis (Goulias and Ma, 1996).

Table 3-1 Choice-based Sample Composition by Wave (Household Level)

Sample Category	Number of Households (including split households)								
	Wave 1 (1989)	Wave 2 (1990)	Wave 3 (1992)	Wave 4 (1993)	Wave 5 (1994)	Wave 6 (1996)	Wave 7 (1997)	Wave 8 (1999)	Wave 9 (2000)
SOV	1138	1212	1072	1240	1170	1169	1332	1213	1193
Transit	381	378	343	464	393	386	410	369	345
Carpool	193	203	180	227	219	204	265	225	190
Unknown	0	8	1	1	0	0	0	0	0
Total	1712	1801	1596	1932	1782	1759	2007	1807	1728

Table 3-2 Choice-based Sample Composition by Wave (Person Level)

Sample Category	Number of Persons								
	Wave 1 (1989)	Wave 2 (1990)	Wave 3 (1992)	Wave 4 (1993)	Wave 5 (1994)	Wave 6 (1996)	Wave 7 (1997)	Wave 8 (1999)	Wave 9 (2000)
SOV	2166	2276	1988	2298	2207	2215	2533	2283	2193
Transit	804	776	693	917	781	780	828	755	666
Carpool	420	431	377	468	473	430	578	497	400
Unknown	0	14	1	1	0	0	0	0	0
Total	3390	3497	3059	3684	3461	3425	3939	3535	3259

Three different sampling methods were used to recruit potential panel participants in 1989. First, telephone random digit dialing (RDD) technique was employed to recruit households from each of the four counties in the Puget Sound region. The RDD technique was primarily used for drive-alone and carpool households. Second, to obtain a larger transit user portion of the sample, Seattle Metro transit survey respondents who showed a willingness to participate in the future research were contacted again. Third, letters to request volunteers were distributed on randomly selected bus routes.

Because of the relocation of households outside the region and panel fatigue from repeatedly filling out the travel diary, the number of households remaining in the panel for all waves declined as the panel survey continued. The phenomenon of sampling units that refuse to participate in subsequent waves of the panel is called panel attrition. To maintain the sample size over time and to reflect changes in the population, new households with similar demographic and trip-making characteristics were recruited in each panel. This is called sample refreshment. These replacement households were recruited only through the RDD technique. Tables 3-3 and 3-4 show the number of stayers and replacements for each wave.

Table 3-3 Panel Participation Pattern (Household Level)

	Number of Participant Households								
	Wave 1 (1989)	Wave 2 (1990)	Wave 3 (1992)	Wave 4 (1993)	Wave 5 (1994)	Wave 6 (1996)	Wave 7 (1997)	Wave 8 (1999)	Wave 9 (2000)
Stayers	1712	1386	1077	937	808	543	468	388	302
Split Households		16	3*	26	13	5	17	14	25
Replacement 1		399	154	137	117	78	68	46	34
Replacement 2			362	267	190	116	94	69	50
Replacement 3				565	319	175	134	96	69
Replacement 4					335	173	124	91	68
Replacement 5						669	443	294	180
Replacement 6							659	357	201
Replacement 7								452	209
Replacement 8									590
Total	1712	1801	1596	1932	1782	1759	2007	1807	1728

* Including one household entering the panel in wave 3

Table 3-4 Panel Participation Pattern (Person Level)

	Number of Participants								
	Wave 1 (1989)	Wave 2 (1990)	Wave 3 (1992)	Wave 4 (1993)	Wave 5 (1994)	Wave 6 (1996)	Wave 7 (1997)	Wave 8 (1999)	Wave 9 (2000)
Stayers	3390	2641	1928	1675	1435	956	813	662	519
Replacement 1*		856	348	289	232	158	137	92	73
Replacement 2*			783	578	413	244	189	134	100
Replacement 3*				1142	639	324	246	173	125
Replacement 4*					742	365	257	172	127
Replacement 5*						1378	906	570	327
Replacement 6*							1391	750	404
Replacement 7*								982	425
Replacement 8*									1159
Total	3390	3497	3059	3684	3461	3425	3939	3535	3259

*All replacements also includes the number of persons newly adding in existing panel households

3.1 Wave 7 and Wave 9

In this thesis, the Wave 7 (1997) and Wave 9 (2000) travel survey databases are used. Since 1997 (Wave 7), the survey participants above 15 years of age were asked some additional questions about their personal use and attitudes towards existing and potential new information sources. In addition, respondents were asked about their familiarity with, and use of, electronic equipment and information services. For example, respondents provided information regarding their use of a desktop computer at home or work with access to the Internet at least once a week on average. Other questions asked if the respondents carried a personal cellular phone, pager, laptop computer (with modem) and a personal digital assistant (PDA) at least ten times a month. The survey also asked if respondents are aware of and use a variety of traffic and transportation information over the radio, television, telephone or the World Wide Web (WWW). Therefore, the PSTP dataset offers a unique opportunity to study the relationship between telecommunication and travel.

Table 3-5 shows descriptive statistics of the sample for Wave 7 and Wave 9. The sample profiles for the two waves are closely matched. The sample consisted of 47 percent males. In addition, 59 percent and 63 percent of respondents were employed in 1997 and 2000, respectively. Professional occupation was the largest portion of the sample, while sales occupation was the least. As expected, the majority of the sample is from two-adult households. The sample consisted of 15 percent of households with one adult, 67 percent of households with 2 adults, 18 percent of households with 3 or more adults in 2000. Only 2 percent of households had no car, 18 percent had one-car, and the majority of households (79 %) had multiple cars.

In terms of ICT use, there was generally a substantial increase in technology use, especially in computer and Internet at home and cellular phone between the two waves. The percent of people who did not use computer and Internet at all decreased from 31 percent to 19 percent. The percent of people who did not use any personal mobile technology (cellular phone, pager, laptop, and PDA) also decrease from 63 percent to 43 percent.

Table 3-5 Sample Characteristics for Wave 7 and Wave 9

Characteristics		Wave 7 (1997)	Wave 9 (2000)
Number of Households in the Sample		2007	1728
Number of Persons in the Sample		3939	3259
Gender	Male	47.3 %	46.6 %
	Female	52.7 %	53.4 %
Age	15-34	22.0 %	17.9 %
	35-64	59.4 %	62.2 %
	65 and above	18.5 %	19.5 %
	No answer	0.2 %	0.4 %
Occupation	Professional	22.9 %	25.3 %
	Managerial	9.2 %	7.9 %
	Secretary	8.3 %	7.3 %
	Sales	3.1 %	3.1 %
	Others	13.9 %	19.7 %
	Unemployed	41.2 %	35.3 %
	No answer	0.3 %	1.4 %
Number of Adults (18 year or older) in the Household	1	13.0 %	14.8 %
	2	68.0 %	67.3 %
	3 or more	19.1 %	17.9 %
Number of Children (6-17 years old) in the Household	0	70.4 %	69.9 %
	1	13.9 %	14.0 %
	2	11.0 %	12.1 %
	3 or more	4.6 %	4.1 %
Number of Children (< 6 years old) in the Household	0	87.3 %	91.2 %
	1	8.6 %	5.7 %
	2	3.8 %	2.9 %
	3 or more	0.3 %	0.3 %
Number of Vehicles in the Household	No vehicles	2.0 %	2.3 %
	1 vehicle	17.7 %	18.2 %
	2 vehicles	45.1 %	43.5 %
	3 or more vehicles	35.0 %	35.7 %
	No answer	0.1 %	0.1 %
Household Income	Less than $35,000	24.0 %	14.7 %
	$35,000 to $75,000	46.7 %	42.4 %
	More than $75,000	21.8 %	28.0 %
	Less than $35,000 (second)	0.5 %	0.9 %
	More than $35,000 (second)	2.3 %	7.4 %
	No answer	4.8 %	6.6 %
Computer & Internet*	Computer at work/School	48.8 %	53.6 %
	Computer at home	52.1 %	68.7 %
	Internet at work/School	30.4 %	40.3 %
	Internet at home	31.9 %	63.2 %
	None of these	30.8 %	19.2 %
	No answer	0.3 %	0.0 %
Personal Technology*	Cellular phone	27.5 %	48.2 %
	Pager	11.5 %	9.5 %
	Laptop	5.1 %	5.3 %
	PDA	0.5 %	2.7 %
	None of these	63.1 %	42.8 %
	No answer	2.3 %	0.0 %

** Number of respondents for Wave 7 and Wave 9 are 3739 and 3129, respectively.*

CHAPTER 4
ANALYSIS METHODS

In this chapter, a variety of statistical analysis techniques employed for this study are presented. They cover a wide range from a simple method, such as the linear regression model, to more sophisticated and advanced ones, such as latent class cluster analysis and structural equation modeling. They can be broadly classified into two groups: single-equation (univariate) approaches and multiple-equation (multivariate) approaches.

4.1 Linear Regression Model

Although many sophisticated and complex models have been developed, the linear regression model is still one of the most popular analysis techniques and provides a good example to illustrate other more complex models. The underlying linear regression model is based on the following specification:

$$Y_i = \beta' X_i + \varepsilon_i \tag{4-1}$$

$$E[\varepsilon_i]=0,\ \ Var[\varepsilon_i]=\sigma^2.$$

where Y_i = a dependent variable for observation i.

X_i = a vector of explanatory variables for observation i.

β = a vector of coefficients of X_i.

ε_i = an error term for observation i.

The linear regression model is based on two components: a systematic component that captures explained variation in a dependent variable and shows the influence of known factors on the mean of the dependent variable and a random component that captures variation from all kinds of unknown reasons such as measurement error and unobserved heterogeneity among the observation units. It is also heavily based on several assumptions:

- Zero mean of error terms ($E[\varepsilon_i]=0$);
- Homoskedasticity ($var(\varepsilon_i) = \sigma^2$ for all i);
- Nonautocorrelation ($cov(\varepsilon_i,\varepsilon_j) = 0$);
- Nonstochastic X; and
- Normality (ε_i is normally distributed), a property needed for hypothesis testing.

Under these assumptions, the ordinary least squares (OLS) estimator ($b= [X'X]^{-1} X'Y$) of the regression coefficients (β) for each equation is the best linear unbiased estimator in the sense that it has the minimum variance of all unbiased estimators. The OLS estimator of covariance matrix, $V = s^2[X'X]^{-1}$ will also give an unbiased estimate of Var[b] (Greene, 2000).

4.2 Seemingly Unrelated Regression Model (SUR Model)

When a series of dependent variables have close conceptual relationship to each other, their disturbances are correlated. In this case, estimating the equations as a set using a single, large regression improves efficiency. The seemingly unrelated regression model that consists of M equations has the following specification:

$$Y^m = \beta^{m\,\prime} X^m + \varepsilon^m \quad (m= 1, 2,\ldots, M) \qquad (4\text{-}2)$$

where Y^m = a ($N \times 1$) vector of dependent variable (m= 1, 2, …, M),

X^m = a ($N \times K^m$) matrix of explanatory variables (m= 1, 2, …, M),

β^m = a ($K^m \times 1$) vector of coefficients (m= 1, 2, …, M),

ε^m = a ($N \times 1$) vector of error terms (m= 1, 2, …, M).

In the seemingly unrelated regression model, it is assumed that ε^m is normally distributed with mean $E[\varepsilon_i^m]=0$, (i =1, 2, …, N), that error terms across observations are uncorrelated ($cov[\varepsilon_i^m \varepsilon_j^{m\,\prime}] = 0$), but error terms across equations are correlated, and thus its variance-covariance matrix is given by $E\left[\varepsilon^m \varepsilon^{p\,\prime}\right] = V = \sigma_{mp} I_N = \Sigma \otimes I$, where I_N is an identity matrix of order [N $\times$ N]; $\otimes$ is the Kronecker product. So the covariance (σ_{mp}) of the error terms of the *m*th and the *p*th equation is assumed to be constant over all observations. In addition, the explanatory variables are assumed to be nonstochastic. In this way we can not only make each of the equations satisfy the assumptions of the classical linear regression model, but also take into account the correlation of the error terms across equations.

To take into account the correlation of the error terms across equations, the M equations are compressed into one large equation:

$$\begin{bmatrix} Y^1 \\ Y^2 \\ \ldots \\ Y^M \end{bmatrix} = \begin{bmatrix} X^1 & 0 & \ldots & 0 \\ 0 & X^2 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & X^M \end{bmatrix} \begin{bmatrix} \beta^1 \\ \beta^2 \\ \ldots \\ \beta^M \end{bmatrix} + \begin{bmatrix} \varepsilon^1 \\ \varepsilon^2 \\ \ldots \\ \varepsilon^M \end{bmatrix} \tag{4-3}$$

or $$Y^* = X^*\beta^* + \varepsilon^* \tag{4-4}$$

where Y* = a (MN $\times$ 1) vector of dependent variable;

X* = a (MN $\times$ $\left(\sum_{m=1}^{M} K^m\right)$) matrix of explanatory variables;

β*= a ($\left(\sum_{m=1}^{M} K^m\right) \times 1$) vector of coefficients; and

ε* = a (MN $\times$ 1) vector of error terms.

Generalized Least Squares is one of the methods used to estimate the parameters in this system of equations. In essence, it is a multi-step estimation method (Greene, 2000). By applying the generalized least squares (GLS) method to the stacked model (Equations 4-3 or 4-4), the efficient estimator, $\hat{\beta} = \left[X'V^{-1}X\right]^{-1} X'V^{-1}Y = \left[X'(\Sigma^{-1} \otimes I)X\right]^{-1} X'(\Sigma^{-1} \otimes I)Y$ can be obtained. Since Σ is unknown, the feasible GLS (FGLS) estimator is obtained in two steps. At the first, single equation ordinary least squares is used one equation at a time to compute b^m, m=1, 2, …, M.

Then, b^m is used to obtain residuals e^m, which are used to compute $\hat{\Sigma} = \frac{e^{m}{}' e^{p}}{N}$, m, p =1, 2, …, M. FGLS is then computed using this estimator of $\sum$.

Zellner (1962) and Dwivedi and Srivastava (1978) analyzed how much efficiency is gained by GLS instead of OLS in some special cases:

1. If the equations are actually unrelated, GLS=OLS;
2. If the equations have identical explanatory variables, GLS=OLS;
3. If the explanatory variables in one block of equations are a subset of those in another, GLS=OLS.

In the more general case, with correlation of the disturbances and different explanatory variables in the equations, two rules of thumb can generally be used (Greene, 2000):

1. The greater the correlation of the disturbance, the greater the efficiency gain by GLS; and
2. The less correlation there is between the X matrices, the greater the gain in using GLS.

4.3 Multilevel Model

The PSTP data may be viewed to have a nesting hierarchical structure, because occasions of measurement are nested within persons, persons in turn are nested within households, households are again nested within residence areas (e.g., counties), and so on. One method to statistically account for the contextual behavior of individuals exploiting this hierarchical nature in the data is called a multilevel model. The method also allows us to exploit strong correlations across observations at different hierarchical levels simultaneously and to quantify relative variations contributed by each hierarchy level.

Although the multilevel models are known by different names in different fields of research: for example, random coefficient models (Greene, 2000; Longford, 1993), mixed models (Searle et al., 1992), full contextual models (Kreft and De Leeuw, 1991) and hierarchical linear models

(Bryk and Raudenbush, 1992), all these models have key common characteristics as follows (Goulias, 2002):

- Explicit recognition in model formulation of the hierarchical, multiple level, and nested structure of the data to analyze; and
- Three groups of regression components in the same regression model. The first group assumes constant sensitivity to explanatory variables among the units of analysis representing the mean effect of an explanatory variable on the dependent variable. The second group assumes a random deviation around this mean and the third group contains the usual random error term(s) of the regression equation.

For these reasons, multilevel models have a more general form than any other model, and they are theoretically more powerful in handling observed and unobserved heterogeneity while at the same time producing unbiased and consistent coefficient estimates.

A simple multilevel model with two levels (persons within households) is based on the following specification:

$$Y_{ij} = \beta_{ij} + \gamma_1 X_{1ij} + \ldots + \gamma_k X_{kij} \qquad (4\text{-}5)$$

$$\beta_{ij} = \gamma_0 + v_j + u_{ij} \qquad (4\text{-}6)$$

where Y_{ij} = the dependent variable by person i in household j.

$\gamma_1 \ldots \gamma_k$ = coefficients which are defined in a similar way as in a typical regression

ν_j, μ_{ij} = random components at household and person level, respectively.

with E(v)=E(u)=0, var(v)=σ_v^2, and var(u)=σ_u^2

$X_{1ij} \ldots X_{kij}$ = the explanatory variables for person i in household j.

The first term (β_{ij}) in the right hand side of the equation 4-5 in the multilevel model is a random intercept. This component has a specific meaning. β_{ij} is the expected value of the dependent variable for person *i* in household *j* when all other explanatory variables are zero. The term u_{ij} is a random person–to–person variation (also called within household variation) and it is a deviation around $\gamma_0 + \nu_j$. The term v_j is a random household-to-household variation and it is a deviation around γ_0. These are also called random error components, and are assumed normally distributed with E(u) = E(v) = 0, and $Var(u) = \sigma_u^2$ and $Var(v) = \sigma_v^2$. The random components (u and v) and their variance represent unobserved heterogeneity at the person and household levels, respectively. In equations all the γ coefficients are defined in a manner similar to a typical regression model. Although all the coefficients of explanatory variables are defined as fixed in the model specification above, the coefficients can be defined as random with a mean and a variation around their means γs. In this way we can define a more general model at each of these levels to represent heterogeneous behavior either due to personal or household variation.

In multilevel models, all the fixed and random parameters can be estimated by iterative generalized least squares (IGLS). This approach separates estimation of the fixed parameters from the random parameters at different steps in sequence repeatedly as follows until subsequent estimates of the parameters changes are very small. First, an estimate of the fixed (non-random) coefficients can be obtained using generalized least squares as: $\hat{\beta} = \left(X^T V^{-1} X\right)^{-1} X^T V^{-1} Y$ with a covariance matrix $\left(X^T V^{-1} X\right)^{-1}$ in which V is a function of the random parts at the two levels in the model. Then, the estimates of random parameters (θ) can be calculated by using a generalized least squares as follows: $\hat{\theta} = \left(Z^{*T} V^{*-1} Z^*\right)^{-1} Z^{*T} V^{*-1} Y^{**}$, $V^* = V \otimes V$, where ⊗ is the Kronecker product. The covariance matrix of $\hat{\theta}$ is given by $\left(Z^{*T} V^{*-1} Z^*\right)^{-1} Z^{*T} V^{*-1} \operatorname{cov}\left(Y^{**}\right) V^{*-1} Z^* \left(Z^{*T} V^{*-1} Z^*\right)^{-1}$. Z^* is the design matrix of the random part in the model and Y^{**} is a vector stacking of the residuals. These procedures iterate using the current estimates of fixed and random parameters until a very small change is observed in the estimates in subsequent steps. However, IGLS procedures produce biased estimates in general, especially in the small sample. Goldstein (1995) has improved the IGLS algorithm by taking account of the sampling variation of the $\hat{\beta}$ leading to restricted iterative generalized least squares (RIGLS).

4.4 Latent Class (LC) Cluster Analysis

In order to identify a finite set of homogenous patterns of activity and travel behavior, the latent class cluster analysis is employed here. This technique is described in Vermunt and Magidson (2002):

- Includes a J-class (category) latent variable, each class representing a cluster;
- Uses a mixture of different types of many dependent or clustering variables (continuous, categorical, ordered, or count);
- Uses covariates of many different types, which allows both classification and cluster description to be performed simultaneously; and
- Is a model-based clustered approach, so it provides probabilistic membership of observation in clusters.

The fundamental assumption underlying LC cluster models is that objects in the same latent class share a common joint probability distribution among the observed variables. Therefore, objects in the same cluster are similar to each other with respect to these observed variables. Objects are classified into the class with the highest posterior membership probability of belonging to that class given a set of observed variables.

The LC cluster models with covariates have the following form:

$$f(Y \mid Z,\theta) = \sum_{x} \pi(X \mid Z)\, f(Y \mid X, Z, \theta) \qquad (4\text{-}7)$$

where Y is a set of dependent (clustering) variables.

Z is a set of covariates.

X is a nominal latent variable (having J classes).

θ is a set of parameters to be estimated.

$\pi(X \mid Z)$ is the probability of belonging to a certain latent class given a set of covariate values.

$f(Y \mid X, Z, \theta)$ is the joint distribution specified for the Y given a certain latent class and a set of covariate values and parameters.

If the Y variables belonging to different clusters (of variable X) are assumed to be mutually independent given the latent class and the covariates, we obtain:

$$f(Y \mid Z,\theta) = \sum_{x} \pi(X \mid Z) \prod_{m=1}^{M} f(Y_m \mid X, Z, \theta) \qquad (4\text{-}8)$$

Since the scores on the latent variable given the covariates are assumed to come from a multinomial distribution, the probability of belonging to a given latent class can be calculated as follows:

$$\pi(X \mid Z) = \frac{e^{\eta_{X|Z}}}{\sum_{X} e^{\eta_{X|Z}}} \qquad (4\text{-}9)$$

where the term η is a linear combination of the main effects of the latent variable (γ_{x_j}) and the covariate effects on the latent variable $(\gamma_{z_l x_j})$ defined as:

$$\eta_{X|Z} = \sum_{j=1}^{J} \gamma_{x_j} + \sum_{l=1}^{L} \sum_{j=1}^{J} \gamma_{z_l x_j} \qquad (4\text{-}10)$$

The two main methods to estimate the parameters of LC cluster models are maximum likelihood (ML) and maximum posterior (MAP). In this study, to get ML estimates of the parameters, we use a combination of Expectation Maximization (EM) algorithm with Newton-Raphson algorithm to take advantage of both algorithms: the stability of EM even when far away from the optimum and the speed of Newton-Raphson when close to the optimum (Vermunt and Magidson, 2002). The local maxima problem of the likelihood function by latent class models is overcome by estimating multiple models with different initial values for the parameters. Estimation of models of this type is in essence a hierarchical iterative process (Goulias, Kilgren, and Kim, 2003):

- Start with a one cluster assumption and a simple model is estimated;

- Continue experimentation by increasing the number of clusters until identification is no longer possible for some parameters, the cluster sizes become too small to be meaningful, or the difference in goodness of fit between successive models is not significant;
- Select one or more models that appear to be a reasonable description of the observed data; and
- Define alternate modeling options such as correlations among clustering variables and variances within each cluster starting another iterative cycle.

This goes on until the addition of a more complex structure no longer yields a significant improvement (for nested models we can use a formal statistical step as a stop criterion).

Statistical goodness-of-fit measures for latent class cluster models are the typical chi-square statistics used also in the cross-categorical data analysis. The first measure is the likelihood ratio chi-square, G^2 or L^2. It has a chi-square distribution with degrees of freedom given by the number of "free" parameters (i.e., total number of different response patterns - the number of estimated model parameters – 1 if there are no covariates in the model). It represents the opposite of an R^2 in regression because it is the amount of unexplained associations among the criteria variables by the model. Therefore, higher values indicate models that do not fit the data well and lower values represent better fitting models. When two models are nested, (i.e., they differ only in the number of estimated parameters), we could create the difference between the G^2 of these two models. This difference is chi-square distributed and can be used for hypotheses testing. This cannot be done between models that differ in the number of clusters because they are not nested. Based on L^2, the Bayes information criterion (BIC), Akaike information criterion (AIC) and the Consistent Akaike information criterion (CAIC) are computed to measure goodness of fit and to take into account model parsimony penalizing models with many parameters. The lower the BIC, AIC or CAIC values, the better the model we estimate (McCutcheon, 2002).

The LC cluster method has some advantages over the more popular cluster analysis using the k-means. First, the latent class cluster method for identifying clusters is designed for combinations of continuous and discrete criteria variables while the k-means method is limited to continuous variables only. Second, the former allows for a probabilistic membership of each observation in each cluster. This provides flexibility in observation classification while the k-means does not allow for that. Third, post-processing of the cluster data using regression is not required because the method used allows the inclusion of covariates. There are other advantages of latent class methods in general and the specific implementation used here that are discussed in Vermunt and Magidson, 2002.

4.5 Structural Equation Model (SEM)

SEM is particularly useful to examine the causal relationship among a large number of endogenous and exogenous variables. The general SEM with latent variables consists of two parts: 1) measurement model and 2) structural model. The measurement model specifies how latent variables are indicated by the observed variables, while the structural model specifies the causal relationships among the latent variables and describes the causal effects of the exogenous variables on the endogenous variables. The measurement model can be further classified into the measurement model for the endogenous variables (y) and the measurement model for the exogenous variables (x). The matrix formulation of the general SEM with latent variables is defined as follows:

Measurement model for y: $y = \Lambda_y \eta + \varepsilon$ (4-11)

Measurement model for x: $x = \Lambda_x \xi + \delta$ (4-12)

Structural model: $\eta = B\eta + \Gamma\xi + \zeta$ (4-13)

where $y = p \times 1$ vector of observed endogenous variables.

$x = q \times 1$ vector of observed exogenous variables.

$\eta = m \times 1$ vector of latent endogenous variables.

$\xi = n \times 1$ vector of latent exogenous variables.

$\varepsilon = p \times 1$ vector of measurement errors in y.

$\delta = q \times 1$ vector of measurement errors in x.

$\Lambda_y = p \times m$ matrix of coefficients of the regression of y on η.

$\Lambda_x = q \times n$ matrix of coefficients of the regression of x on ξ.

$\mathrm{B} = m \times m$ matrix of coefficients of the η -variables in the structural relationships.

$\Gamma = m \times n$ matrix of coefficients of the ξ -variables in the structural relationships.

$\zeta = m \times 1$ vector of equation errors in the structural relationships.

Given the complexity and operational difficulties in estimation of a full SEM, it is rarely found in practice (Golob, 2003). Like in the SEM used in this paper, the most common SEM application is SEM with observed variables. Since no latent variables are involved in the SEM, the measurement models for x and y are dropped. Structural equations models with observed variables are therefore reduced to the following form:

$$y = \mathrm{B}y + \Gamma x + \zeta \tag{4-14}$$

where $y = p \times 1$ vector of observed endogenous variables.

$x = q \times 1$ vector of observed exogenous variables.

$\mathrm{B} = p \times p$ matrix of coefficients of the y-variables.

$\Gamma = p \times q$ matrix of coefficients of the x-variables.

$\zeta = p \times 1$ vector of equation errors.

In the SEM with observed variables, y and x are assumed to exactly represent the latent η and ξ, respectively. So the number of y variables equals the number of η variables (p=m) and the number of x variables equals the number of ξ variables (q=n).

SEM is a covariance–based model, because structural equations systems are estimated by covariance analysis. In the procedure, the difference between the sample covariances and the covariances predicted by the model is minimized, instead of minimizing the difference between observed and predicted individual values. The underlying theory of this estimation procedure is that the population covariance matrix of the observed variables (Σ) is a function of a set of parameters:

$$\Sigma = \Sigma(\theta) = \begin{bmatrix} \text{covariance matrix of y} & \text{covariance matrix of y and x} \\ \text{covariance matrix of x and y} & \text{covariance matrix of x} \end{bmatrix}$$

$$= \begin{bmatrix} (I - \mathrm{B})^{-1}(\Gamma\Phi\Gamma' + \Psi)[(I - \mathrm{B})^{-1}]' & (I - \mathrm{B})^{-1}\Gamma\Phi \\ \Phi\Gamma'[(I - \mathrm{B})^{-1}]' & \Phi \end{bmatrix} \tag{4-15}$$

where Φ = covariance matrix of x.

Ψ = covariance matrix of ζ .

The matrix $\Sigma(\theta)$ basically consists of three covariance matrices. The unknown parameters $\mathrm{B}, \Gamma, \Phi,$ and Ψ are simultaneously estimated by finding the parameters such that the covariance matrix ($\hat{\Sigma}$) implied by the model is as close as possible to the sample covariance matrix (S). To know when the estimates are as close as possible, a fitting function that is to be minimized is defined.

The most commonly used estimation methods include maximum-likelihood (ML), unweighted least squares(ULS) , generalized least squares (GLS), scale-free least squares (SLS), and asympotically distribution-free (ADF). The choice of the estimation method depends mainly on the assumption of the probability distribution, the type of variables, and sample size. ML estimation method assuming a multivariate normal distribution was employed for this study. ML estimation was found fairly robust to deviation of multivariate normality and sample size commonly used in transportation research (Golob, 2003). The ML fitting function that is minimized is:

$$F_{ML} = \log|\Sigma(\theta)| + tr(S\Sigma^{-1}(\theta)) - \log|S| - (p + q) \tag{4-16}$$

In SEM, there are three type of effects of one variable on another: direct, indirect, and total effects. The direct effects, which are estimated as B and Γ, are the influences of one variable on another that is not mediated by any other variable, while the indirect effects are ones mediated by at least one intervening variable. The total effects are the sum of the direct and indirect effects. It should be noted that interpreting a model with the direct effects only provides misleading conclusions when the direct and the total effects are very different. It is the total effects that should be used in interpretation. As implied in equation (4-15), the decomposition of effects for SEM with observed variables can be made as follows:

Decomposition of Effects		Effects on Y
Effect of x	Total Effect	$(I-\mathrm{B})^{-1}\Gamma$
	Direct Effect	Γ
	Indirect Effect	$(I-\mathrm{B})^{-1}\Gamma-\Gamma$
Effect of y	Total Effect	$(I-\mathrm{B})^{-1}-I$
	Direct Effect	B
	Indirect Effect	$(I-\mathrm{B})^{-1}-I-\mathrm{B}$

Structural Equations are less widely known and for this reason below additional information is provided for this technique. Many indices of fit have been developed to evaluate the goodness-of-fit of a SEM. However, which measure should be used is still one of the most difficult and controversial issues (Arbuckle and Wothke, 1999). The commonly used measures are:

- χ^2 **statistic and its p-value**: χ^2 statistic measures the discrepancy between the observed covariance matrix and the one predicted by the model. It is calculated by multiplying the minimum value of the fit function by N (sample size)-1. So the smaller the chi-square value is the better the model is. Its p-value indicates the probability that the discrepancy between the two matrices is due to sampling variation. However, this measure is problematic for the case of large sample size and when the multivariate normality assumption is violated.

- χ^2**/df**: The use of the ratio of chi-square to its degrees of freedom is also suggested. The problem of this measure is that it is not clear what value of ratio should be used for a satisfactory model. One of the rules of thumb for good fit suggested by Bryne (1989) is that the ratio should be less than 2.

- **Normed Fit Index (NFI)**: NFI measures the proportion reduction in minimum discrepancy by comparing a proposed model to a baseline model. The independence model in which the observed variables are assumed to be uncorrelated with each other, is most often used as the baseline model. In general, the NFI value greater than 0.90 indicates that the model fit is acceptable. Other goodness-of-fit indices calculated by comparisons to a baseline model, include Relative Fit Index (RFI), Incremental Fit Index (IFI), Tucker Lewis Index (TLI) and Comparative Fit Index (CFI). For all these indices, values close to 1 indicate a good fit. Hu and Bentler (1999) and Yu and Muthen (2002) suggested a cut-off value of 0.95 for TLI and CFI for good models.

- **Akaike Information Criterion (AIC)**: Using Akaike information criterion based on Bayesian theory allows us to compare the performance of models with quite different number of parameters. Smaller values are associated with better models.

- **Browne-Cudeck Criterion (BBC)**: BBC is a similar measure to AIC, but it assigns a slightly greater penalty for model complexity than does AIC. So this measure favors more parsimonious models.

- **Root Mean Square Error of Approximation (RMSEA)**: RMSEA is a measure of the population discrepancy per degree of freedom to compensate for the effects of model complexity. In general, a value of RMSEA for a good model should be less than 0.05 (Browne and Cudeck, 1993) or 0.06 (Hu and Bentler, 1999; Yu and Muthen, 2002). Browne and Cudeck (1993) also suggested that the entire 90% confidence interval for RMSEA should be less than 0.05 for a good fit.

- **Critical Number (CN)**: CN is the largest sample size for which one would accept the hypothesis that a model is correct. Generally, a CN of 200 or more indicates a satisfactory fit with a significance level of 0.05 (Tanka, 1987).

CHAPTER 5
A MULTIVARIATE MULTILEVEL ANALYSIS OF TECHNOLOGY CHOICE

5.1 Introduction

The first step to forecast impacts of ICT on activity and travel behavior is to develop a technology choice model that identifies user groups for each ICT device and estimate the number of its users. In this chapter, the trend of people' ICT adoption during the period of 1997-2000 are examined. In addition, multivariate multilevel technology choice models are developed to account for a strong correlation within household members as well as a high degree of people heterogeneity in technology adoption.

5.2 Data Description

For the analysis in this study, we used the data from 1480 persons in 866 households who provided detailed information in both waves 7 and 9 for all the variables used in this analysis. Table 5-1 shows the number of persons, households, and a few social and demographic characteristics of the sample. Table 5-1 also contains information about technology ownership and use with focus on the more modern technologies. Computers and the Internet at home are the two fastest growing technologies. Computers at work appear to be stabilizing at 50 percent of the sample, and although Internet use at work is increasing, it did not reach the level of penetration of computers at work. Cellular phone ownership is increasing even faster than computers and the Internet, causing a potential negative impact on pagers. Laptop computers and personal digital assistants (PDA) are used by a small sample segment as reported.

Table 5-1 Sample Characteristics

Characteristics			Wave 7 (1997)	Wave 9 (2000)
Number of persons in the sample			1480	1480
Number of households in the sample			866	866
Person & Household	Percent of males		46.9	46.9
	Number of employed persons		859	881
	Number of persons in household		2.5	2.5
	Number of cars per household		2.2	2.2
Information & Communication Technology	Number of persons who use computer regularly (%*)	At home	751 (50.7)	982 (66.4)
		At work	700 (47.3)	717 (48.4)
	Number of persons who use the Internet regularly (%*)	At home	458 (30.9)	896 (60.5)
		At work	438 (29.6)	544 (36.8)
	Number of persons having cellular phones (%*)		419 (28.3)	685 (46.3)
	Number of persons having pagers (%*)		156 (10.5)	129 (8.7)
	Number of persons having laptops (%*)		71 (4.8)	79 (5.3)
	Number of persons having PDAs (%*)		6 (0.4)	38 (2.6)

** % over total number of person in the sample*

5.3 Model Formulation

Two groups of ICT variables are used as the dependent variables in the model. The first group of the dependent variables is whether or not a person uses computer or the Internet at work/school or home in the year 2000. The second group is whether or not a person carries personal mobile technologies in the year 2000, such as cellular phones, pagers, and laptops. PDAs are excluded in the model due to its usage by a small sample segment. All the dependent variables are binary: if persons use a technology, the dependent variable is coded as 1; otherwise, it is coded as 0.

Table 5-2 List of Dependent Variables

Dependent Variables		Descriptions
Computer and Internet	CW	Computer use at work/school
	NW	Internet use at work/school
	CH	Computer use at home
	NH	Internet use at home
Personal Mobile Technology	CL	Cellular phone use
	PG	Pager use
	LP	Laptop use

For independent variables, two groups of variables were used: household-level variables and person-level variables. We used cross-sectional information in the year 2000 as well as longitudinal information between the years 1997 and 2000 about household-level and person-level social, economic, demographic characteristics.

To account for task allocation and roles within the household, number of adults, number of children by age group as well as vehicles owned and income representing resource availability are included as exogenous variables. In addition, in order to account for the sampling stratification of the panel participants, the county of residence and sample indicators (TRANSIT, CARPOOL) are also included as independent variables. Appendix contains a comprehensive description of the independent variables used here.

Using information between 1997 and 2000 a large set of variables is defined to capture the changes in social and economic circumstances experienced by each respondent and include them as explanatory variables of ICT adoption in the year 2000. In other words, indicators for changes in household and person characteristics, such as increase or decrease in car-ownership, changes in household composition, and changes in employment, were used to examine the effect of the changes on technology choice and use.

The use of multivariate multilevel modeling techniques is employed in this study, due to their capability to explicitly formulate the hierarchical data structure in the model, consider observed and unobserved household interactions in technology use, relax the usual regression assumption of independent observations, and account for the correlations among the observations in the model formulation.

The multivariate multilevel technology choice models are defined for seven ICT dependent variables with the following specifications:

$$
\begin{aligned}
\text{logit}(\pi_{ij}^{CW}) &= \beta_{ij}^{CW} + \gamma_1^{CW} x_{1ij}^{CW} + \ldots + \gamma_{k_{CW}}^{CW} x_{k_{CW}ij}^{CW} \\
\text{logit}(\pi_{ij}^{NW}) &= \beta_{ij}^{NW} + \gamma_1^{NW} x_{1ij}^{NW} + \ldots + \gamma_{k_{NW}}^{NW} x_{k_{NW}ij}^{NW} \\
\text{logit}(\pi_{ij}^{CH}) &= \beta_{ij}^{CH} + \gamma_1^{CH} x_{1ij}^{CH} + \ldots + \gamma_{k_{CH}}^{CH} x_{k_{CH}ij}^{CH} \\
\text{logit}(\pi_{ij}^{NH}) &= \beta_{ij}^{NH} + \gamma_1^{NH} x_{1ij}^{NH} + \ldots + \gamma_{k_{NH}}^{NH} x_{k_{NH}ij}^{NH} \qquad (5\text{-}1) \\
\text{logit}(\pi_{ij}^{CL}) &= \beta_{ij}^{CL} + \gamma_1^{CL} x_{1ij}^{CL} + \ldots + \gamma_{k_{CL}}^{CL} x_{k_{CL}ij}^{CL} \\
\text{logit}(\pi_{ij}^{PG}) &= \beta_{ij}^{PG} + \gamma_1^{PG} x_{1ij}^{PG} + \ldots + \gamma_{k_{PG}}^{PG} x_{k_{PG}ij}^{PG} \\
\text{logit}(\pi_{ij}^{LT}) &= \beta_{ij}^{LT} + \gamma_1^{LT} x_{1ij}^{LT} + \ldots + \gamma_{k_{LT}}^{LT} x_{k_{LT}ij}^{LT}
\end{aligned}
$$

$\beta_{ij}^{m} = \gamma_0^{m} + v_j^{m} + u_{ij}^{m}$, where m= CW, NW, CH, NH, CL, PG, LT

where π_{ij}^{CW} is the probability that person i in household j uses a computer at work/school.

π_{ij}^{NW} is the probability that person i in household j uses the Internet at work/school.

π_{ij}^{CH} is the probability that person i in household j uses a computer at home.

π_{ij}^{NH} is the probability that person i in household j uses the Internet at home.

π_{ij}^{CL} is the probability that person i in household j uses a cellular phone.

π_{ij}^{PG} is the probability that person i in household j uses a pager.

π_{ij}^{LT} is the probability that person i in household j uses a laptop.

γ is a coefficient which is defined in a similar way as in a typical regression.

β_{ij}^{m} is a random intercept.

ν_j^{m}, μ_{ij}^{m} are random components at household and person level, respectively, with E(v)=E(u)=0, var(v)=σ_v^2, and var(u)=σ_u^2.

5.4 Model Results

The first model presented here contains no explanatory variables (Table 5-3) which is in essence an error components model. It is called the null or fully unconditional model and it is used as a benchmark to assess other model specifications that include explanatory variables and regression coefficients (fixed and/or random) at each level. The estimation method used is Goldstein's RIGLS. Table 5-3 shows the proportion of variance of across persons within a household (person level) and across households (household level) in terms of the probability of ICT usage. There is a greater variance in ICT usage across households (50.1 percent to 80.0 percent) than between persons within a household (20.0 percent to 49.9 percent), especially in the home-based technologies and cellular phone usage. It is because decisions of ICT ownership and usage are most likely to be joint decisions among members of the same household. Key finding here indicates that the household level variance in ICT usage is too large to be neglected and should be taken into account in the model formulation. The multilevel specification is therefore justified. It also indicates that it is necessary to specify models using explanatory variables capturing and/or depicting factors affecting a person's and household's technology choice.

The bottom half of Table 5-3 contains the estimated covariances (below the diagonal) and the estimated correlation coefficients (above the diagonal) within each of the levels for the combination of the seven dependent variables. In terms of correlations among ICT usage, there is a strong, positive correlation between computer usage and Internet usage at both the household and person levels, regardless the location of the technologies. In general, the correlations among ICT usage are higher across households than between persons within a household, except for laptop.

Table 5-3 Multivariate Multilevel Technology Choice Error Components Models

Model Component		CW	NW	CH	NH	Cellular	Pager	Laptop
Fixed Effect		Coef. [S.E.]	Coef. [S.E.]	Coef. [S.E.]	Coef. [S.E.]	Coef. [S.E.]	Coef. [S.E.]	Coef. [S.E.]
Intercept		-0.079 [0.056]	-0.557 [0.060]	0.633 [0.063]	0.383 [0.062]	-0.162 [0.060]	-2.363 [0.096]	-2.881 [0.119]
Random Effects		σ^2 [%]	σ^2 [%]	σ^2 [%]	σ^2 [%]	σ^2 [%]	σ^2 [%]	σ^2 [%]
Person variation within households (u_{ij})		0.794 [48.8]	0.750 [40.5]	0.616 [26.9]	0.509 [20.0]	0.626 [29.2]	0.938 [49.9]	0.958 [49.8]
Between households variation (v_j)		0.833 [51.2]	1.101 [59.5]	1.675 [73.1]	2.038 [80.0]	1.517 [70.8]	0.943 [50.1]	0.965 [50.2]
Total		1.627 [100]	1.851 [100]	2.291 [100]	2.547 [100]	2.143 [100]	1.881 [100]	1.923 [100]
-2LogL		7236.76						
Variance / Covariance Matrices (upper triangle correlations)								
		CW	NW	CH	NH	Cellular	Pager	Laptop
Between Persons	CW	0.794	0.709	0.200	0.123	0.122	0.176	0.246
	NW	0.547	0.750	0.213	0.153	0.137	0.218	0.307
	CH	0.140	0.145	0.616	0.656	0.156	0.079	0.127
	NH	0.078	0.095	0.367	0.509	0.120	0.001	0.108
	Cellular	0.086	0.094	0.097	0.068	0.626	0.107	0.155
	Pager	0.152	0.183	0.060	0.001	0.082	0.9381	0.138
	Laptop	0.214	0.260	0.098	0.075	0.120	0.131	0.958
Between Households	CW	0.833	0.931	0.570	0.633	0.201	0.506	0.020
	NW	0.892	1.101	0.474	0.495	0.176	0.259	0.029
	CH	0.673	0.644	1.675	0.924	0.338	0.233	0.344
	NH	0.825	0.742	1.708	2.038	0.363	0.251	0.288
	Cellular	0.226	0.227	0.539	0.638	1.517	0.208	0.168
	Pager	0.449	0.264	0.293	0.349	0.249	0.943	-0.373
	Laptop	0.018	0.030	0.438	0.404	0.203	-0.356	0.965

Tables 5-4 and 5-5 gives the estimates along with t-statistic for the simultaneous equation model of all seven dependent variables as a function of household-level and person-level cross-sectional and longitudinal variables.

5.4.1 Cross-sectional Effects

As expected, working and attending a school are major factors to use computers and the Internet at work/school. Persons employed as managers have a higher propensity to use computers and the Internet at work/school than their counterparts employed in other occupations. The higher household income is accompanied by the higher probability of using both technologies at work and at home. As expected, old people are less likely to use computers and the Internet at both places. A person with a driver's license is more likely to use most of ICT, except for pagers and laptops. Respondents with more children between 1 and 17 years, tend to make more use of computers and the Internet at home. People living in Pierce county are less likely to use computers and Internet at home than those living in the other counties.

In terms of personal mobile technology usage, cellular phones seem to be more popular among people with household income more than $75,000 and multi-cars in the household. People in a secretary position and males are less likely to use cellular phones. Managers are more likely to use pagers while professionals are less likely to use them. Males and students also tend to make greater use of pagers. Persons with household income more than $75,000, men, students, or managers are more likely to use laptop computers.

A likelihood ratio comparison between the error components model and the final model yields a difference in likelihood of 5448.49 with 98 degrees of freedom, which indicates that the explanatory variables give a statistically significant improvement over the error components model.

Table 5-4 Multivariate Multilevel Technology Choice Models (Fixed Cross-sectional Effects)

Variable	CW Coef. [t-stat]	NW Coef. [t-stat]	CH Coef. [t-stat]	NH Coef. [t-stat]	Cellular Coef. [t-stat]	Pager Coef. [t-stat]	Laptop Coef. [t-stat]
constant	-3.646 [-5.956]	-5.608 [-8.034]	-2.060 [-4.852]	-0.662 [-1.932]	-1.900 [-4.989]	-5.682 [-8.537]	-5.884 [-12.980]
transit	0.589 [3.281]				-0.526 [-3.145]		
pierce			-0.346 [-2.140]	-0.349 [-2.156]			
totadult			0.203 [2.415]				
tot6_17			0.389 [3.495]	0.229 [2.237]			
tot1_5			0.604 [2.856]	0.940 [4.294]			
midinc	0.369 [2.062]	0.459 [2.341]				0.510 [1.687]	
highinc	0.877 [4.203]	1.144 [5.358]	0.456 [2.592]	0.574 [3.375]	1.033 [6.613]	0.532 [1.695]	0.818 [3.128]
mhinc					0.395 [1.772]		
dkinc			-0.551 [-2.177]	-0.593 [-2.272]			
car1				-0.435 [-2.700]			
car2			0.574 [3.388]		0.503 [2.891]		
car3_			0.492 [2.593]		0.809 [4.373]		
male		0.352 [2.971]	0.063 [0.762]		-0.434 [-4.381]	0.613 [2.806]	0.921 [3.535]
midage	-0.641 [-2.558]					0.693 [1.490]	
old	-1.367 [-4.180]	-1.090 [-3.632]	-0.791 [-4.817]	-0.850 [-5.730]		0.975 [1.580]	
wk5	0.742 [3.952]	0.465 [2.686]				0.526 [1.802]	
prof	1.225 [6.417]	1.343 [7.858]				-0.501 [-3.404]	
manag	1.610 [4.971]	1.707 [6.785]				0.757 [2.840]	0.997 [3.337]
secre	1.237 [4.228]	0.859 [3.540]			-0.738 [-3.249]	-0.763 [-1.633]	
dlicen	1.820 [3.462]	1.811 [2.868]	1.719 [4.678]	1.151 [3.506]	0.964 [2.609]		
dbpass	0.815 [3.232]	1.035 [4.894]	0.283 [2.360]			-0.455 [-1.462]	
dpupil	1.108 [2.338]	1.941 [4.440]				2.221 [3.423]	1.664 [2.316]
-2LogL	1788.27						
Deviance from Error Component Model (Table 8-1) = 5448.49 with d.f.=98							

5.4.2 Longitudinal Effects

Table 5-5 shows the effect of social and demographic changes at the person and household levels on the probability of each ICT use. An increase in the number of children (6-17 years old) shows a lower likelihood of computer and Internet use at home, while a decrease in the number of children (6-17 years old) shows a higher likelihood of Internet use at home. One explanation for this could be the roles younger individuals play in the household as a computer and Internet expert. A decrease in the number of employed persons in the household is also more likely to increase the probability of computer and Internet use at home. Interestingly, a decrease in the number of driver's license holders is accompanied by a lower likelihood of pager usage. A decrease in the number of vehicles and an increase in number of employed persons in the household are more likely to increase the probability of laptop usage. In general, the employed people are more likely to use most of ICT with a higher propensity for those who are employed in both years 1997 and 2000, than for those who are employed in 2000 only.

Table 5-5 Multivariate Multilevel Technology Choice Models (Fixed Longitudinal Effects)

Variable	CW Coef. [t-stat]	NW Coef. [t-stat]	CH Coef. [t-stat]	NH Coef. [t-stat]	Cellular Coef. [t-stat]	Pager Coef. [t-stat]	Laptop Coef. [t-stat]
inkid			-1.434 [-2.852]	-1.210 [-2.428]	0.417 [1.753]		
dnkid				0.360 [2.186]		0.361 [1.306]	
dnbaby			1.111 [2.123]	1.068 [2.092]			
dnveh	-0.292 [-1.925]			-0.184 [-1.621]	0.307 [1.953]		0.796 [2.815]
inemp							0.622 [2.169]
dnemp			0.541 [2.679]	0.524 [2.671]			0.664 [1.866]
dnlicen						-0.948 [-2.483]	
inbpass	-0.455 [-2.040]						0.455 [1.245]
dnbpass							-2.413 [-2.153]
expemp	1.955 [7.858]	2.144 [6.878]	0.245 [2.142]		0.628 [4.354]	1.969 [3.964]	1.989 [4.875]
novemp	0.751 [2.612]	1.560 [4.551]	0.462 [1.854]	0.618 [2.744]	0.656 [2.902]	1.768 [3.235]	
quitemp		0.712 [1.941]					

Table 5-6 shows the variances for the multivariate multilevel model for ICT use and ownership when explanatory variables are included in the model. The table also shows the covariances (below the diagonal) and correlations (above the diagonal). From Table 5-6, it can be seen that there is again a greater variance in ICT usage across households as compared to between persons within household.

Table 5-6 Multivariate Multilevel Technology Choice Models (Random Effects)

Variance / Covariance Matrices (upper triangle correlations) [Std. Error]								
		CW	NW	CH	NH	Cellular	Pager	Laptop
Between Persons	CW	0.905 [0.043]	0.484	0.147	0.087	0.119	0.111	0.071
	NW	0.387 [0.030]	0.705 [0.034]	0.180	0.158	0.150	0.018	0.100
	CH	0.120 [0.029]	0.129 [0.263]	0.728 [0.039]	0.644	0.128	0.068	0.126
	NH	0.065 [0.028]	0.103 [0.024]	0.427 [0.030]	0.605 [0.033]	0.100	-0.004	0.079
	Cellular	0.093 [0.029]	0.104 [0.025]	0.089 [0.027]	0.064 [0.025]	0.671 [0.037]	0.098	0.097
	Pager	0.109 [0.032]	0.016 [0.029]	0.060 [0.031]	-0.003 [0.029]	0.082 [0.030]	1.068 [0.482]	0.031
	Laptop	0.063 [0.029]	0.079 [0.026]	0.102 [0.028]	0.058 [0.027]	0.075 [0.027]	0.030 [0.031]	0.896 [0.039]
Between Households	CW	0.351 [0.248]	1.180	0.371	0.624	-0.118	-0.208	0.322
	NW	0.803 [0.199]	1.315 [0.237]	0.113	0.112	-0.071	0.947	0.297
	CH	0.271 [0.178]	0.160 [0.176]	1.526 [0.217]	0.902	0.227	-0.279	0.027
	NH	0.531 [0.173]	0.184 [0.171]	1.599 [0.188]	2.059 [0.210]	0.278	-0.112	0.019
	Cellular	-0.087 [0.160]	-0.101 [0.157]	0.348 [0.146]	0.495 [0.143]	1.539 [0.187]	0.046	0.067
	Pager	-0.040 [0.239]	0.355 [0.227]	-0.113 [0.241]	-0.052 [0.232]	0.019 [0.214]	0.107 [0.401]	-0.061
	Laptop	0.202 [0.295]	0.360 [0.281]	0.035 [0.298]	0.029 [0.285]	0.088 [0.261]	-0.021 [0.357]	1.120 [0.547]

5.5 Summary

In this chapter the trend of people' ICT adoption during the period of 1997-2000 is examined. The fastest growing ICT are the home-based that have a practical ceiling equal to the number of computer users in the household. Computers at work appear to be stabilizing at 50 percent of the sample. Cellular telephony use is also on the rise in this sample during the period 1997 to 2000, causing a potential negative impact on pagers. However, laptop computers and personal digital assistants (PDA) are still used by a small sample segment. In addition, using a multivariate multilevel model specification, technology choice models are developed. When compared to more traditional regression models, the multivariate multilevel model provides additional insights on components of variance and heterogeneous behavior of persons and their households.

The results of the analysis show that there is more variability between households when compared to the variability contributed by persons within a household, which implies that decisions of ICT ownership and usage are most likely to be joint decisions among members of the same household. It is found that income level, employment, and age are important factors in ICT choice and usage. For example, the employed and persons with household income more than $75,000 are more likely to use most of ICT types. Old persons tend to make less use of computer and Internet than their young counterparts. In addition, the length of employment seems to have positive effects on ICT usage.

CHAPTER 6
COMPARATIVE ANALYSIS OF THREE DIFFERENT ESTIMATION METHODS

6.1 Introduction

In this chapter, the relationship of telecommunication technology usage with out-of-home activity and travel expenditures is examined using data from 3450 people in 1910 households in the 1997 survey of the Seattle metropolitan area. The relationship is examined using three different model systems that include a set of single-equation regression models, seeming unrelated regression models (SUR Model), and multivariate multilevel models. The technologies examined include desktop computers and Internet usage at home and workplace/school, cellular phones, pagers, laptop computers, and personal digital assistants.

6.2 Data Used

Although the 1997 PSTP data originally consist of information provided by 3939 persons (from 2007 households), models were developed using information from 3450 persons (from 1910 households) who provide valid information to both travel dairy and personal daily travel choices survey.

Table 6-1 summarizes the social, demographic, and economic characteristics of the sample of 3450 people from 1910 households. There are a slightly higher number of females than males in the sample. Majority of the respondents in the sample are between 25 and 64 years old. In terms of employment characteristics, 40 percent of the sample is unemployed. Among people employed, professionals occupy the largest portion of the occupations. In terms of income, 70 percent of the sample belongs to middle and high income categories ($35,000 or more). There is a very small portion of the sample without cars.

Table 6-1 Summary of Socioeconomic Characteristics of the Sample

Characteristics		Wave 7 (1997)
Number of Households in the Sample		1910
Number of Persons in the Sample		3450
Gender	Male Female	47.9 % 52.1 %
Age	15-24 25-44 45-64 65 and above	8.6 % 34.2 % 39.2 % 18.1 %
Occupation	Professional Managerial Secretary Sales Others Unemployed	23.6 % 9.8 % 8.5 % 4.4 % 14.1 % 39.7 %
Number of Vehicles in the Household	No vehicles 1 vehicle 2 vehicles 3 or more vehicles	1.4 % 17.6 % 46.1 % 34.9 %
Household Income	Less than $35,000 $35,000 to $74,999 $75,000 or more No answer	23.0 % 47.8 % 22.3 % 6.9 %

Table 6-2 shows the characteristics of technology use in the sample. There are about 50 percent of the respondents who use computers in their daily lives. Males seem to use computers more than females do. For about 30 percent of the sample (27.5 to 33.7 percent), computers are not part of their daily lives.

In terms of mobile technology, the use of mobile devices has not yet reached the level of the use of desktop computers. It is found that more than 60 percent of the survey participants do not use any of the mobile technologies. Men seem to use technologies more than women, but cellular phones are used more by women (30.5 percent) than men (27.1 percent).

Table 6-2 Summary of Technology Use in the Sample

Technology	Male (N_1=1654)	Female (N_2=1796)
Use desktop computer at work/school	54.2%	44.9%
Use desktop computer at home	56.4%	48.8%
Use Internet at work/school	36.1%	25.2%
Use Internet at home	36.6%	26.6%
None of these	27.5%	33.7%
Carry a portable cellular phone	27.1%	30.5%
Carry a personal pager	16.1%	8.3%
Carry a portable computer	7.8%	3.1%
Carry a personal digital assistant (PDA)	1.0%	0.2%
None of these	62.4%	65.0%

Table 6-3 also reports the values of the variables that are used as dependent variables in the analysis here. Total out-of-home activity time includes the entire time each person spends in activities outside home in a day. Total travel time includes the sum of travel time durations for all trips made by a person in a day. In terms of activity-travel, the sample spends an average of about 400 minutes to participate in various activities outside home and an average of about 80 minutes in traveling per day.

Table 6-3 Average Total Out-of–home Activity and Travel Durations

	Day 1 (std. deviation)	Day 2 (std. deviation)
Total out-of–home activity (minutes/day)	405.14 (266.12)	402.08 (273.48)
Total travel (minutes/day)	83.03 (63.25)	80.01 (60.36)

6.3 Model Formulation

With four dependent variables (T1, A1, T2, and A2) described in Table 6-4, three different models (single-equation regression models, seeming unrelated regression models, and multivariate multilevel models) were developed as a function of household characteristics, personal characteristics, various telecommunication technology ownership and usage, to assess the impact of various telecommunication technologies on people's time allocation to out-of-home activity and travel. The main objectives of these model formulations are to: a) identify if there are significant differences in daily activity and travel durations between people who use telecommunication technologies and those who don't use; and b) estimate the effect of each telecommunication technology on activity and travel duration, while controlling for other socio-economic factors.

Table 6-4 List of Dependent Variables

Dependent Variables	Descriptions
T1	Total Travel Duration in Day 1 [min] (Min: 0, Max: 780)
A1	Total Out-of-home Activity Duration in Day 1 [min] (Min: 0, Max: 1440)
T2	Total Travel Duration in Day 2 [min] (Min: 0, Max: 598)
A2	Total Out-of-home Activity Duration in Day 2 [min] (Min: 0, Max: 1440)

6.3.1 Single-Equation Regression Model

The first possible approach to estimate models is to apply the ordinary least squares method to each equation separately. Because of the simplicity, this model is most widely used to analyze continuous variables. The single-equation regression models have the following specification:

$$Y_i^{T1} = \beta^{T1\prime} X_i^{T1} + \varepsilon_i^{T1}, \quad \varepsilon_i^{T1} \sim N(0, \sigma_{T1}^2) \tag{6-1}$$

$$Y_i^{A1} = \beta^{A1\prime} X_i^{A1} + \varepsilon_i^{A1}, \quad \varepsilon_i^{A1} \sim N(0, \sigma_{A1}^2) \tag{6-2}$$

$$Y_i^{T2} = \beta^{T2\prime} X_i^{T2} + \varepsilon_i^{T2}, \quad \varepsilon_i^{T2} \sim N(0, \sigma_{T2}^2) \tag{6-3}$$

$$Y_i^{A2} = \beta^{A2}{}' X_i^{A2} + \varepsilon_i^{A2}, \quad \varepsilon_i^{A2} \sim N(0, \sigma_{A2}^2) \tag{6-4}$$

where Y^m = a ($N \times 1$) vector of dependent variable (m=T1, A1, T2, A2)

X^m = a ($N \times K^m$) matrix of explanatory variables (m=T1, A1, T2, A2)

β^m = a ($K^m \times 1$) vector of regression coefficients (m=T1, A1, T2, A2)

ε^m = a ($N \times 1$) vector of error terms (m=T1, A1, T2, A2)

In this approach, each of the regression equations above is separately and independently estimated. Each separate regression equation ((6-1) through (6-4)) is based on the five basic assumptions: normality (ε_i is normally distributed), zero mean ($E[\varepsilon_i]=0$), homoskedasticity ($var(\varepsilon_i) = \sigma_m^2$, (m=T1, A1, T2, A2)), nonautocorrelation ($cov(\varepsilon_i,\varepsilon_j) = 0$), and nonstochastic X. Under these assumptions, the ordinary least squares (OLS) estimators of the regression coefficient for each equation are unbiased, consistent, and efficient (Greene, 2000). However, these desirable properties of the ordinary least squares are derived on the understanding that the specification of the model represents all information about the regression equation and variables involved. In other words, if there exists some other piece of information that has not been taken into account, then the result concerning the properties of the ordinary least squares estimators can no longer be established. One such additional information would be the knowledge that the error terms in the regression equation under consideration could be correlated with the error terms in some other regression equation. In other words, when the error terms across equations are correlated, if each equation is estimated separately and independently and thus the information about the mutual correlation of the disturbances is disregarded, the ordinary least squares estimators of the regression coefficients are still unbiased and consistent, but not efficient.

6.3.2 Seemingly Unrelated Regression Model (SUR Model)

The second model used in this study is the seemingly unrelated regression model, which is the system of the 4 equations. The seemingly unrelated regression model has the following specification:

$$Y^m = \beta^{m}{}' X^m + \varepsilon^m \quad \text{(m= T1, A1, T2, A2)} \tag{6-5}$$

where Y^m = a (N × 1) vector of dependent variable (m=T1, A1, T2, A2)

X^m = a (N × K^m) matrix of explanatory variables (m=T1, A1, T2, A2)

β^m = a (K^m × 1) vector of regression coefficients (m=T1, A1, T2, A2)

ε^m = a (N × 1) vector of disturbances (m=T1, A1, T2, A2)

To take into account the correlation of the disturbances across equations, the four equations are compressed into one big equation:

$$\begin{bmatrix} Y^{T1} \\ Y^{A1} \\ Y^{T2} \\ Y^{A2} \end{bmatrix} = \begin{bmatrix} X^{T1} & 0 & 0 & 0 \\ 0 & X^{A1} & 0 & 0 \\ 0 & 0 & X^{T2} & 0 \\ 0 & 0 & 0 & X^{A2} \end{bmatrix} \begin{bmatrix} \beta^{T1} \\ \beta^{A1} \\ \beta^{T2} \\ \beta^{A2} \end{bmatrix} + \begin{bmatrix} \varepsilon^{T1} \\ \varepsilon^{A1} \\ \varepsilon^{T2} \\ \varepsilon^{A2} \end{bmatrix} \tag{6-6}$$

$$\text{or} \qquad Y^* = X^*\beta^* + \varepsilon^* \tag{6-7}$$

where Y^* = a (4N × 1) vector of dependent variables.

X^* = a (4N × (K^{T1}+K^{A1}+K^{T2}+K^{A2})) matrix of the explanatory variables.

β^* = a ((K^{T1}+K^{A1}+K^{T2}+K^{A2}) × 1) vector of the regression coefficients.

ε^* = a (4N × 1) vector of the disturbances.

6.3.3 Multivariate Multilevel Model

Since trip diaries are collected from a few household members within a household, and information on each trip and activity, the person making the trip and activity, and the household is available, the PSTP data may be viewed to have a nesting hierarchical structure. One method to statistically account for the contextual behavior of individuals exploiting this hierarchical nature in the data is called a multilevel model. In addition, the method allows us to exploit strong correlations across observations at different hierarchical levels simultaneously and to quantify relative variations contributed by each hierarchy level to the behavior indicators.

Given the structure of the data in PSTP, since we are considering four indicators simultaneously at two levels (the person and his/her household), the multivariate multilevel model has the following specification:

$$
\begin{aligned}
Y_{ij}^{T1} &= \beta_{ij}^{T1} + \gamma_{1}^{T1} X_{1ij}^{T1} + \ldots + \gamma_{k_{T1}}^{T1} X_{k_{T1}ij}^{T1} \\
Y_{ij}^{A1} &= \beta_{ij}^{A1} + \gamma_{1}^{A1} X_{1ij}^{A1} + \ldots + \gamma_{k_{A1}}^{A1} X_{k_{A1}ij}^{A1} \\
Y_{ij}^{T2} &= \beta_{ij}^{T2} + \gamma_{1}^{T2} X_{1ij}^{T2} + \ldots + \gamma_{k_{T2}}^{T2} X_{k_{T2}ij}^{T2} \\
Y_{ij}^{A2} &= \beta_{ij}^{A2} + \gamma_{1}^{A2} X_{1ij}^{A2} + \ldots + \gamma_{k_{A2}}^{A2} X_{k_{A2}ij}^{A2}
\end{aligned} \tag{6-8}
$$

$$\beta_{ij}^{m} = \gamma_{0}^{m} + v_{j}^{m} + u_{ij}^{m} \quad \text{where m= T1, A1, T2, A2.}$$

Y_{ij}^{T1} is the total amount of time traveled in day 1 by a person *i* within household *j* (with *i* =1,2, … number of people in household *j*, *j* = 1,2, … number of households in the sample). Similarly, we define the other three dependent variables (Y_{ij}^{A1}, Y_{ij}^{T2}, and Y_{ij}^{A2}) in Equation 6-8.

With this multilevel model approach, we can assess the effects of each telecommunication technology on activity and travel behavior, while at the same time controlling for complex correlations within a person's behavior (one day to the next), within a household (one person to the next) and among households.

6.4 Model Results

This section describes the estimation results of the three different models for all the four dependent variables. Key difference among these models is that single-equation models assume the disturbances across equations are uncorrelated and thus each equation is independently and separately estimated, while SUR models and multivariate multilevel models assume the disturbances across equations to be correlated and thus all the four equations are simultaneously estimated. In addition, the multilevel models take into account the hierarchy of level in the data and enable estimation of variance-covariance and correlation among the four dependent variables within each level.

6.4.1 Single-Equation Model Results

The models have estimated mean baseline values of between 44.2 and 48.4 minutes for traveling and between 432.6 and 458.3 minutes for out-of-home activity participation per day. Appendix contains a comprehensive description of the independent variables used here for the regression coefficients reported in Table 6-5. The presence of children in the age of 0 to 5 affects negatively the amount of traveling, while children in the age of 6-17 have a positive effect on out-of-home activity with each child contributing an additional 20.3 to 32.9 minutes per day. High-income group (annual household income ≥ \$75,000) spend much more time for out-of-home activities than other groups.

Men tend to travel for 5.4 to 9.2 minutes per day more than women and spend an average of 26 to 36 minutes per day more than women on activities. In terms of age, the middle-age group (age 25-64) spends on average 6.7 to 12.0 minutes more time for traveling per day than other age groups, because the age group is more likely to be active in their daily life. The old age group (age 65 or more) has the least expenditure in out-of-home activity participation, due to some constraints such as physical mobility. As expected, there are big differences in the daily travel and out-of–home activity expenditure between employed and unemployed people. The unemployed spend on average 12.1 to 14.1 minutes less time for traveling and 161.9 to 174.0 minutes less time for out-of-home activity per day. However, the type of occupation does not affect the travel time, but persons involved in secretarial and sales positions tend to spend 15.6 to 29.6 minutes and 70.1 to 73.7 minutes less on out-of-home activities, respectively. In addition, it is found that people who work 5 times or more per week spend about 2 hours more time for out-of-home activities, mainly because of their work outside home. People who have a bus pass travel 17.3 to 24.0 minutes more per day. In addition, these people spend 20.1 minutes (at 90% significance level) less time on activities in the first day, but in the second day this drops to zero. This is an indication of the extreme variation in activity time exhibited by this group.

Table 6-5 Single-Equation Regression Model Estimates

	T1			A1			T2			A2		
	Coef.	S.E.	t-stat	Coef.	S.E.	t-stat	Coef.	S.E.	t-stat	Coef.	S.E.	t-stat
Constant	44.17	6.48	6.82	432.59	25.60	16.90	48.42	6.15	7.87	458.31	27.03	16.96
HHSIZE	4.64	1.01	4.59	-19.17	4.56	-4.20	0.63	0.96	0.66	-27.62	4.82	-5.73
TOT1_5	-4.74	2.49	-1.90				-3.11	2.37	-1.31			
TOT6_17				20.28	6.06	3.35				32.90	6.40	5.14
NUMVEH	-0.28	1.05	-0.27	1.03	3.56	0.29	2.58	0.99	2.60	11.20	3.76	2.98
MIDINC	-7.64	2.11	-3.62	16.25	8.62	1.89	-0.53	2.01	-0.27	-3.95	9.09	-0.44
HIGHINC				60.03	10.64	5.64				29.93	11.23	2.66
MALE	5.39	2.14	2.52	26.31	7.39	3.56	9.19	2.03	4.52	36.14	7.81	4.63
AGE2544	6.69	3.56	1.88	-44.12	18.05	-2.45	11.97	3.38	3.54	-72.77	19.05	-3.82
AGE4564	9.72	3.18	3.06	-41.59	18.41	-2.26	11.34	3.02	3.76	-65.13	19.43	-3.35
AGE65_				-102.21	20.96	-4.88				-128.38	22.12	-5.80
DPUPIL	10.44	4.60	2.27	191.24	19.22	9.95	12.97	4.37	2.97	173.23	20.29	8.54
SECRET				-29.57	13.33	-2.22				-15.57	14.07	-1.11
SALES				-70.13	17.42	-4.03				-73.66	18.39	-4.01
UNEMP	-12.07	2.96	-4.07	-174.00	13.60	-12.80	-14.41	2.81	-5.12	-161.92	14.35	-11.28
WK5				121.92	12.08	10.09				126.89	12.75	9.95
DLICEN	15.79	5.19	3.04				6.76	4.93	1.37			
DBPASS	24.00	3.21	7.48	20.27	10.75	1.89	17.29	3.05	5.68	-1.92	11.34	-0.17
CW	6.45	2.98	2.17	51.84	9.02	5.75	3.66	2.83	1.29	54.40	9.53	5.71
CH				0.69	9.10	0.08				-17.40	9.60	-1.81
NW	0.94	3.71	0.25				7.66	3.52	2.18			
NH	5.20	3.11	1.67	-16.84	9.42	-1.79	3.60	2.95	1.22	-12.68	9.95	-1.28
INTERNET	-14.31	4.92	-2.91				-16.68	4.67	-3.57			
CELLULAR	11.68	2.41	4.84	8.62	8.08	1.07	14.03	2.29	6.12	19.02	8.53	2.23
PAGER	11.22	3.36	3.34	23.62	11.20	2.11	3.87	3.19	1.21	23.45	11.83	1.98
LAPTOP	14.59	4.90	2.98				14.10	4.65	3.03			
F-test	F[18, 3431]=17.03			F[20, 3429]= 123.61			F[18, 3431]=19.06			F[20, 3429]=108.20		
Deviance -2(L(c)-(β))	295.24 d.f.=18			1872.94 d.f.=20			328.72 d.f.=18			1687.96 d.f.=20		

In terms of telecommunication technology usage, each of the technologies has different degree of impact on travel and activity participation. People who use computers at work or school travel an average of 0 to 6.5 minutes more, and they spend an average of 51.8 to 54.4 minutes more on activities than the non-users.

However, using the Internet or computers at home has marginal negative effects on activity duration (they are significant only at 90 % significance level). Interestingly, using the Internet at both work and home, people tend to travel 14.3 to 16.7 minutes less. It implies that there is a systematic difference in the daily traveling behavior between regular Internet users and non-users.

It is found that users of mobile technologies such as cellular phones and pagers are usually involved in more traveling and higher activity time. However, the use of laptop computers does not significantly affect the amount of time spent on out-of-home activities. In addition, using a PDA is found not to affect the travel and activity behavior, and this is most likely due to the small sample size. F-test and Likelihood Ratio (LR) test for each equation indicate that the choice of explanatory variables is satisfactory.

6.4.2 Seemingly Unrelated Regression (SUR) Model Results

The SUR Model produces very similar coefficient values to those from the single-equation models. Although two coefficients (NW for T1; CH for A1) have different signs from the single-equation models, these differences occur when the coefficients are not significantly different from zero. However, as can be seen in Table 6-6, there appear to be some gains in efficiency by going from ordinary least squares (single-equation models) to feasible generalized least squares (SUR model). In other words, as expected, the standard errors of the coefficient estimates in the SUR model are always smaller than those in the single-equation model, but the differences are not large. The reason for this relatively low gain in efficiency might be in part the high degree of correlation between the explanatory variables in the 4 equations. The bottom of Table 6-6 shows the estimated variance-covariance and the estimated correlation coefficients for the combination of the four dependent variables, which is calculated based on person level. The high correlations between T1 and T2 and between A1 and A2 indicate that people have similar activity and travel patterns in consecutive days. The very similar F-test and LR-test statistics to those from the single-equation models confirm that the choice of explanatory variables is satisfactory.

Table 6-6 Seemingly Unrelated Regression Model Estimates

	T1			A1			T2			A2		
	Coef.	S.E.	t-stat	Coef.	S.E.	t-stat	Coef.	S.E.	t-stat	Coef.	S.E.	t-stat
Constant	44.64	6.42	6.95	435.90	25.33	17.21	48.39	6.09	7.95	459.12	26.72	17.18
HHSIZE	4.54	1.01	4.50	-19.68	4.53	-4.35	0.67	0.96	0.70	-27.52	4.78	-5.76
TOT1_5	-4.16	2.47	-1.69				-3.29	2.34	-1.41			
TOT6_17				21.02	5.99	3.51				32.96	6.32	5.22
NUMVEH	-0.23	1.04	-0.22	1.03	3.55	0.29	2.56	0.99	2.59	11.33	3.74	3.03
MIDINC	-7.64	2.11	-3.63	16.66	8.56	1.95	-0.55	2.00	-0.28	-5.05	9.03	-0.56
HIGHINC				61.14	10.48	5.83				27.68	11.05	2.50
MALE	5.40	2.14	2.53	26.76	7.37	3.63	9.22	2.03	4.55	36.49	7.77	4.69
AGE2544	6.64	3.55	1.87	-46.59	17.87	-2.61	12.00	3.37	3.56	-71.45	18.85	-3.79
AGE4564	9.80	3.17	3.09	-44.45	18.20	-2.44	11.35	3.01	3.77	-63.55	19.20	-3.31
AGE65_				-106.28	20.64	-5.15				-126.70	21.77	-5.82
DPUPIL	10.56	4.59	2.30	188.90	19.07	9.90	12.87	4.36	2.95	174.06	20.13	8.65
SECRET				-27.02	13.13	-2.06				-14.85	13.84	-1.07
SALES				-69.97	17.16	-4.08				-72.85	18.10	-4.03
UNEMP	-12.15	2.96	-4.11	-173.03	13.48	-12.84	-14.41	2.81	-5.13	-164.29	14.22	-11.55
WK5				121.81	11.90	10.24				123.75	12.55	9.86
DLICEN	15.51	5.12	3.03				6.67	4.85	1.38			
DBPASS	24.05	3.20	7.52	20.44	10.71	1.91	17.32	3.04	5.71	-1.92	11.31	-0.17
CW	6.62	2.96	2.24	51.73	8.99	5.75	3.85	2.81	1.37	55.00	9.49	5.80
CH				-0.90	8.96	-0.10				-17.29	9.45	-1.83
NW	-0.10	3.65	-0.03				7.63	3.46	2.21			
NH	4.62	3.09	1.50	-16.06	9.36	-1.72	4.00	2.93	1.37	-12.65	9.88	-1.28
INTERNET	-12.57	4.85	-2.59				-17.48	4.59	-3.81			
CELLULAR	11.73	2.41	4.87	8.69	8.05	1.08	14.07	2.29	6.15	19.13	8.50	2.25
PAGER	11.25	3.35	3.36	23.65	11.17	2.12	3.94	3.18	1.24	23.73	11.79	2.01
LAPTOP	14.02	4.83	2.91				13.73	4.57	3.01			
F-test	F[18, 3431]=17.02			F[20, 3429]= 123.60			F[18, 3431]=19.05			F[20, 3429]=108.19		
Deviance -2(L(c)-(β))	314.10 d.f.=18			1893.88 d.f.=20			347.72 d.f.=18			1708.9 d.f.=20		

Variance / Covariance Matrices (upper triangle correlations)

	T1	A1	T2	A2
T1	3671.34	0.151	0.383	0.050
A1	1851.12	41141.1	0.021	0.491
T2	1334.63	242.56	3311.22	0.161
A2	651.6	21334.4	1985.33	45842.3

6.4.3 Multivariate Multilevel Model Results

Table 6-7 shows the results of an error component model, which contains no explanatory variables. This model is used as a benchmark to assess other model specifications that include explanatory variables. As shown in the "Random Effects" part of the table, the proportion of variance for two variation sources ("person variation within household" and "between household variation") for all four dependent variables are calculated. The household level variance is about 1/4 to 1/3 of the person level variance, which indicates that it is not negligible, and thus multilevel specification appears to be justified. In addition, it confirms that it is necessary to specify models using explanatory variables depicting person and household characteristics to reduce the unexplained variance.

Table 6-7 Multivariate Error Component Model

Model Component	T1		A1		T2		A2	
Fixed Effect	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Grand Mean	82.44	1.19	401.5	5.08	79.61	1.13	399.1	5.09
Random Effects	σ^2	%	σ^2	%	σ^2	%	σ^2	%
Person variation within households (u_{ij})	3073.1	77.1	52983.7	74.5	2903.5	79.6	60619.0	80.8
Between households variation (v_j)	912.6	22.9	18157.3	25.5	745.1	20.4	14404.6	19.2
Total	3985.7	100.0	71141.0	100.0	3648.6	100.0	75023.6	100.0
-2LogL	169604.4							

Variance / Covariance Matrices (upper triangle correlations)								
	Between Persons				Between Households			
	T1	A1	T2	A2	T1	A1	T2	A2
T1	3073.1	0.208	0.468	0.159	912.6	0.331	0.298	0.143
A1	2654.4	52983.7	0.122	0.659	1347.8	18157.3	0.353	0.825
T2	1397.0	1517.3	2903.5	0.236	245.8	1299.3	745.1	0.406
A2	2173.9	37333.6	3127.8	60619.0	517.9	13359.0	1329.7	14404.6

Unlike SUR models that produce only one level variance-covariance matrix, the multilevel models estimate variance-covariance matrix and correlation coefficients for each of multiple levels, by decomposing variance and covariance into multiple levels as specified. This information provides deeper insights about unobserved heterogeneity and complex correlations at each level. The bottom half of Table 6-7 contains the estimated variance-covariances and the estimated correlation coefficients at the two levels (person level and household level) for the combination of the four dependent variables.

The estimates in Table 6-8 are obtained using the explanatory variables with a multivariate multilevel model in which only the constant terms are random at the household and person level. The estimated coefficient values are very similar to those from the other types of models (single-equation models and SUR model) used in this chapter, but the standard errors of the coefficient estimates in the multilevel model are not always smaller than those in the single-equation model. In addition, the multilevel model produced slightly different results in significance for two variables (NH for T1, and CH for A2) from those from the other two models. Like the SUR model, two coefficients (NW for T1; CH for A1) have different signs from the single-equation models when the coefficients are not significantly different from zero. However, as mentioned earlier, the multilevel model provides additional insight on unobserved heterogeneity both at the person and at the household level. For example, the variance-covariance at one level in Table 6-6 from the SUR model is decomposed into variance-covariance at two levels in the multilevel model. It is confirmed by the fact that the sum of variance-covariance (Table 6-8) at the two levels from the multilevel model is almost equal to variance-covariance (Table 6-6) from the SUR model. The variance-covariance matrix in Table 6-8 shows that there is significant heterogeneity for all dependent variables, in both days and at both person and household levels. Compared to Table 6-7, the amount of variation in Table 6-8 is lower, because explanatory variables explain some portion of the variance in activity and travel expenditures. There is again a greater variation in activity and travel expenditure between persons within a household as compared to between households.

Table 6-8 Multivariate Multilevel Model Estimates

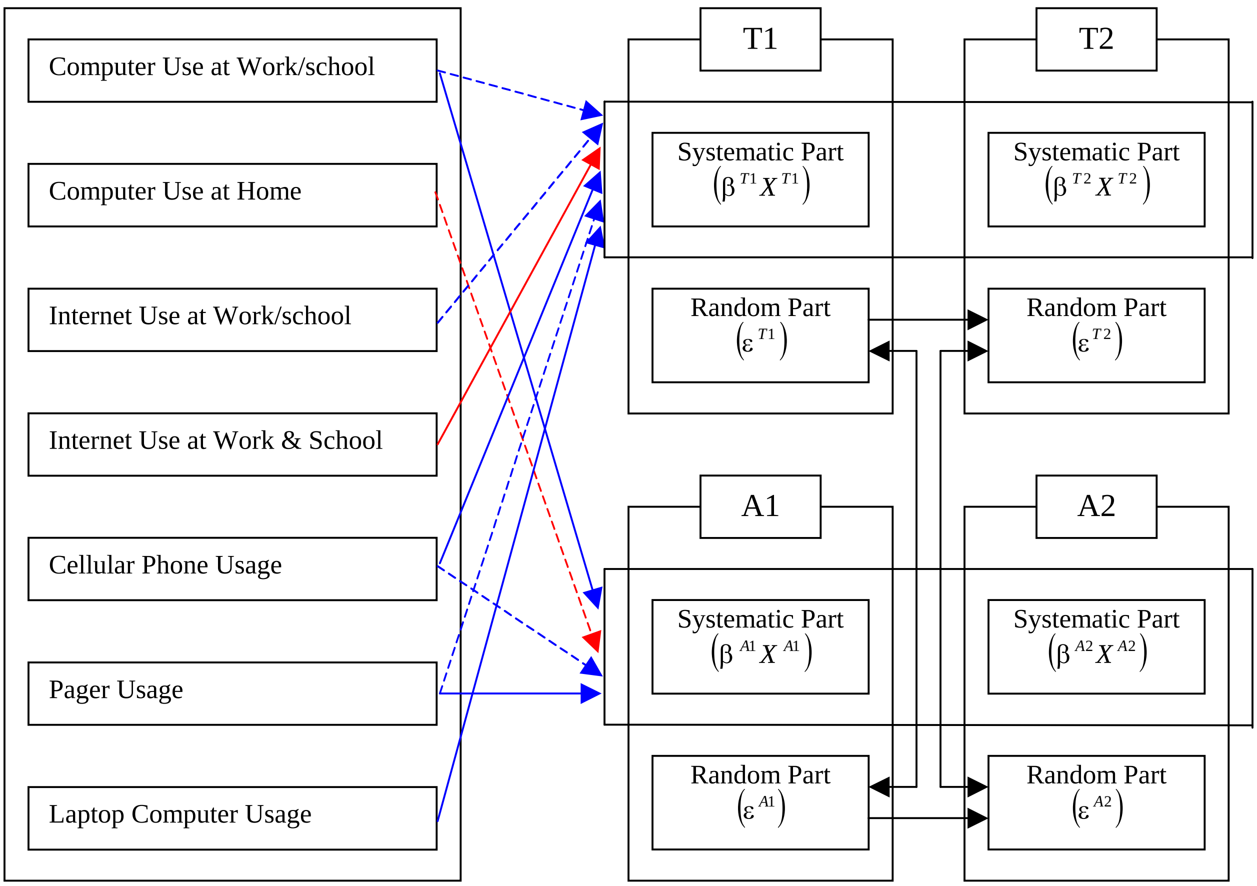
	T1			A1			T2			A2		
	Coef.	S.E.	t-stat	Coef.	S.E.	t-stat	Coef.	S.E.	t-stat	Coef.	S.E.	t-stat
Constant	44.74	6.36	7.04	438.90	25.30	17.35	49.07	6.07	8.08	460.80	26.79	17.20
HHSIZE	4.11	1.14	3.61	-21.05	5.03	-4.18	0.74	1.06	0.70	-27.71	5.15	-5.38
TOT1_5	-3.94	2.72	-1.45				-3.14	2.54	-1.23			
TOT6_17				20.79	6.69	3.11				32.35	6.84	4.73
NUMVEH	-0.12	1.16	-0.10	0.49	3.90	0.13	2.53	1.08	2.33	11.00	4.00	2.75
MIDINC	-7.73	2.34	-3.31	17.69	9.24	1.91	-0.42	2.18	-0.19	-4.37	9.52	-0.46
HIGHINC				63.00	11.39	5.53				28.21	11.72	2.41
MALE	6.00	1.95	3.07	28.62	6.92	4.14	8.94	1.90	4.70	37.43	7.49	5.00
AGE2544	8.40	3.55	2.37	-43.65	17.66	-2.47	10.72	3.39	3.16	-71.02	18.79	-3.78
AGE4564	11.33	3.16	3.59	-43.35	17.83	-2.43	10.33	3.02	3.42	-63.85	19.03	-3.36
AGE65_				-103.50	20.48	-5.05				-126.20	21.74	-5.80
DPUPIL	10.24	4.44	2.30	188.50	18.75	10.05	12.98	4.28	3.03	171.20	19.99	8.56
SECRET				-28.16	12.92	-2.18				-16.11	13.74	-1.17
SALES				-71.45	16.95	-4.22				-72.59	18.02	-4.03
UNEMP	-12.45	2.88	-4.32	-175.40	13.29	-13.20	-15.51	2.77	-5.60	-165.80	14.15	-11.72
WK5				119.10	11.74	10.14				123.20	12.48	9.87
DLICEN	14.99	4.95	3.03				7.82	4.74	1.65			
DBPASS	24.23	3.18	7.61	18.31	10.74	1.70	17.42	3.05	5.72	-2.20	11.37	-0.19
CW	6.56	2.90	2.26	54.04	8.87	6.09	2.49	2.78	0.90	55.71	9.45	5.90
CH				-3.54	9.07	-0.39				-19.02	9.56	-1.99
NW	-0.38	3.61	-0.10				7.35	3.44	2.13			
NH	4.19	3.12	1.34	-14.97	9.62	-1.56	4.18	2.97	1.41	-12.04	10.10	-1.19
INTERNET	-11.86	4.74	-2.50				-16.55	4.54	-3.65			
CELLULAR	11.56	2.44	4.74	9.07	8.18	1.11	13.75	2.33	5.91	18.19	8.62	2.11
PAGER	11.35	3.27	3.47	26.35	11.04	2.39	3.83	3.15	1.22	25.72	11.75	2.19
LAPTOP	13.10	4.69	2.79				13.68	4.49	3.05			
-2LogL	167126.9											

Deviance from Error Component Model (Table 6) = 2477.5 with d.f.=76

Variance / Covariance Matrices (upper triangle correlations) [Std. Error]

	Between Persons				Between Households			
	T1	A1	T2	A2	T1	A1	T2	A2
T1	2795.9 [97.0]	0.095	0.422	0.043	864.7 [93.6]	0.353	0.245	0.085
A1	913.0 [236.9]	33208.9 [1146.0]	-0.011	0.472	930.2 [223.7]	8041.9 [1039.6]	0.161	0.612
T2	1159.4 [72.8]	-104.2 [230.9]	2698.7 [93.0]	0.146	178.8 [66.6]	359.0 [208.2]	616.3 [83.3]	0.247
A2	459.4 [258.1]	17223.9 [980.7]	1522.6 [255.2]	40097.8 [1369.1]	190.5 [229.6]	4186.2 [854.7]	467.3 [219.4]	5814.5 [1125.4]

The correlations indicate that there are strong positive correlations for travel times across two days (T1 and T2) and for out-of home activity times across two days (A1 and A2) at both the person and household level. This indicates people and households have similar activity and travel patterns in consecutive days. In addition, there are no significant negative trade-offs among the indicators. At the person level, travel time has a higher correlation between days than activity durations, while at the household level, activity duration has a higher correlation than travel time.



- Colored line: Tested relation in the study
- Black line: Assumed relation
- Blue line: Positive relation
- Red line: Negative relation
- Solid line: Significant relation in both days
- Dashed line: Significant relation in only one day

Figure 6-1 Relationships between Telecommunication Technology Usage and Daily Allocation to Travel and Out-of–home Activities Using Multivariate Multilevel Models

The LR statistic, which is -2(L(c) –L(β)) = -2(-84802.2-(-83563.45)) = 2477.5 with 76 degrees of freedom, suggests that the choice of explanatory variables is satisfactory.

Figure 6-1 summarizes the correlation structures examined between ICT ownership and use and time use of out-of-home activity and travel and the related hypotheses tested using these data and multivariate multilevel regression model systems.

6.5 Summary

In this chapter, the effects of telecommunication technology usage on out-of-home activity and travel durations for day1 and day2 in Wave 7 are examined using three different models (single-equation regression models, seeming unrelated regression models, and multivariate multilevel models). The technologies examined include desktop computers and Internet usage at home and workplace/school, cellular phones, pagers, laptop computers, and PADs.

Although the three different models produce very similar coefficient values, multivariate models (SUR models and multivariate multilevel models) are more advantageous over single-equation models. The multivariate group of models takes into account the correlation of the error terms across equations, and as a result, in these models, the parameters of all the equations are estimated simultaneously. They produce smaller standard errors of the coefficient estimates than those from single-equation models. Between the two multivariate models, the multilevel models are superior because they consider the hierarchy of level in the data and provide more information by estimating variance-covariance matrices and correlations for each of the multiple levels, offering additional insight on behavioral heterogeneity at each level.

Based on the results of the analysis, it is found that there is a greater variation in activity and travel expenditure across persons within a household as compared to between households. The household level variance is about 19.2 to 25.5 percent of the total variance. It indicates that household level variation should not be neglected and should be accounted for.

The strong positive correlations for out-of-home activity and travel times across two days at both the person and household level indicate that many people and many households have similar activity and travel patterns in consecutive days. However, there is also a significant heterogeneity in the daily activity and travel expenditures between persons within households and between households.

Each telecommunication technology affects travel and out-of-home activity durations in different ways. For example, people who use computers at work or school tend to travel slightly more and spend much more time on out-of-home activities than the non-users. Desktop computer usage at home, however, exhibits no statistically significant impact on travel time, but, a marginal decrease in out-of-home activity durations. In contrast, persons using the Internet at both work and home tend to expend less time traveling. This implies that regular Internet users are more likely to have lower travel time budgets. It is also found that users of mobile technologies such as cellular phones and pagers are usually involved in more traveling and higher activity time. Yet, another group, laptop computer users, tends to travel more. In addition persons in this group do not engage in higher amounts of out-of-home activity participation, which may be an indication of the effect of mobile technologies allowing users to have more flexible activity schedules leading to more travel.

CHAPTER 7
CROSS-SECTIONAL AND LOGITUDINAL RELATIONSHIPS AMONG INFORMATION AND TELECOMMUNICATION TECHNOLOGIES, DAILY TIME ALLOCATION TO ACTIVITY AND TRAVEL, AND MODAL SPLITS

7.1 Introduction

As activity-based approaches to travel demand modeling are emerging a need arises to examine the relationship between time allocation and technology ownership and use. In addition, with longitudinal data the effect of changes in technology ownership and use on time allocation can be examined in more detail and compared to the effect of other social and demographic changes we all experience. To accomplish this, a structural equation model adopting a broader perspective was developed. The model includes time use indicators and modal split indicators in a system of equations viewed as dependent variables jointly to capture activity and travel patterns in a day. The complex relationships among social and demographic change, information and telecommunication technology change, daily time allocation, and mode choice are then studied using traditional hypotheses testing of regression coefficients and an examination of the magnitude of effects an indicator has on another indicator considering both the direct influence of one factor on another and any other indirect effects in a system of non recursive relationships. Some of the more recent simultaneous equation modeling applications in travel behavior data analysis are used here for guidance in developing the model system and in interpreting some of the findings. The activity classification follows Golob (1998) and Chung and Ahn (2002). Explanatory variable definition and model specification is based on a series of more recent studies using subsets of the PSTP and reported in Kim and Goulias (2003) and Goulias and Kim (2003) using a single equation regression approach. Figure 7-1 shows the conceptual framework of the model. A plethora of relationships can be studied using this system. For example, the correlation among the amount of time allocated to subsistence, maintenance, leisure, and travel, as well as the total number of trips by the most important modes (drive alone, car sharing, public transportation, walking, biking, and all other modes used) can be estimated. The model system is designed to parallel other past studies and for this reason variables at the household and person level are also used. In addition, some specific variables to the database in PSTP are also employed to account for stratification and potential participation fatigue. Like in the previous chapters, using information between 1997 and 2000, a large set of variables is defined to capture the changes in social and economic circumstances experienced by each respondent and include them as explanatory variables of the behavior in the year 2000. In this way, we can test if there is a behavioral symmetry when opposite events occur. Another feature that characterizes the research work here is the study of ICT on activity and travel behavior considered jointly with all the other determinants of travel behavior.

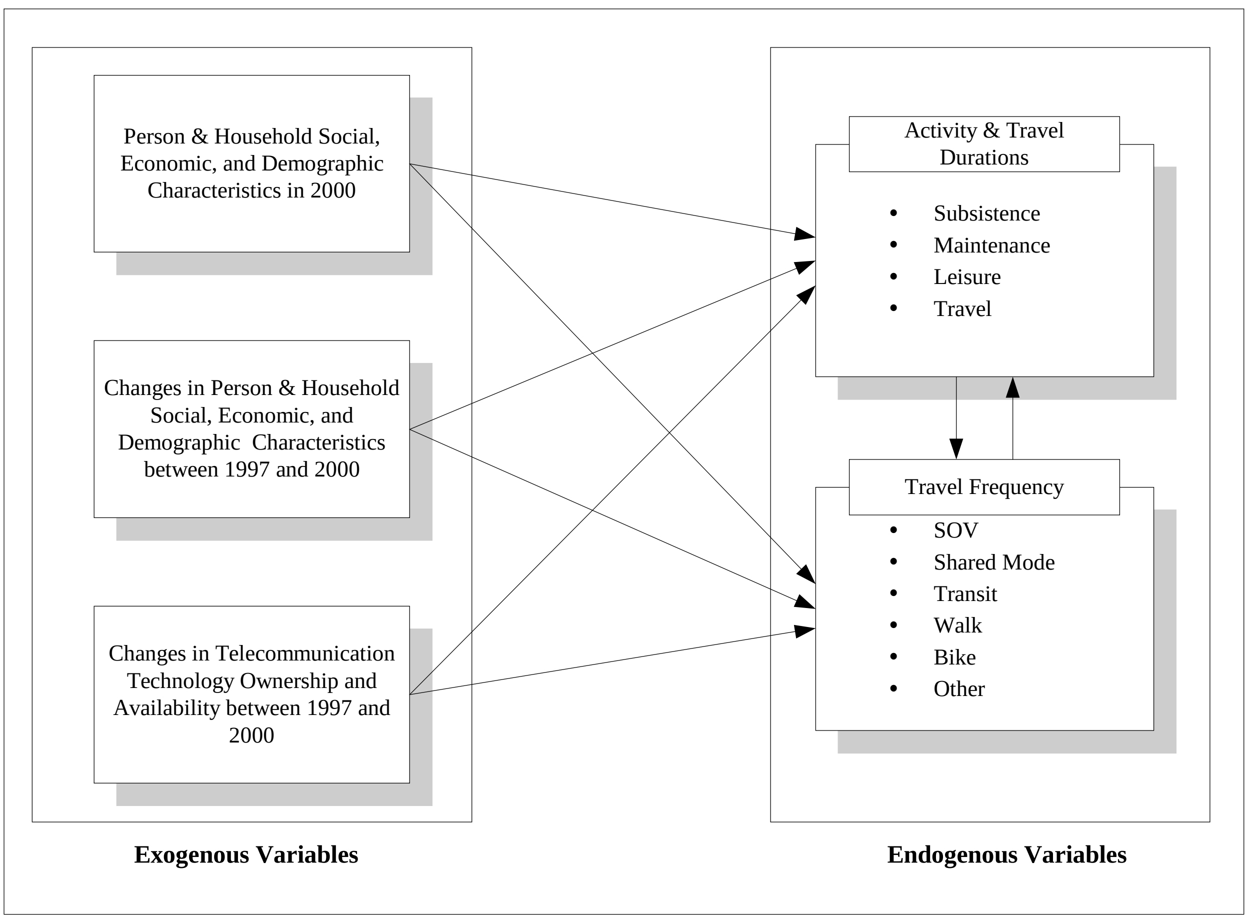


Figure 7-1 Conceptual Model

Within this framework, we are addressing the following key questions:

- What is the relationship among different activities and travel in terms of time use when we control for many other exogenous factors?
- What is the relationship among the use of different travel modes and activity participation?
- Are there systematic differences in time use for specific activities and travel among population segments and is the time use changing with changes of person and household socio-demographics and ICT ownership and availability?
- Are there systematic differences in daily mode choice among population segments and is the mode choice changing with changes of person and household socio-demographics and ICT ownership and availability?
- If the time use and mode choice are changing with changes of person and household socio-demographics and ICT ownership and availability, are these changes symmetric?

7.2 Data Used

For the analysis in this study, we used the data from 1480 persons in 866 households who provided detailed information in both waves 7 and 9 for all the variables used in this analysis. In the original trip data of PSTP, the mode chosen for each trip has been classified into 17 different types: car, carpool, vanpool, bus, para-transit, taxi, walking, bicycle, motorcycle, school bus, drive-on ferry, walk-on ferry, monorail, boat, train, airplane, and other. In this case, car indicates a single occupant vehicle trip mode by car/truck/sport utility vehicle (SUV), while carpool and vanpool implies an official carpool or vanpool as well as an informally shared trip mode by car/truck/SUV or van. The public transportation trips are mostly by bus, and taxi. To make this analysis tractable the modes have been grouped into 6 categories:

- Single occupant vehicle (car/truck/SUV);
- Shared ride (carpool and vanpool);
- Transit (bus, para-transit, and taxi);

- Walk;
- Bike; and
- Others (all other categories).

In addition, activity types have been also grouped, according to the level of constraints involved, into:

- Subsistence (work, school, and college);
- Maintenance (shopping, personal business, appointment, and errand/picking-up/dropping-off); and
- Leisure (free time, recreation/exercise, visiting, and home staying).

Total activity duration includes the amount of time each person spends in activities, including in–home activities (between the first and last out–of–home activity), during a day but neither before the first trip in the morning nor after the final return to home in the evening. Total travel time is the total amount of time spent by a person traveling during the day.

Table 7-1 shows the number of persons, households, and a few social and demographic characteristics of the sample. It also shows amount of time dedicated to various activities and traveling as well as travel frequency of each mode during the two interview days in wave 7 (1997) and wave 9 (2000). As expected, people show a similar pattern of activity and travel behavior between the two days and between the two waves, except for activity and travel durations between the waves. The rather large discrepancy in activity and travel durations is most likely a result of genuine change but also the use of different schemes for trip purposes in the travel survey between the waves. In the year 2000, the respondents spent an average of 230.1 minutes in subsistence activity, 46.7 minutes in maintenance activity, 93.3 minutes in leisure activity, and 74.4 minutes in travel per day. The respondents are heavily dependent on cars/truck/SUV for their travel mode. Traveling alone with car/truck/SUV is the most popular mode accounting for 56.6 percent of total trips, while bike is the least used mode accounting for only 0.5 percent.

Table 7-1 A Selection of Sample Characteristics

Characteristics			Wave 7 (1997)	Wave 9 (2000)
Number of persons in the sample			1480	1480
Number of households in the sample			866	866
Person & Household	Percent of males in the sample		46.9	46.9
	Number of employed persons in the sample		859	881
	Number of persons in household		2.5	2.5
	Number of cars per household		2.2	2.2
Activity & Travel	Total amount of time in subsistence activities (min.)	Day 1	275.0	235.3
		Day 2	265.2	224.9
	Total amount of time in maintenance activities (min.)	Day 1	43.3	46.4
		Day 2	39.4	46.9
	Total amount of time in leisure activities (min.)	Day 1	109.8	93.5
		Day 2	106.9	93.0
	Total amount of time traveling (min.)	Day 1	84.7	75.0
		Day 2	79.0	73.8
Travel Mode*	Total Number of trips per person	Day 1	4.57	4.08
		Day 2	4.30	3.98
	Number of trips driving alone per person (%*)	Day 1	2.52 (55.1)	2.31 (56.6)
		Day 2	2.37 (55.1)	2.25 (56.5)
	Number of trips by shared modes per person (%*)	Day 1	1.57 (34.4)	1.34 (32.8)
		Day 2	1.52 (35.3)	1.34 (33.7)
	Number of trips by transit per person (%*)	Day 1	0.19 (4.2)	0.17 (4.2)
		Day 2	0.15 (3.5)	0.15 (3.8)
	Number of trips by walking per person (%*)	Day 1	0.20 (4.4)	0.20 (4.9)
		Day 2	0.16 (3.7)	0.18 (4.5)
	Number of trips by biking per person (%*)	Day 1	0.02 (0.4)	0.02 (0.5)
		Day 2	0.02 (0.5)	0.02 (0.5)
	Number of trips by other modes per person (%*)	Day 1	0.06 (1.3)	0.05 (1.2)
		Day 2	0.07 (1.6)	0.05 (1.3)
Information & Communication Technology**	Number of persons who use computer regularly (%**)	At home	751 (50.7)	982 (66.4)
		At work	700 (47.3)	717 (48.4)
	Number of persons who use the Internet regularly (%**)	At home	458 (30.9)	896 (60.5)
		At work	438 (29.6)	544 (36.8)
	Number of persons having cellular phones (%**)		419 (28.3)	685 (46.3)
	Number of persons having pagers (%**)		156 (10.5)	129 (8.7)
	Number of persons having laptops (%**)		71 (4.8)	79 (5.3)
	Number of persons having PDAs (%**)		6 (0.4)	38 (2.6)

**% over total number of trips per person*

*** % over total number of person in the sample*

7.3 Model Formulations

Two groups of activity-travel variables are used as the endogenous variables in the model. The first group of the endogenous variables is total amount of time dedicated to a specific activity (subsistence, maintenance, and leisure) and traveling in a day. The second group is the frequency of trips by a specific mode (SOV, shared mode, transit, walk, bike, other modes) a person makes in a day.

Table 7-2 List of Endogenous Variables

Endogenous Variables		Descriptions
Activity and Travel Durations	Sdur	Total subsistence activity duration per day (min)
	Mdur	Total maintenance activity duration per day (min)
	Ldur	Total leisure activity duration per day (min)
	Ttime	Total travel time per day (min)
Travel Frequency by Mode	Ssov	Number of trips per day by driving alone
	Shared	Number of trips per day by shared ride
	Transit	Number of trips per day by transit
	Walk	Number of trips per day by walking
	Bike	Number of trips per day by bike
	Others	Number of trips per day by other modes

For exogenous variables, four groups of variables were used: household-level variables, person-level variables, time-related variables, and ICT variables. We used cross-sectional information in the year 2000 as well as longitudinal information between the years 1997 and 2000 about household-level and person-level social, economic, demographic characteristics and ICT ownership and availability. Appendix contains a comprehensive description of the independent variables used here.

To account for task allocation and roles within the household, number of adults, number of children by age group as well as vehicles owned and income representing resource availability are included as exogenous variables. In addition, in order to account for the sampling stratification of the panel participants, the county of residence and sample indicators (TRANSIT, CARPOOL) are also included as exogenous variables.

Indicators for changes in household and person characteristics, such as increase or decrease in car-ownership, changes in household composition, and changes in employment, were used to examine the effect of the changes on time use and mode choice.

Two types of time variables are also included. The first type is person-level time elapsed in panel since the first time participating and it can capture two effects: a) a genuine change in activity and travel behavior by a person during the time of her/his panel participation; and b) possible travel diary and/or panel fatigue in reporting trips. The second type is the set of day of week indicators to account for different activity and travel behaviors among weekdays (weekends are not targeted in PSTP) and a correlation between the first and second diary day.

To examine the effect of changes in information and telecommunication technology between the years 1997 and 2000, we defined indicator variables for four groups of persons for each ICT:

- Persons that started using these technologies some time after 1997 and they are using them in 2000 (*new users*);
- Persons that stopped using these technologies since 1997 (*past users*);
- Persons that never used them (*non users*); and
- Persons that started some time before 1997 and never stopped (*experienced users*).

The use of structural equation modeling techniques is employed in this study, due to their capability to estimate a set of simultaneous equations capturing the interrelationship among a large number of endogenous and exogenous variables. This modeling technique has been used in the analysis of travel behavior since the middle of 1970's. A comprehensive and informative review of many transportation research applications using structural equation models (SEM) can be found in Golob (2003).

7.4 Model Results

Figure 7-2 and Table 7-3 provide an overview of the complex relationships found among the amount of time allocated to activities in each day by each person and the number of trips made by each mode. The sum of the number of trips by mode is also the frequency of activity episodes that involve the change of an activity location. In the section with label "goodness-of-fit indices" we see that every indicator reviewed in a previous chapter shows a model with excellent fit to the data.

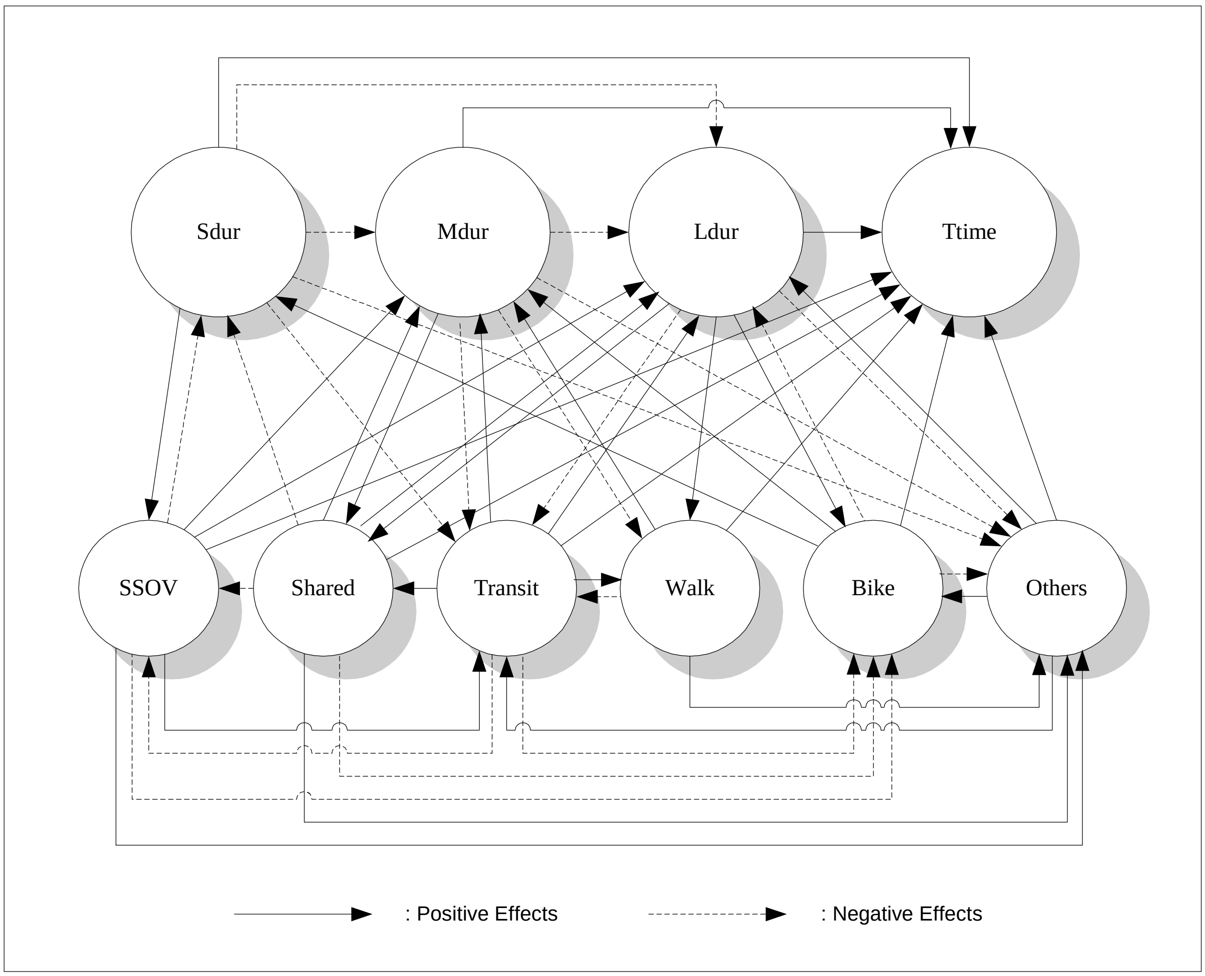


Figure 7-2 Path Diagram among Endogenous Variables Based on Direct Effects

Table 7-3 Total, Direct, and Indirect Effects among Endogenous Variables

Causal Endogenous Variables		Resulting Endogenous Variables									
		sdur	mdur	ldur	ttime	ssov	shared	transt	walk	bike	others
sdur	total	-0.019	-0.062	-0.129	0.032	0.002	0.000	-0.000	0.000	0.000	-0.000
	direct	0.000	-0.094	-0.225	0.020	0.002	0.000	-0.000	0.000	0.000	-0.000
	indirect	-0.019	0.033	0.096	0.012	0.000	0.000	0.000	0.000	0.000	0.000
mdur	total	-0.041	-0.181	-0.311	0.024	0.000	0.004	-0.002	-0.004	0.000	-0.000
	direct	0.000	0.000	-0.383	0.058	0.000	0.006	-0.003	-0.003	0.000	-0.000
	indirect	-0.041	-0.181	0.072	-0.034	0.000	-0.002	0.001	-0.001	0.000	0.000
ldur	total	-0.003	0.003	-0.120	-0.012	0.000	0.001	-0.001	0.000	+0.000	-0.001
	direct	0.000	0.000	0.000	0.015	0.000	0.001*	-0.001	0.001	+0.000	-0.001
	indirect	-0.003	0.003	-0.120	-0.027	0.000	0.000	0.000	-0.001	0.000	0.000
ttime	total	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	direct	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	indirect	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ssov	total	-10.491	13.452	30.448	11.654	-0.069	0.121	0.026	-0.002	-0.007	-0.002
	direct	-10.074	11.813	30.497	9.456	0.000	0.000	0.094	0.000	-0.019	0.021
	indirect	-0.417	1.639	-0.049	2.198	-0.069	0.121	-0.068	-0.002	0.013	-0.023
shared	total	-5.644	3.934	17.626	9.538	-0.206	0.037	-0.039	-0.023	-0.004	0.003
	direct	-7.330	7.917	24.923	11.543	-0.218	0.000	0.000	0.000	-0.017	0.020
	indirect	1.686	-3.984	-7.298	-2.005	0.012	0.037	-0.039	-0.023	0.013	-0.017
transt	total	4.059	34.685	18.765	17.877	-0.691	0.381	-0.243	0.365	-0.003	-0.012
	direct	0.000	31.913	60.697	21.346	-0.815	0.216	0.000	0.596	-0.021	0.000
	indirect	4.059	2.772	-41.932	-3.469	0.123	0.165	-0.243	-0.231	0.018	-0.012
walk	total	-1.918	31.807	-10.625	6.346	0.124	0.121	-0.189	-0.210	0.006	0.048
	direct	0.000	44.333	0.000	5.453	0.000	0.000	-0.153	0.000	0.000	0.067
	indirect	-1.918	-12.525	-10.625	0.893	0.124	0.121	-0.036	-0.210	0.006	-0.020
bike	total	29.075	22.214	-121.959	-7.157	0.072	-0.041	-0.005	-0.149	-0.132	-0.293
	direct	33.985	35.926	-79.274	5.494**	0.000	0.000	0.000	0.000	0.000	-0.407
	indirect	-4.910	-13.711	-42.685	-12.651	0.072	-0.041	-0.005	-0.149	-0.132	0.115
others	total	7.519	12.001	89.963	38.195	-0.051	0.193	0.029	0.044	0.248	-0.167
	direct	0.000	0.000	133.056	38.460	0.000	0.000	0.176	0.000	0.249	0.000
	indirect	7.519	12.001	-43.094	-0.265	-0.051	0.193	-0.147	0.044	-0.002	-0.167
Goodness-of-fit–Indices		Chi-Square =305.287, d.f.=471, P-value=1.000 Chi-Square/d.f =0.650 NFI=0.998 TLI =1.007 CFI =1.000 RMSEA =0.000, 90 Percent C.I. of RMSEA=(0.000 0.000), Probability(RMSEA <=0.05) =1.000 CN=5049									

7.4.1 Cross-sectional Effects

Turning to the effects of variables, travel time does not influence any other variable and therefore implicitly treated as the outcome of all the other indicators. One way of looking at the relationships among daily subsistence duration (sdur), daily maintenance duration (mdur), daily leisure duration (ldur), and daily travel time (ttime) is to consider the possible effect of a minute more in one type of activity on another. Subsistence duration's effect is very clear: persons that work longer are more likely to spent less time in leisure (-0.129) and maintenance (-0.062). Golob (1998) claims this as evidence of time budgeting by individuals and their households. In another analysis, however, Goulias, Kilgren, and Kim (2003) find extreme variation in "budgeting" and the existence of multiple groups with very different budgets. Note also the circular effect through the indirect effects. The direct effect on leisure, however, is the highest. As expected persons that spend more time working/studying are also more likely to travel longer (0.032). Time expenditure on maintenance (e.g., shopping) has also a negative effect on leisure and subsistence and considerably larger than the two effects of subsistence before. The total effect of leisure on maintenance is positive and small and the total effect of maintenance on leisure is negative (inhibiting) and large. None of the effects is larger than one (no substitution one for one minute) and the largest appears to be the "trade-off" between maintenance and leisure (1 minute of maintenance leads to a third less leisure).

Moving to the effects of activity daily durations on the number of trips by mode a striking finding is the overall lack of influence time allocation has on the modal frequencies. As expected it is more likely that the number of episodes determine activity duration and not the other way around. In addition, persons with longer durations are more likely to make more trips driving alone and with others in the same private car than to take the bus. Leisure duration appears to have a positive effect on bicycle trips but very small, while, the use of most "others" modes are inhibited by longer durations of any activity type.

When we consider the number of trips effect on time allocation we see a few systematic relationships. The frequency of traveling by transit and other modes are accompanied by a positive and fairly large effect on the amount of time allocated to activities on maintenance (34.7 minutes per day for transit) but also leisure (18.8 minutes) and as expected travel time (17.8

minutes). Walking has a similar effect on maintenance and exactly the opposite on leisure duration. Using a car either alone or with others is accompanied by longer daily allocations to maintenance, leisure, and travel but not subsistence. The difference between direct and total effect in car sharing lead us to believe that using a simultaneous equation technique is a worthwhile exercise leading to better understanding of the effect one variable has on another. Overall, the effect of mode frequencies on duration of activities appears to be much stronger than the effect of activity duration on the trips made.

Effects among the use of travel modes generally seem to be quite different in magnitude as well as in signs by direction. These different effects by direction may be due to the fact that each mode has unique characteristics, thus each pair of modes cannot be a complete alternative to each other. For example, SOV has positive and small total effects (0.121) on transit, while transit on SOV has negative and large effects (-0.691). So the net effects of transit on SOV (-0.570) indicate that transit could be a good substitute to SOV, but not true vice versa. In the case between shared modes and transit, shared modes has small, negative total effects (-0.039) on transit, while transit has relatively large, positive effects (0.381) on shared modes, resulting in the net effect of (0.342). It indicates that transit has enhancement effects on share mode. However, it should be noted that caution is required in interpretation, because trip frequency by each mode in this study was treated as a continuous variable rather than a count variable, which may influence the magnitude of the coefficient.

In PSTP sampling follows a stratification scheme that requires us to either weight the observations or to include as explanatory variables factors used in the stratifications (e.g., county of residence and household classification with respect to usual mode used). The first five rows of Table 7-4 show the inclusion of these variables explains some of the variation in the endogenous variables and as expected there are large differences among the segments that reside in different counties.

Table 7-4 Total and Direct Effects of Cross-sectional Household-level Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables									
		sdur	mdur	ldur	ttime	ssov	shared	transt	walk	bike	others
carpool	total	-0.640	-3.391	-5.915	-0.426	-0.531	0.728	-0.043	-0.020	-0.019	-0.062
	direct	0.000	0.000	0.000	0.000	-0.406	0.764	0.000	0.000	0.000	-0.078
transit	total	3.525	-3.007	19.800	9.761	-0.418	0.116	0.490	0.314	0.005	-0.001
	direct	0.000	-28.411	0.000	0.000	0.000	0.000	0.584	0.000	0.000	0.000
kitsap	total	2.472	3.643	-4.885	5.253	-0.031	0.022	0.038	0.009	0.068	0.286
	direct	0.000	0.000	-37.454	-7.123	0.000	0.000	0.000	0.000	0.000	0.312
pierce	total	0.329	4.858	0.914	1.056	-0.075	0.046	0.080	-0.082	-0.003	-0.008
	direct	0.000	6.584*	0.000	0.000	0.000	0.000	0.092	-0.117	0.000	0.000
snoho	total	17.973	-3.623	1.345	6.499	-0.051	0.005	0.106	-0.105	-0.003	-0.009
	direct	17.598	0.000	0.000	5.448	0.000	0.000	0.091	-0.179	0.000	0.000
tot1_5	total	-4.226	2.945	13.197	7.141	-0.154	0.776	-0.029	-0.017	-0.003	0.002
	direct	0.000	0.000	0.000	0.000	0.000	0.749	0.000	0.000	0.000	0.000
tot6_17	total	-4.791	5.002	17.449	5.045	0.077	0.564	-0.014	-0.011	0.003	0.023
	direct	0.000	0.000	0.000	-3.171	0.198	0.516	0.000	0.000	0.000	0.026
totadult	total	1.936	-1.139	-6.552	-1.632	-0.382	0.259	-0.017	-0.076	0.000	-0.003
	direct	0.000	5.429	0.000	0.000	-0.343	0.277	0.000	-0.065	0.000	0.000
midinc	total	10.425	1.011	16.658	11.370	0.219	0.209	0.047	0.036	0.009	0.040
	direct	13.852*	-5.680	0.000	3.569	0.282	0.171	0.043*	0.000	0.000	0.048
highinc	total	15.557	7.352	16.201	10.327	0.405	0.341	0.006	-0.006	0.039	0.033
	direct	20.798	0.000	0.000	0.000	0.453	0.277	0.000	0.000	0.037	0.053
mhinc	total	-3.339	18.628	10.350	6.619	0.287	0.113	-0.018	-0.057	0.011	0.054
	direct	0.000	16.730	0.000	0.000	0.304*	0.000	0.000	0.000	0.000	0.070
dkinc	total	0.000	0.000	0.000	11.018	0.000	0.000	0.000	0.000	0.000	0.000
	direct	0.000	0.000	0.000	11.018	0.000	0.000	0.000	0.000	0.000	0.000
car1	total	-11.985	-3.901	15.675	-12.155	0.678	0.704	-1.050	-0.605	0.000	-0.019
	direct	0.000	41.714	39.615*	0.000	0.000	0.932	-1.206	0.000	0.000	0.000
car2	total	-11.855	-9.982	34.722	-13.414	0.714	0.668	-1.084	-0.595	0.007	-0.032
	direct	0.000	35.906	60.416	0.000	0.000	0.912	-1.244	0.000	0.000	0.000
Car3_	total	-10.688	-12.274	27.915	-16.643	0.799	0.394	-1.113	-0.610	0.007	-0.031
	direct	0.000	36.451	58.894	0.000	0.000	0.665	-1.295	0.000	0.000	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

In the same table, the effect of children is very interesting showing that in general households with more children spend more time engaging in leisure and second in maintenance and as expected travel time. The effect on the number of trips is positive for persons in households with children in the age group of 1 to 17. These effects, however, are not the same as when the person analyzed resides in a household with more adults. The use of transit and walking, however, is consistently lower for persons in households that have more children of any age and more other adults. Interestingly, the presence of more adults in the household is also accompanied by lower frequencies of driving alone and almost similar and opposite effect on sharing rides. Presumably adults in multi adult households share rides more often. The household income indicators show that in general wealth is accompanied with spending more time in all activities and traveling more in terms of number of trips and time traveling. To account for the second coding allowed in the PSTP stated household income, we also include variable, MHINC.

Table 7-5 shows the effect of person-level and time-related variables. As expected, working more than 5 times a week and attending a school or college are the two largest factors on subsistence activity durations. Additionally, having a driver’s license or bus pass are the largest contributors to total travel time in a day. Males in the age group of 35-64 spend more time on subsistence activity and traveling than the other age groups. People have different patterns of time use within the various occupation types. For example, on one hand, people having a professional or managerial position spend more time on subsistence but less on leisure than those in other occupations. On the other hand, people who are in secretarial or sales occupations are engaged less in subsistence and more in leisure activities. The sales persons travel more than any other occupation as expected.

Table 7-5 Total and Direct Effects of Cross-sectional Person-level and Time-related Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables									
		sdur	mdur	ldur	ttime	ssov	shared	transt	walk	Bike	others
male	total	38.030	-12.521	-7.504	6.312	-0.104	-0.280	0.033	-0.012	0.012	0.040
	direct	34.509	-6.465	0.000	8.351	-0.215	-0.207	0.000	-0.062	0.000	0.050
young	total	0.533	4.551	2.462	2.346	-0.091	0.050	0.099	0.048	0.000	-0.002
	direct	0.000	0.000	0.000	0.000	0.000	0.000	0.131	0.000	0.000	0.000
midage	total	0.656	5.608	3.034	2.890	-0.112	0.062	0.122	0.059	-0.001	-0.002
	direct	0.000	0.000	0.000	0.000	0.000	0.000	0.162	0.000	0.000	0.000
prof	total	0.956	-0.175	-10.935	3.307	-0.115	0.190	0.092	0.048	0.035	-0.002
	direct	0.000	-6.580*	-14.597	0.000	0.000	0.185	0.102	0.000	0.044	0.000
manag	total	0.081	-0.066	-21.401	0.297	-0.010	-0.025	0.019	-0.003	-0.006	0.017
	direct	0.000	0.000	-24.321	0.000	0.000	0.000	0.000	0.000	0.000	0.000
secre	total	-3.387	4.343	9.829	-4.572	0.301	0.039	0.008	-0.001	-0.002	-0.001
	direct	0.000	0.000	0.000	-8.335	0.323	0.000	0.000	0.000	0.000	0.000
sales	total	-4.995	6.404	14.496	5.548	0.443	0.058	0.012	-0.001	-0.003	-0.001
	direct	0.000	0.000	0.000	0.000	0.476*	0.000	0.000	0.000	0.000	0.000
wk5	total	178.074	-22.055	-22.621	9.542	0.337	-0.138	0.067	0.010	0.012	-0.008
	direct	180.039	-11.155	0.000	4.799*	0.000	0.000	0.000	-0.077	0.031	0.000
dpupil	total	94.030	-26.197	-12.568	-1.830	0.259	-0.588	0.074	0.110	-0.001	0.005
	direct	92.378	-22.889	0.000	0.000	0.000	-0.442*	0.000	0.000	0.000	0.000
dlicen	total	20.883	4.912	39.699	14.082	1.613	0.064	-0.073	-0.222	-0.014	-0.009
	direct	38.085	0.000	0.000	0.000	1.525	0.000	-0.206	-0.192	0.000	0.000
dbpass	total	30.441	-1.471	-13.367	10.741	-0.364	0.082	0.500	0.047	0.036	0.046
	direct	26.144	-14.301	-31.699	0.000	0.000	0.000	0.527	-0.247	0.036	0.060
pelap	total	-0.155	1.819	-0.466	0.754	0.006	0.031	-0.016	0.076	0.004	0.004
	direct	0.000	-1.509	0.000	0.000	0.000	0.025	0.000	0.091	0.003	0.000
pelap2	total	0.012	-0.197	0.066	-0.039	-0.001	-0.001	0.001	-0.005	0.000	0.000
	direct	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.006	0.000	0.000
tue	total	14.324	6.244	0.457	3.339	-0.042	0.223	0.027	-0.001	-0.004	-0.001
	direct	15.661*	5.634*	0.000	0.000	0.000	0.182	0.054	0.000	0.000	0.000
wed	total	18.784	-2.836	0.519	6.279	0.028	-0.012	0.016	-0.044	0.004	0.018
	direct	18.836	0.000	0.000	5.104	0.000	0.000	0.000	-0.062	0.000	0.025*
thu	total	31.287	-2.003	-14.633	6.580	0.057	-0.027	0.015	0.005	-0.006	0.009
	direct	31.858	0.000	-11.966	5.422	0.000	0.000	0.000	0.000	0.000	0.000
fri	total	-1.811	1.262	5.655	9.050	-0.066	0.333	-0.013	-0.007	-0.001	0.001
	direct	0.000	0.000	0.000	5.990	0.000	0.321	0.000	0.000	0.000	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.

** Significant at 90% level; all others are significant at 95% level.*

In terms of mode use, SOV usage is higher for students, people having a secretary or sales occupation, and people who work more than 5 times per week. In addition, it is found that a driver's license is one of main factors on mode choice. Having a driver's license has positive effects on the use of SOV and shared mode, but negative effects on the other modes, especially on transit. On the other hand, having a bus pass discourages the use of SOV, and expectedly encourages the use of transit. Being a male has negative effects on frequency of SOV, shared mode, and walking, but positive effects on transit, bike, and others. Older generations seem to use transit less often but SOV more often than other age groups.

Time related variables in the bottom of Table 7-5 confirm our expectation about people's time allocation patterns during weekdays. They have quite different patterns in time use between Thursday and Friday. On Thursday, people work the longest and spend the least time on leisure. On the contrary, it is on Friday that people work the least and spend the most time on leisure during the weekdays. In terms of mode frequency, there are some similarities between Tuesday and Friday, and between Wednesday and Thursday, but the two groups of days show almost opposite patterns of mode frequency.

7.4.2 Longitudinal Effects

One of the advantages in using panel data is our ability to measure change in a variable and concomitant effect on another. From a travel behavior viewpoint it is also interesting and useful to know if there is behavioral symmetry when these changes happen. For example, is the difference in activity participation the same when a household looses a car and when it gains a car? Or what is the effect of an arrival of a young child and how is that different from that child growing older? This type of effects and relationships were hypothesized some time ago (Goodwin, Kitamura, and Meurs, 1990) but not tested empirically in a comprehensive fashion.

The variables reported in Table 7-6 aim to describe the difference in activity and travel behavior among households and individuals that experienced diametrically opposed events such as increase in children versus a decrease in children, increase in household cars versus a decrease in household cars, as well as personal changes such as change in employment status. Figures 7-3 and 7-4 provide a pictorial representation of this lack of symmetry.

Table 7-6 Total and Direct Effects of Household-level & Person-level Change Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables									
		sdur	mdur	ldur	ttime	ssov	Shared	transt	walk	bike	others
inbaby	total	12.835	-7.524	-41.476	-17.528	-0.287	-1.314	0.000	0.161	0.009	0.006
	direct	0.000	0.000	0.000	0.000	-0.599	-1.217	0.000	0.167	0.000	0.000
dnbaby	total	0.381	-7.690	25.364	-1.864	-0.020	-0.003	0.026	-0.189	0.005	-0.029
	direct	0.000	0.000	25.879	0.000	0.000	0.000	0.000	-0.244	0.000	0.000
inkid	total	21.708	10.752	-14.115	-0.374	0.174	-0.365	-0.061	0.350	0.002	0.019
	direct	20.710*	0.000	0.000	0.000	0.000	-0.392	0.000	0.427	0.000	0.000
dnkid	total	39.033	-2.359	30.666	0.773	0.094	0.023	-0.024	0.013	0.006	-0.028
	direct	39.936	0.000	40.696	0.000	0.000	0.000	0.000	0.000	0.000	0.000
inadult	total	-3.343	0.295	5.668	0.148	0.520	-0.265	-0.071	-0.039	-0.001	0.000
	direct	0.000	0.000	0.000	0.000	0.411	-0.259*	-0.121	0.000	0.000	0.000
dnadult	total	29.866	3.417	8.124	12.263	0.453	0.034	0.017	0.006	-0.006	0.000
	direct	34.883	0.000	0.000	6.326	0.414	0.000	0.000	0.000	0.000	0.000
inlicen	total	9.637	-5.847	-26.735	-8.293	-0.659	-0.238	0.060	0.034	0.037	-0.011
	direct	0.000	0.000	0.000	0.000	-0.682	-0.183*	0.093	0.000	0.037	0.000
dnlicen	total	-0.802	-0.613	3.365	0.197	-0.002	0.001	0.000	0.004	-0.024	0.008
	direct	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.028*	0.000
inbpass	total	-1.892	-6.465	2.249	-12.584	0.107	-0.059	-0.120	-0.052	-0.037	0.014
	direct	0.000	0.000	0.000	-10.051	0.000	0.000	-0.159	0.000	-0.043	0.000
dnbpass	total	1.271	-0.886	-3.969	-2.148	0.046	-0.233	0.009	0.005	0.001	-0.001
	direct	0.000	0.000	0.000	0.000	0.000	-0.225*	0.000	0.000	0.000	0.000
inveh	total	-1.136	-0.868	4.764	5.837	-0.003	0.002	0.000	0.006	-0.034	0.011
	direct	0.000	0.000	0.000	5.558	0.000	0.000	0.000	0.000	-0.039	0.000
dnveh	total	2.743	-6.741	-10.430	-4.856	-0.217	-0.066	-0.069	-0.029	0.002	0.002
	direct	0.000	0.000	0.000	0.000	-0.293	0.000	-0.081	0.000	0.000	0.000
inemp	total	-19.246	5.948	13.289	3.816	0.314	0.052	0.007	-0.004	-0.001	-0.001
	direct	-15.663*	0.000	0.000	0.000	0.370	0.000	0.000	0.000	0.000	0.000
dnemp	total	2.395	1.567	-4.767	-1.913	0.015	-0.343	0.079	0.040	0.001	-0.002
	direct	0.000	0.000	0.000	0.000	0.000	-0.362	0.086	0.000	0.000	0.000
expemp	total	202.274	-13.913	-26.542	10.082	1.025	-0.718	-0.026	0.006	-0.020	0.002
	direct	207.993	0.000	0.000	6.462	0.437	-0.600	-0.132	0.000	0.000	0.000
novemp	total	94.609	-18.695	-0.429	3.945	0.609	-0.422	0.076	0.098	-0.006	0.004
	direct	97.839	-20.190	0.000	0.000	0.387*	-0.334	0.000	0.000	0.000	0.000
quitemp	total	20.980	-3.097	5.669	2.128	0.593	-0.040	-0.140	-0.071	-0.005	0.002
	direct	26.819*	0.000	0.000	0.000	0.427	0.000	-0.207	0.000	0.000	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.

** Significant at 90% level; all others are significant at 95% level.*

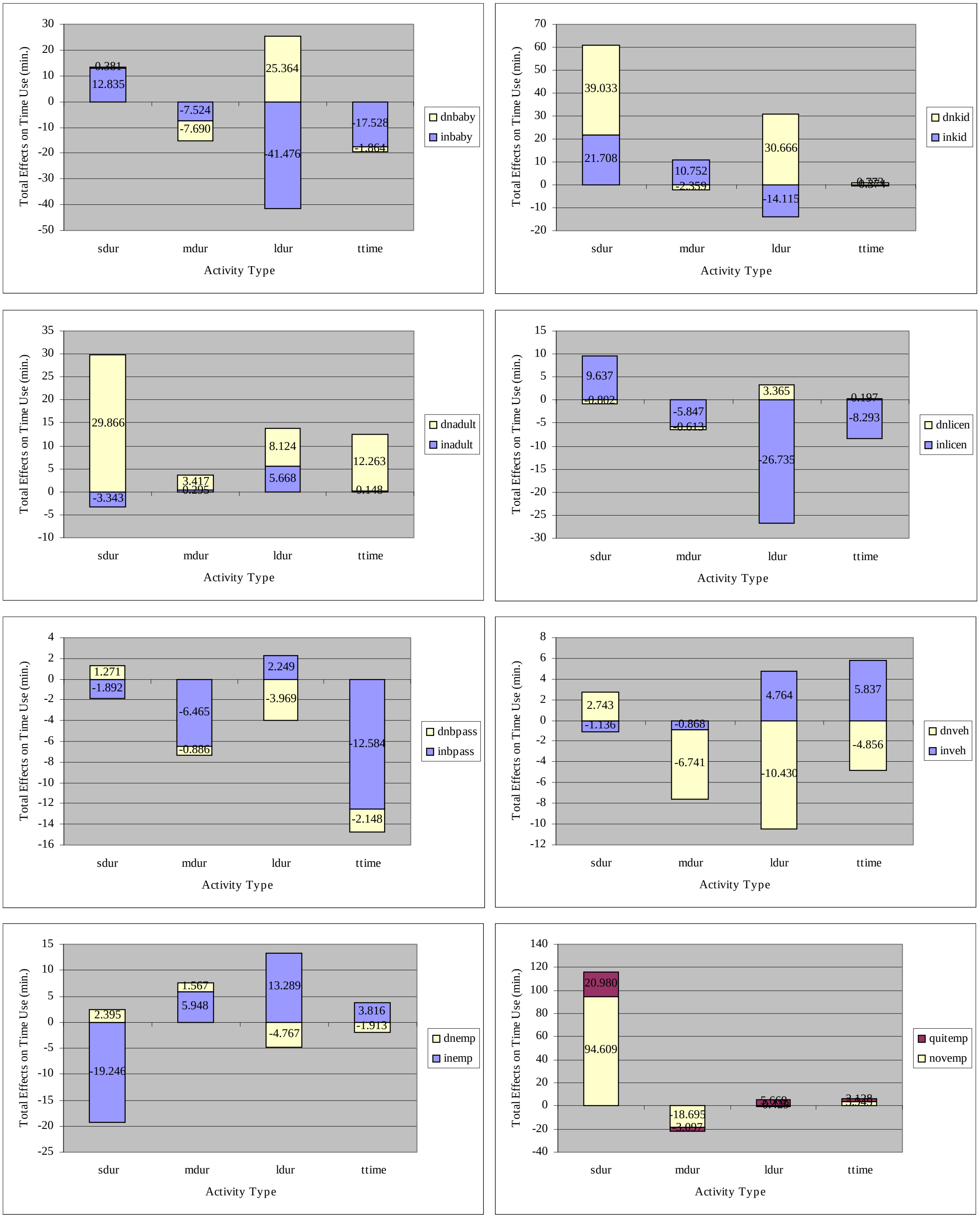


Figure 7-3 Total Effects of Changes in Household and Personal Characteristics on Time Use

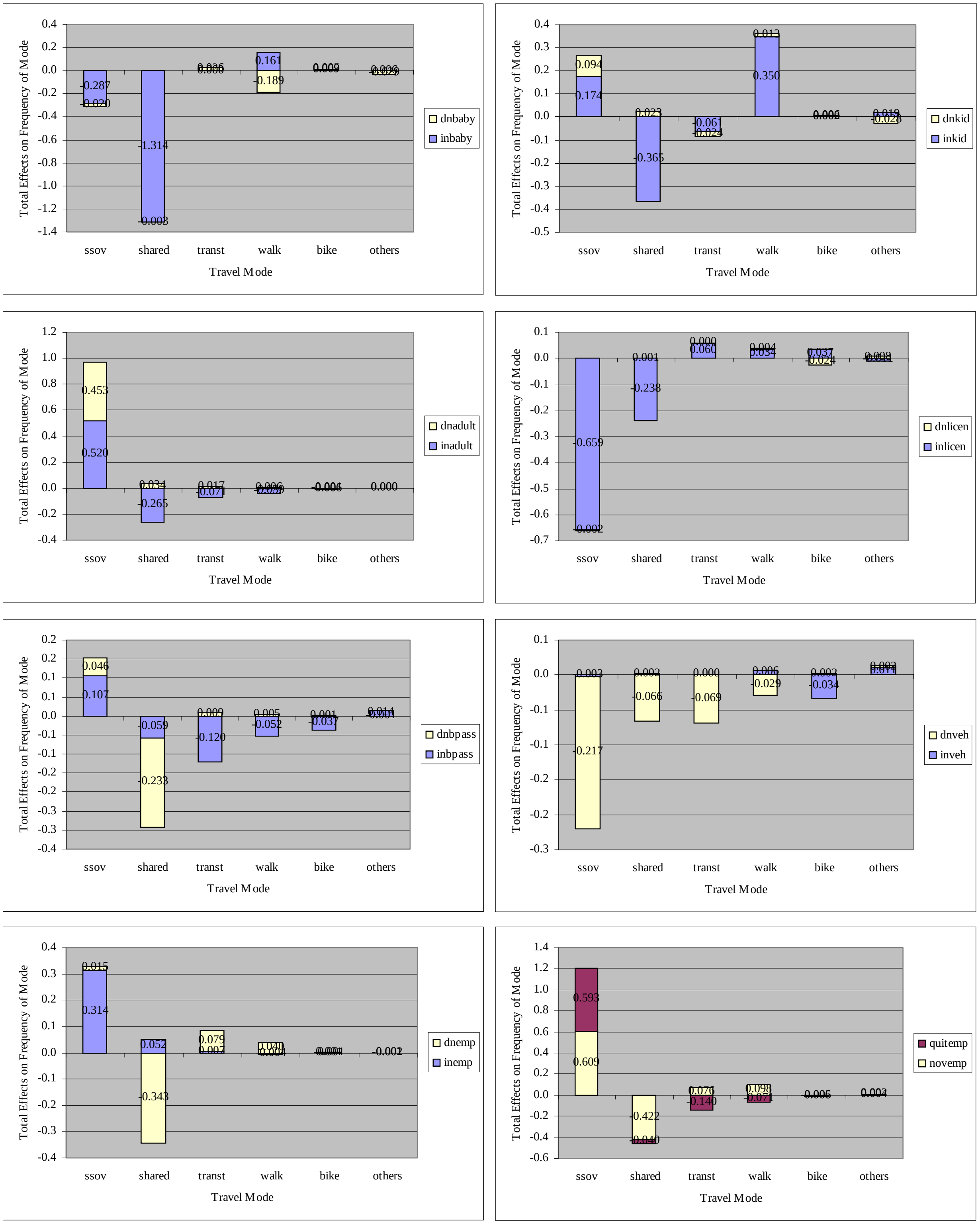


Figure 7-4 Total Effects of Changes in Household and Personal Characteristics on Mode Frequencies

Very important for transportation policy is the effect of car ownership on travel but also the effect of providing incentives for bus use. An increase in the number of vehicles in the household has no effect in the use of transit but a decrease has exactly the opposite from what one would expect. Most likely because this was accompanied by lower activity participation that in turn leads to lower trip making overall.

Tables 7-4, 7-5, and 7-6 allow us to perform some additional calculations. Regression coefficients defined for a group of indicators are relative to the excluded group (implicitly assumed to have a zero coefficient). For example, let's assume a man in a young couple with a child finds a professional job working 5 days per week, thus increasing his household income from low income to middle income. Also, let's assume the man buys a car resulting in one car available in the household. From this situation, we can compute how much more time he spends on subsistence activity in a day as a difference from the time he spent previously as an unemployed man in a couple with a child and no car in the household. This would compute as follows: (0.956 + 178.074 + 10.425 - 11.985 - 1.136 -19.246 + 94.609) = 251.697, which means on average 251.697 minutes more on subsistence activity than his previous status. Similar calculations lead to 38.735 minutes less on maintenance activity, 2.039 trips more by SOV, 0.597 trips more by sharing a car than his previous status. Examining travel time, however, we see that fewer trips do not necessarily mean less traveling. For example, these same users that make less frequent trips may also travel long distances or in congested conditions for longer times.

7.4.3 Longitudinal Effects of ICT

Turning to the effects of information and communication technologies on activity participation and travel summarized in Table 7-7, again we see evidence of a lack of symmetry and linearity. The ICT effect, however, is not always asymmetrical. For example, acquiring access to a computer at work is accompanied by 34 more minutes of work. In contrast, loosing access of computer at work is accompanied by 41 less minutes working. The net difference is a small number of about 7 minutes per day. When we look at these same two ICT variables and maintenance duration, gaining access of computers shows a negative 6.368 and loosing access a positive 6.398 demonstrating an almost perfectly symmetric effect. Then, turning to leisure duration we see that gaining access has an effect that is more than three times (-14.063) that of loosing access (4.135).

Comparing the experienced information and telecommunication users to the new users and non-users, we find the overall effect of computers and Internet at work to be an increase in subsistence participation and a decrease in leisure participation accompanied by less trip making. However, computers and Internet at home have the opposite effect on the two activities. The example is the amount of time allocated for leisure by the persons that are experienced users of computers at work and at home. The first group spends 20 minutes less in leisure per day and the second 22.7 more. As the average values of the ICT user indicators show we have an increase in technology users over time at home but not a substantial increase at work/school. The new computer users are 20.8 percent at home and new Internet users are 32 percent at home. The first group spends more time in all activities and travels more and the second group spends less time in activities and travels less. New users of computers at home, use public transportation more often and bike more often but exactly the opposite happens to the new users of the internet at home but at lower levels because of less trip making in general. Laptop users increase rapidly if one considers that experienced laptop users are 2 percent of the sample and new users are 3.2 percent. Experienced mobile technology users are also diverse but the experienced mobile technology users spend less time in subsistence and traveling, except that experienced cellular phone users travel more.

Table 7-7 Total and Direct Effects of ICT Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables									
		Sdur	mdur	ldur	ttime	ssov	shared	transt	walk	bike	others
Expcw	total	80.446	-10.356	-20.034	-1.284	-0.274	-0.083	0.004	0.018	0.006	0.036
	direct	76.868	0.000	0.000	0.000	-0.453	0.000	0.000	0.000	0.000	0.041
Novcw	total	34.121	-6.368	-14.063	-2.848	-0.246	-0.055	-0.003	0.007	-0.001	0.001
	direct	31.263	0.000	0.000	0.000	-0.330	0.000	0.000	0.000	0.000	0.000
Quitcw	total	-41.395	6.398	4.135	-0.575	-0.067	0.034	-0.030	0.086	0.005	0.005
	direct	-41.971	0.000	0.000	0.000	0.000	0.000	0.000	0.120	0.000	0.000
Expnw	total	5.690	-4.318	-8.281	5.581	-0.181	-0.423	0.010	0.013	0.023	0.064
	direct	0.000	0.000	0.000	9.547	-0.276	-0.390	0.000	0.000	0.000	0.078
Quitnw	total	0.324	-5.371	1.794	-1.072	-0.021	-0.020	0.032	-0.133	-0.001	-0.008
	direct	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.169	0.000	0.000
Expch	total	-2.831	6.622	22.699	10.719	0.228	0.079	0.054	0.029	0.001	-0.011
	direct	0.000	0.000	13.991	6.105	0.295	0.000	0.076	0.000	0.000	0.000
Novch	total	1.916	6.191	5.470	11.996	-0.095	0.064	0.104	0.048	0.042	0.049
	direct	0.000	0.000	0.000	7.056	0.000	0.000	0.136	0.000	0.029	0.071
Quitch	total	-0.555	-4.741	-2.565	-2.444	0.095	-0.052	-0.103	-0.050	0.000	0.002
	direct	0.000	0.000	0.000	0.000	0.000	0.000	-0.137	0.000	0.000	0.000
expnh	total	-16.479	1.039	2.164	-0.534	-0.033	0.008	-0.003	-0.003	0.002	0.000
	direct	-16.801	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
novnh	total	-0.845	-2.784	1.123	-7.318	0.045	-0.025	-0.051	-0.022	-0.017	0.007
	direct	0.000	0.000	0.000	-6.248	0.000	0.000	-0.068	0.000	-0.020*	0.000
quitnh	total	5.452	4.165	-22.869	10.004	0.014	-0.008	-0.001	-0.028	0.163	-0.055
	direct	0.000	0.000	0.000	11.346*	0.000	0.000	0.000	0.000	0.188	0.000
expcel	total	-1.499	-0.024	-4.238	7.743	-0.036	0.138	0.003	-0.001	-0.025	0.015
	direct	0.000	0.000	-11.155*	6.063	0.000	0.143*	0.000	0.000	-0.025	0.000
quitcel	total	4.452	-5.708	-12.919	-4.945	-0.395	-0.051	-0.011	0.001	0.003	0.001
	direct	0.000	0.000	0.000	0.000	-0.424	0.000	0.000	0.000	0.000	0.000
exppag	total	-30.531	1.925	4.009	-0.989	-0.060	0.015	-0.006	-0.006	0.003	0.000
	direct	-31.129	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
novpag	total	-0.511	6.506	30.782	0.821	0.040	0.063	-0.067	0.164	0.010	-0.016
	direct	0.000	0.000	37.413	0.000	0.000	0.000	0.000	0.201	0.000	0.000
explap	total	-91.257	5.754	11.983	-2.956	-0.180	0.044	-0.017	-0.019	0.009	-0.001
	direct	-93.043	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
novlap	total	-1.515	-7.502	-12.755	2.877	0.130	-0.089	-0.139	-0.070	-0.025	-0.085
	direct	0.000	0.000	0.000	10.078	0.000	0.000	-0.180	0.000	0.000	-0.104
novpda	total	42.700	-2.693	-5.607	1.383	0.084	-0.021	0.008	0.009	-0.004	0.001
	direct	43.536	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

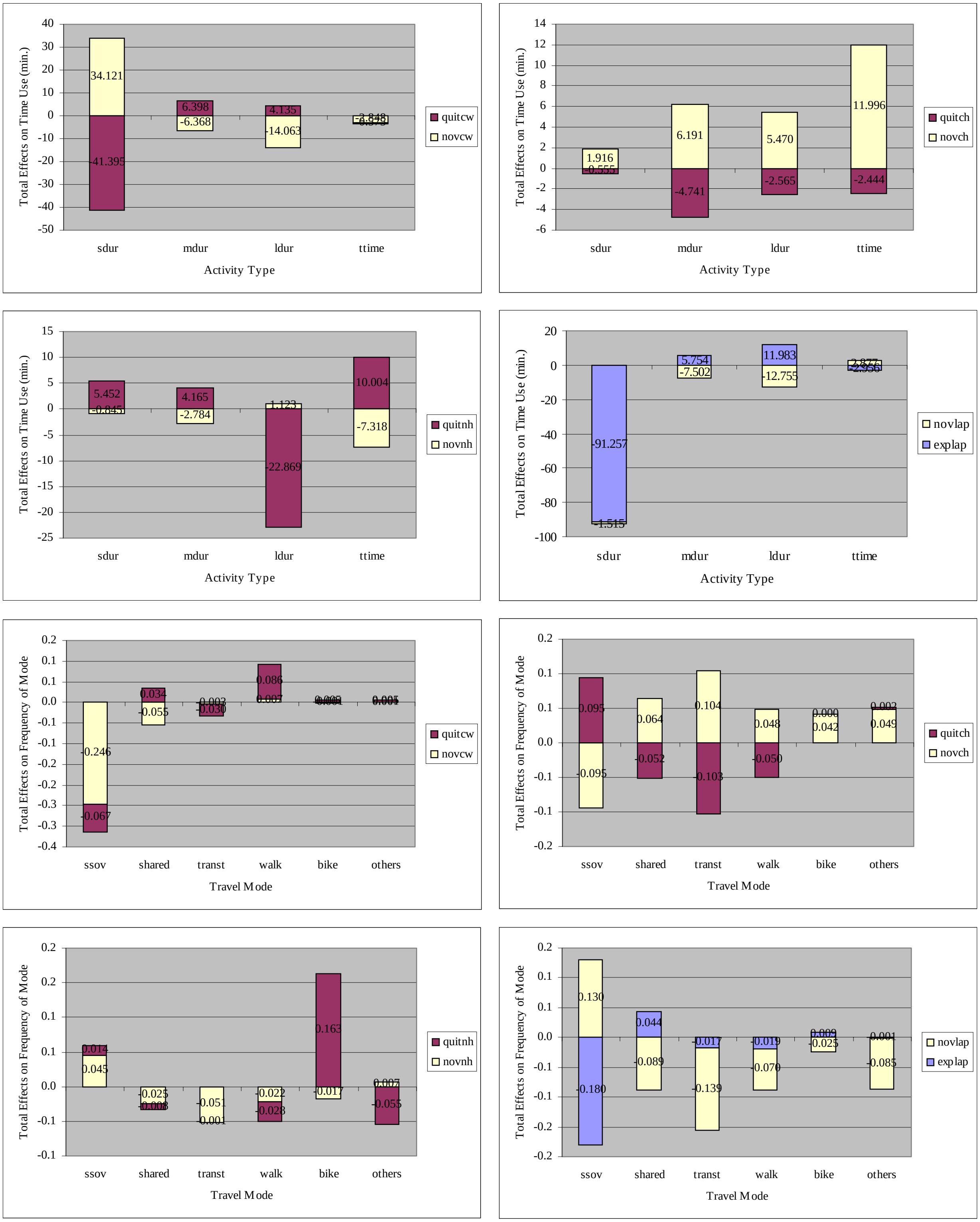


Figure 7-5 Total Effects of ICT Variables on Time Use and Mode Frequencies

Figure 7-5 provides a pictorial summary of the lack of symmetry and linearity in time use and mode frequencies for ICT user groups at different stages. One interesting occurrence found in Figure 7-5 is a quite different pattern in time use between the experienced laptop users and the new laptop users. Experienced and new users of ICT generally show a similar pattern in time use and trip frequency by mode (in Table 7-7, the same sign of the coefficients but different coefficients in magnitude). However, this is not the case for the laptop. Although both the experienced users and new users spend less time on subsistence activity than non-users and past-users, their magnitudes are quite different (-91.257 for experienced users and –1.515 for new users). In addition, these two groups of laptop users have the opposite patterns of time use for other activities and traveling (they have almost the same magnitude of coefficients but different signs). This opposite pattern of the two groups holds true for trips by SOV and shared modes.

7.5 Implications of ICT Changes

Policy makers and transportation planners are more concerned about how these ICT changes affect travel demands as a whole. As an example, the percent of people who use Internet regularly at home doubles from 30.9 percent to 60.5 percent between 1997 and 2000. Based on the model results and number of different levels of users in the sample, total effects of this substantial increase in Internet use at home on leisure duration are calculated. As shown in Figure 7-6, the total effects consist of three components:

- 915 minutes more in leisure activity by 423 experienced users;
- 531 minutes more in leisure activity by 473 new users; and
- 800 minutes less in leisure activity by 35 past users.

Therefore, the net effect of changes in Internet use at home between 1997 and 2000 is 646 minutes more in leisure activity by 1480 persons. It indicates that on an average, each person spend 0.44 minutes more in leisure activity per day, due to the changes in internet use at home.

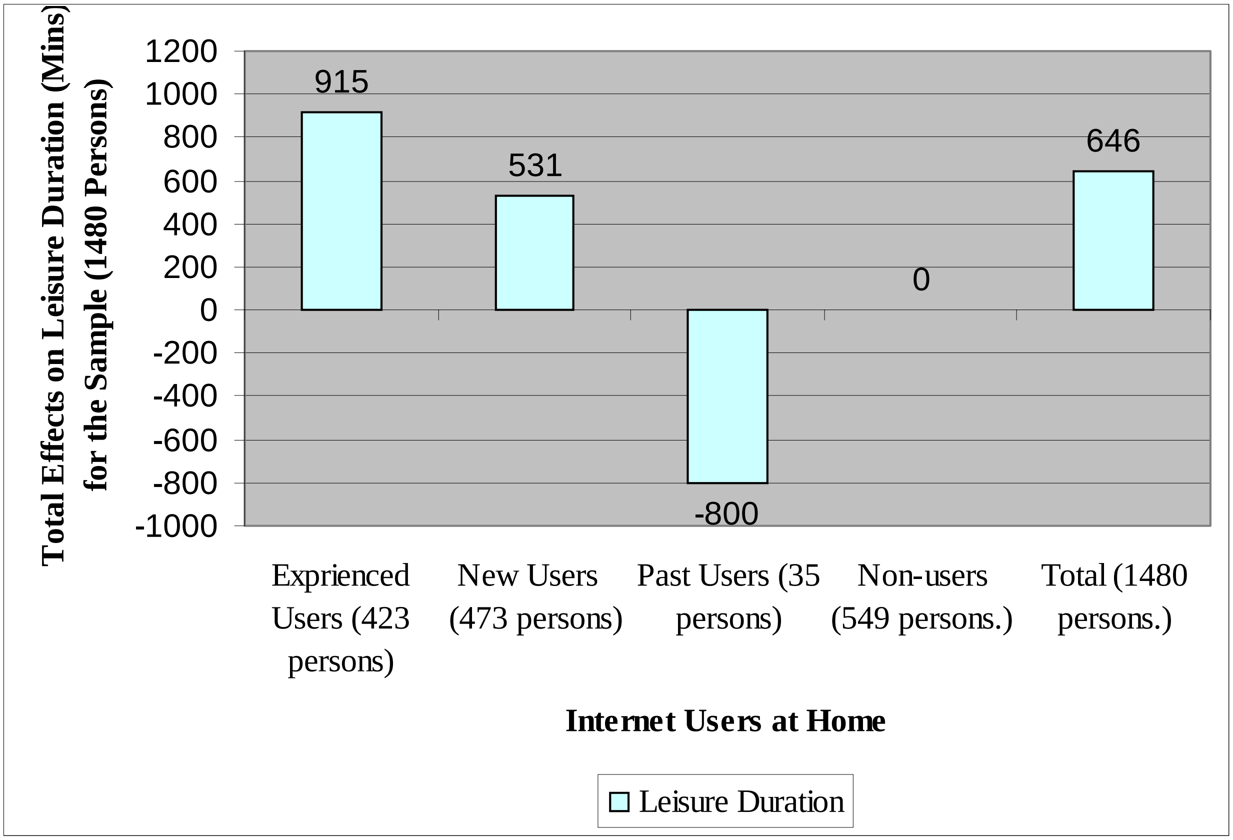


Figure 7-6 Total Effects of Changes in Internet Use at home between 1997 and 2000 on Leisure Duration

In a similar way, the effects of changes in Internet use at home on travel time are also calculated. Figure 7-7 shows that 1480 persons in the sample are predicted to spend 3337 minutes less in traveling as a whole. It indicates each person on average spends 2.25 minutes less in traveling. Although this appears to be a small number, when we consider the population of the Puget Sound, which is 3.3 million persons and if this result can be generalized we obtain a substantial travel impact.

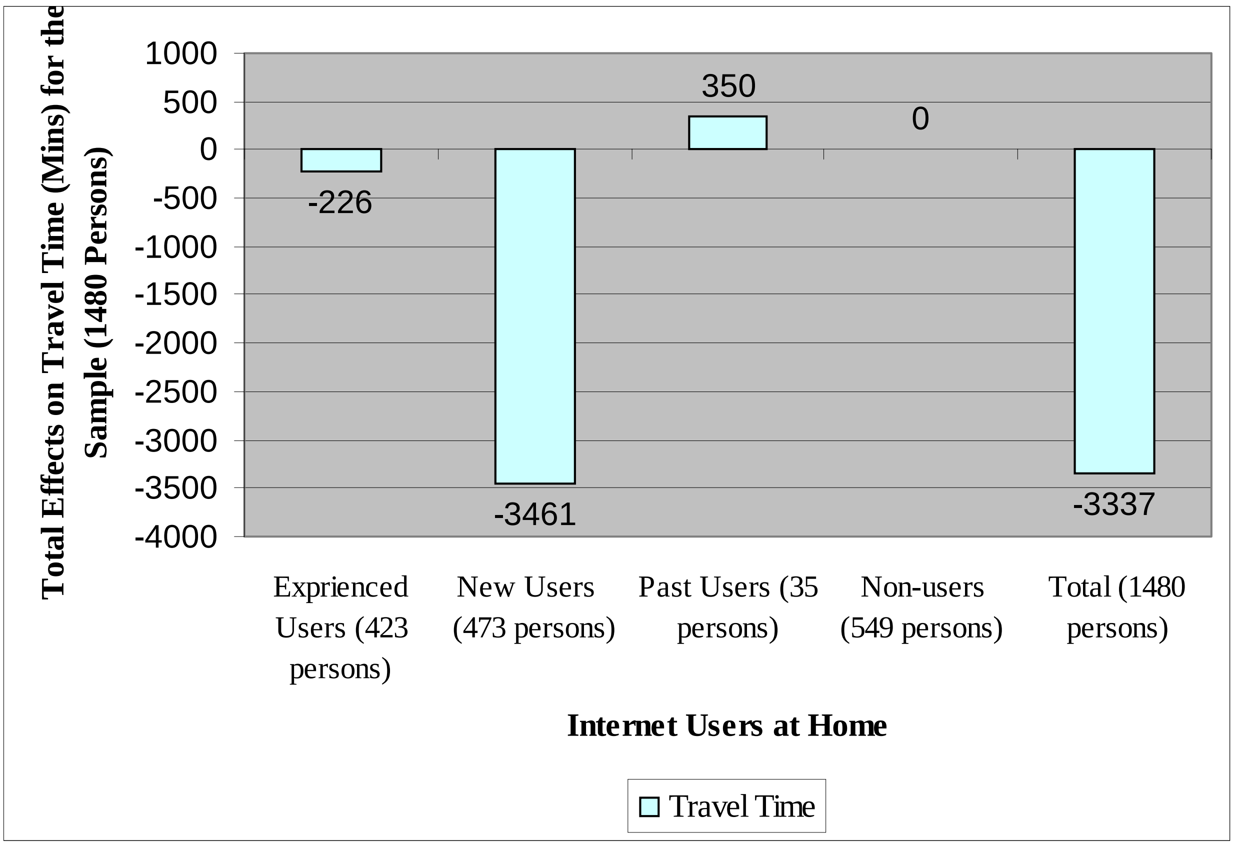


Figure 7-7 Total Effects of Changes in Internet Use at Home between 1997 and 2000 on Travel Time

In terms of the effect on travel frequency by SOV, the 1480 persons in the sample are predicted to spend only 7.8 more trips by SOV (Figure 7-8). It indicates each person on average make a 0.005 trips more by SOV.

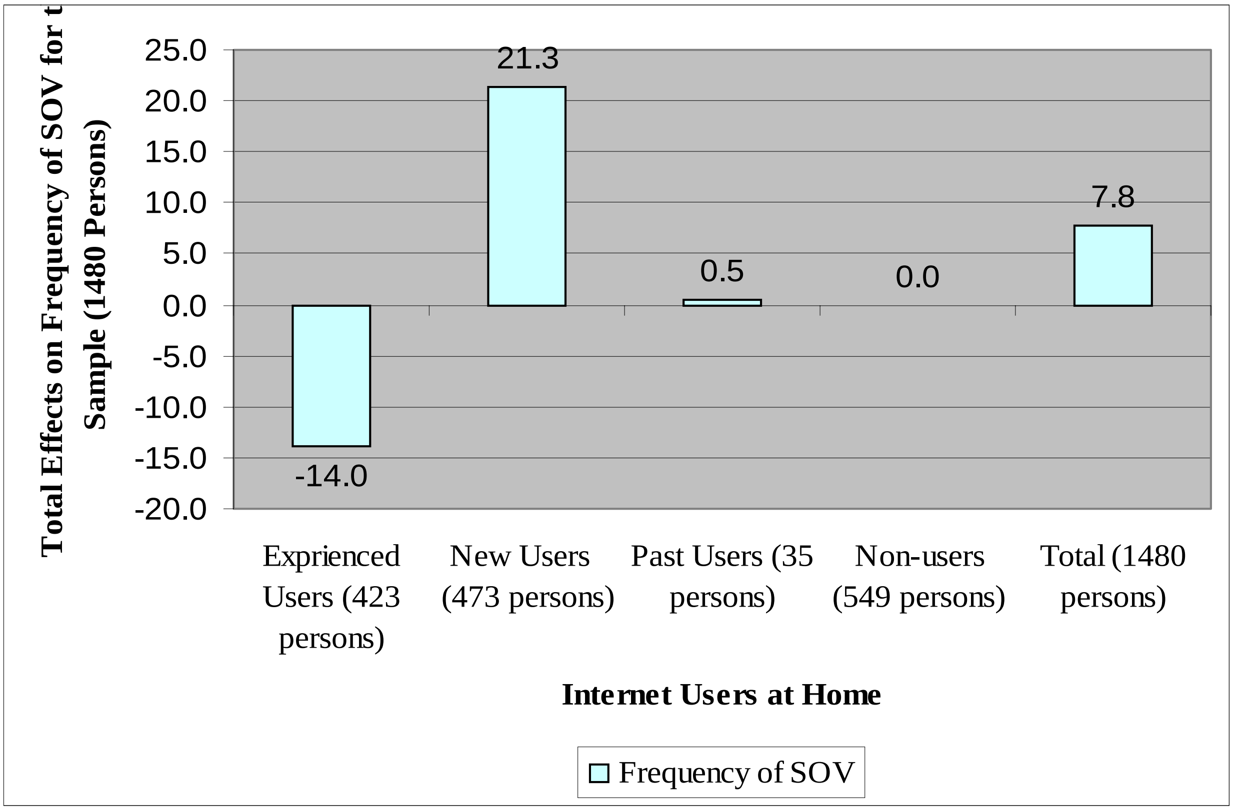


Figure 7-8 Total Effects of Changes in Internet Use at Home between 1997 and 2000 on the Frequency of SOV

In sum, the changes of Internet use at home between 1997 and 2000 have desirable net effects (more leisure activity and less travel) at a small cost (a tiny increase in SOV trip).

7.6 Summary

In this chapter a plethora of relationships among the most popular travel behavior indicators are studied. A system of equations is first defined that includes as dependent variables the amount of time allocated to subsistence, maintenance, leisure, and travel, as well as the total number of trips by the most important modes (drive alone, car sharing, public transportation, walking, biking, and all other modes used). The model system is designed to parallel other past studies and for this reason variables at the household and person level are used. In addition, some specific variables in the PSTP database are also employed to account for stratification and potential participation fatigue.

A key variant of the model system in this chapter that sets it aside from other studies is the inclusion of "experience" variables. Using information between 1997 and 2000 a large set of variables is defined to capture the changes in social and economic circumstances experienced by each respondent and include them as explanatory variables of the behavior in 2000. In this way we can detect if the experience of a specific event can explain behavior and if its opposite event has the same but of opposite sign effect on behavior. In the striking majority of social and economic changes we find significant, many times substantial, and asymmetric effects.

The second element that characterizes the research work here is the study of ICT on activity and travel behavior considered jointly with all the other determinants of travel behavior. Comparing experienced information and telecommunication users to the new users and to the non-users we find a variety of interesting results. The overall "technology" effect seems to depend on the location of technology. The overall effect of computers and Internet at work shows an increase in subsistence participation and a decrease in leisure participation accompanied by less trip making. Additionally, computers and the Internet at home have the opposite effect on the two activities. As the average values of these variables show we have an increase in technology users over time at home but not a substantial increase at work/school. The new computer users are 20.8 percent at home and new Internet users are 32 percent at home. The first group spends more time in all activities and travels more and the second group spends less time in activities and travels less. New users of computers at home, use public transportation more often and bike more often but exactly the opposite happens to the new users of the Internet at home but at lower levels because of less trip making in general.

The substantial increase in Internet use at home between 1997 and 2000 seems to have desirable net effects (more leisure activity and less travel) at a small cost (a tiny increase in SOV trip) on the sample as a whole.

CHAPTER 8

DYNAMIC ANALYSIS OF TIME USE AND FREQUENCY OF ACTIVITY AND TRAVEL WHILE ACCOUNTING FOR HISTROTY DEPENDENCY

8.1 Introduction

In activity analysis the core of model development is about time allocation of individuals. Understanding activity engagement and time use patterns, however, requires us to examine the effects of correlates on time allocation behavior, habit persistence and history dependence, and the impact of changes in the correlates. One very important correlate to time allocation behavior is the growing Information and Communications Technology (ICT) that has changed our traditional concept of accessibility (Golob, 2001; Golob and Regan, 2001).

As mentioned above, another important aspect in activity and travel behavior is the temporal state dependence in activity engagement and time use patterns. There have been several studies examining the role of state dependence in activity and travel behavior from temporal perspectives. Early applications include Kitamura and Kermanshah (1983), Kitamura (1983), a state dependent microsimulation model system in Goulias and Kitamura (1997), and lately Kasturirangan, Pendyala, and Koppelman (2002), who studied the role of history dependency in explaining activity-travel patterns of travelers. These studies confirm that the choice of activity and the amount of time allocated to an activity is dependent on the preceding activity engagement and time allocation pattern, and the extent of the dependency is likely to reduce as one proceeds back in time within a one- or two-day time frame. With the availability of panel surveys we can examine the state dependence in a longer period of time (behavioral habits), which is an important behavioral component but is hardly measured in a one- and two-day time frame.

To accomplish the needs described above, using the Puget Sound Transportation Panel (PSTP) data collected in 1997 and 2000, we developed a structural equation model (SEM) in which time use for a specific activity (in-home activity, out-of-home subsistence activity, and out-of home non-subsistence activity) and travel, and each activity frequency in 2000 are modeled as a function of cross-sectional and longitudinal information. The information analyzed includes personal and household socio-demographics in the year 2000, changes in socio-demographics and ICT ownership and availability between the years 1997 and 2000, and the activity and travel behavior patterns in 1997. In addition, a new approach to account for the effects of state dependence in activity engagement and time use is proposed to test if behavioral habits of individuals still persist within the 3-year time interval. We first employ a pattern recognition technique known as latent class (LC) cluster analysis to identify relatively homogenous behavioral groups with observed activity engagement and time use variables in 1997. Then we use group membership indicators as explanatory variables in a structural equation model. This way also allows us to avoid serial correlation problems in panel data.

Figure 8-1 shows the conceptual framework of the model. A plethora of relationships can be studied using this system. For example, the correlation among the amount of time allocated to in-home, out-of-home subsistence, out-of-home non-subsistence and travel, as well as the total number of activity episodes (in-home, out-of-home subsistence, out-of-home non-subsistence) can be estimated. The model system is designed to extend and parallel other past studies, and for this reason, variables at the household and person level are also used. In addition, some specific variables to the database in PSTP are also employed to account for its double stratification sampling.

This study attempts to develop a new method to account for state dependence effects in a time allocation model. Using activity engagement and time use indictors in 1997, homogenous groups are identified through LC cluster analysis and the group indicators are included as explanatory variables of the behavior in the year 2000 to account for behavioral habit persistence.

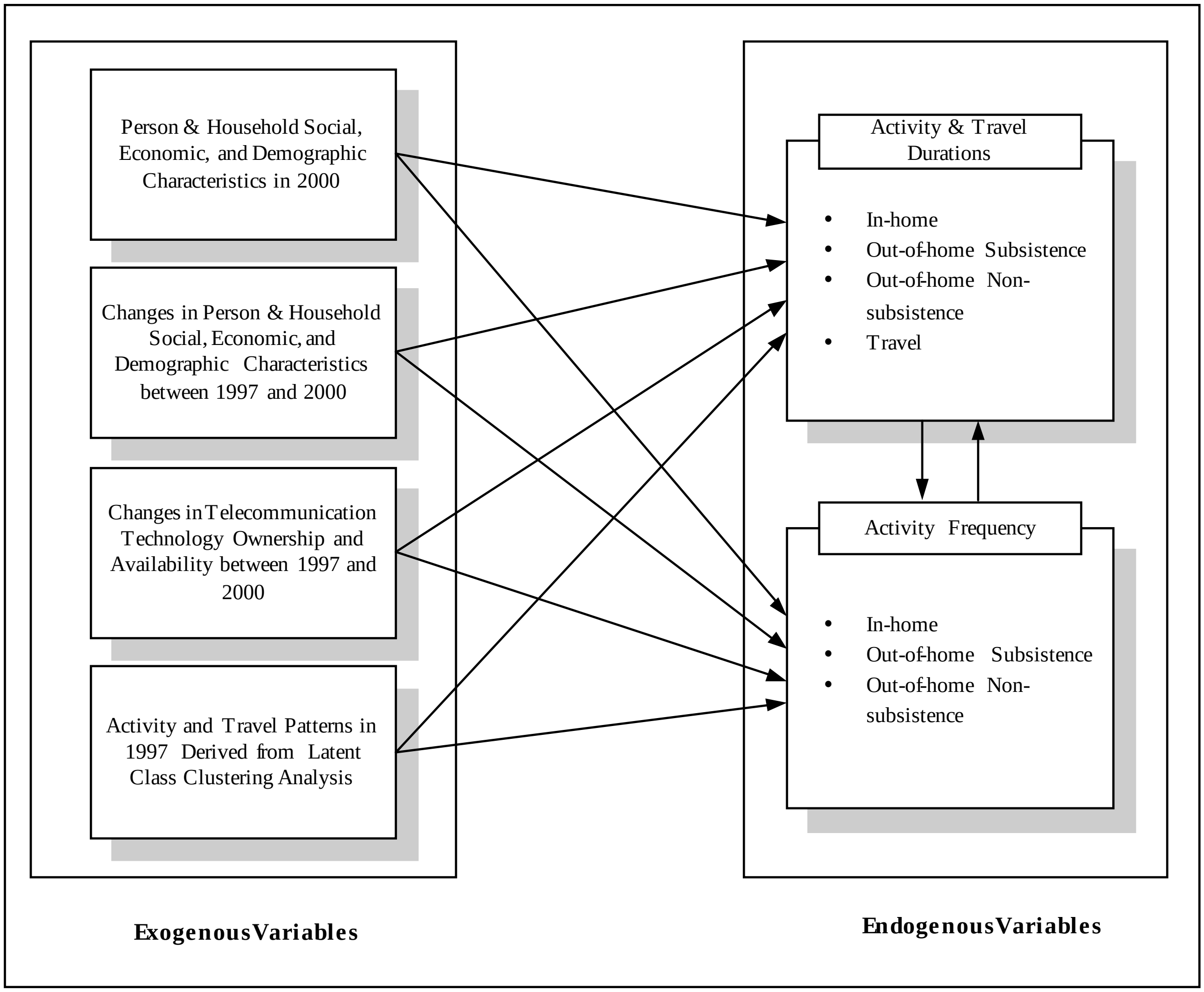


Figure 8-1 Conceptual Model

This allows us to achieve several research objectives at the same time, such as:

- Identifying complex relationships among in-home and out-of home activities and travel in terms of time use and frequency of activity participations;
- Checking if there are systematic differences in time use and frequency of specific activities among population segments, while controlling for other exogenous variables;
- Examining whether or not there are symmetric effects of changes of person and household socio-demographics and ICT ownership and availability on the time use and frequency of specific activities ; and

- Developing a new technique to account for state dependence (past activity and travel behavior effects) in models that assess the effects of ICT on activity participation and travel.

8.2 Data Used

For the analysis in this chapter, we used the same dataset that is used in Chapter 7. The data are from 1480 persons in 866 households who participated in both waves 7 and 9, and provided detailed information for all the variables used in this analysis. However, the extra efforts were made on the data set to extract additional information on activity durations before the first trip in the morning and after the final return trip to home in the evening, so that all respondents have 1440 minute time budget per day. It allows us to assess trade-off relationships more accurately among different activities and travel in time use.

In the original trip data of PSTP, the trip purpose for each trip has been classified into 9 different types at Wave 7 (work, school, college, shopping, personal business, appointment, visiting, free-time, and home) and 21 different types at Wave 9. The use of these different schemes for trip purposes between the waves makes it difficult to compare the two waves. To make the data for the two waves comparable and this analysis tractable, activity types have been grouped into:

- In-home;
- Out-of-home Subsistence (work, school, and college); and
- Out-of-home Non-subsistence (shopping, personal business, appointment, errand/picking-up/dropping-off, free time, recreation/exercise, visiting, etc)

Table 8-1 A Selection of Sample Characteristics

Characteristics			Wave 7 (1997)	Wave 9 (2000)
Number of persons in the sample			1480	1480
Number of households in the sample			866	866
Person & Household	Percent of males in the sample		46.9	46.9
	Number of employed persons in the sample		859	881
	Number of persons in household		2.5	2.5
	Number of cars per household		2.2	2.2
Activity & Travel Duration	Total amount of time in in-home activities (min.)	Day 1	965.2	1009.7
		Day 2	978.5	1017.7
	Total amount of time in out-of-home subsistence activities (min.)	Day 1	285.0	244.9
		Day 2	274.0	233.1
	Total amount of time in out-of-home non-subsistence activities (min.)	Day 1	104.9	110.4
		Day 2	108.2	115.4
	Total amount of time traveling (min.)	Day 1	84.9	75.0
		Day 2	79.4	73.8
Activity Frequency	Total number of trips per person	Day 1	4.57	4.08
		Day 2	4.30	3.98
	Number of in-home activity episodes	Day 1	2.43	2.26
		Day 2	2.36	2.23
	Number of out-of-home subsistence activity episodes	Day 1	0.98	0.81
		Day 2	0.93	0.81
	Number of out-of-home non-subsistence activities episodes	Day 1	2.15	2.01
		Day 2	2.01	1.93
Information & Communication Technology**	Number of persons who use computers regularly (%*)	At home	751 (50.7)	982 (66.4)
		At work	700 (47.3)	717 (48.4)
	Number of persons who use the Internet regularly (%*)	At home	458 (30.9)	896 (60.5)
		At work	438 (29.6)	544 (36.8)
	Number of persons having cellular phones (%*)		419 (28.3)	685 (46.3)
	Number of persons having pagers (%*)		156 (10.5)	129 (8.7)
	Number of persons having laptops (%*)		71 (4.8)	79 (5.3)
	Number of persons having PDAs (%*)		6 (0.4)	38 (2.6)

***** % over total number of person in the sample***

Table 8-1 shows the number of persons, households, and a few social and demographic characteristics of the sample. It also shows a descriptive summary of key variables during the two interview days in wave 7 (1997) and wave 9 (2000). Activity duration is the total amount of time each person spends in a specific activity in a day. Total travel time is the total amount of time spent by a person traveling during the day. Therefore, the sum of activity durations for various activities and total travel time is equal to 1440 minutes per day for each person. Activity frequency is the number of activity episodes for each activity type each person engaged in a day. However, it should be noted that in this study all activities before the first trip and after the last trip are considered as one activity episode, because travel diaries do not provide information on activities before the first trip and after the last trip (usually at home). Therefore, the total number of trips is the sum of activity episodes minus one.

As expected, and as found in earlier studies (Ma and Goulias, 1997a, 1997b) using PSTP data, people show more similar patterns of activity and travel behavior between the two days than between the two waves. The relatively large discrepancy between the two waves is most likely a result of genuine change but also the use of different coding schemes for trip purposes in the travel survey between the waves. However, it was found that there has been an increase in in-home activity and out-of-home non-subsistence activity durations between the waves but a decrease in out-of-home subsistence activity and traveling. In terms of activity–travel, in the year 2000, the respondents spent an average of 1013.7 minutes in in-home activity, 239.0 minutes in out-of-home subsistence activity, 112.9 minutes in out-of-home non-subsistence activity, and 74.4 minutes in travel per day.

8.3 Model Formulations

Two groups of activity-travel variables are used as the clustering variables in latent class cluster analysis for the data in 1997 and as the endogenous variables, using the 2000 data in the SEM. The first group of the variables is total amount of time dedicated to a specific activity (in-home, out-of-home subsistence and out-of-home non-subsistence) and traveling in a day. The second group is the number of activity episodes by the specific activity a person engaged in a day.

Table 8-2 List of Endogenous Variables

Endogenous Variables		Descriptions
Activity and Travel Durations	Hdur	Total in-home activity duration per day (min)
	Sdur	Total out-of-home subsistence activity duration per day (min)
	Nsdur	Total out-of-home non-subsistence activity duration per day (min)
	Ttime	Total travel time per day (min)
Number of Activity Episodes	Finhome	Number of in-home activity episodes per day
	Fsub	Number of out-of-home subsistence activity episodes per day
	Fnsub	Number of out-of-home non-subsistence activity episodes per day

For exogenous variables, five groups of variables were used: household-level variables, person-level variables, time-related variables, ICT variables, and previous activity participation pattern variables. We used cross-sectional information in the year 2000, as well as longitudinal information between the years 1997 and 2000 about household-level and person-level social, economic, demographic characteristics and ICT ownership and availability. In addition, to take into account state dependence effects, we also used activity engagement and time use patterns in the year 1997 derived from latent class cluster analysis.

Two types of time variables are included. The first type is a diary day indicator to account for a correlation between the first and second diary day. The second type is the set of day of week indicators to account for different activity and travel behaviors among weekdays. Appendix contains a comprehensive description of the exogenous variables used here.

The use of structural equation modeling techniques is employed in this study, due to their capability to estimate a set of simultaneous equations capturing the interrelationship among a large number of endogenous and exogenous variables. The model building and analysis using SEM parallels the previous chapter.

8.4 Model Results

8.4.1 Activity Participation Patterns in 1997

In order to derive the latent class clusters to find relatively homogenous groups of activity participation behavior in 1997, the following clustering variables are used:

- Total in-home activity duration in day1 and day2 (Hdur1, Hdur2);
- Total out-of-home subsistence activity duration in day1 and day2 (Sdur1, Sdur2);
- Total out-of-home non-subsistence activity duration in day1 and day2 (Nsdur1, Nsdur2);
- Total travel time in day1 and day2 (Ttime1, Ttime2);
- Number of in-home activity episodes in day1 and day2 (Finhome1, Finhome2);
- Number of in-home activity episodes in day1 and day2 (Fsub1, Fsub2); and
- Number of out-of-home non-subsistence activity episodes in day1 and day2 (Fnsub1, Fnsub2).

Table 8-3 The Sequence of Models Estimated for Activity and Travel Behaviors

		LL	BIC(LL)	AIC(LL)	Npar
Model 1	1-Cluster	-92338.7865	184838.1685	184721.5729	22
Model 2	2-Cluster	-86319.8193	172968.1294	172729.6385	45
Model 3	3-Cluster	-83766.9011	168030.1885	167669.8023	68
Model 4	4-Cluster	-82626.8309	165917.9434	165435.6618	91
Model 5	5-Cluster	-81587.2689	164006.7146	163402.5377	114
Model 6	6-Cluster	-80811.3452	162622.7627	161896.6905	137
Model 7	7-Cluster	-80265.0504	161698.0683	160850.1008	160
Model 8	7-Cluster*	-79319.8912	160289.5366	159091.7824	226

** final model with covariates*

As seen in Table 8-3, with these variables, we start from a one-cluster model, then build in a sequence of models with more clusters until the cluster sizes become too small to be meaningful and the difference in goodness of fit between successive models is not significant, and finally reach the final 7-cluster model. As the number of clusters increases, the goodness-of–fit of a model is also improving. Table 8-4 shows the seven types of activity–travel behavior and their average profiles showing wide variability in time allocation and frequency of activity episodes among clusters. Table 8-5 shows the distribution of average membership probability for employment, gender, age, group, and residence place.

Table 8-4 Average Profile of Activity and Travel Clusters

Variables used to create clusters		Cluster1 (Nworker)	Cluster2 (Worker_a)	Cluster3 (Worker_b)	Cluster4 (Worker_c)	Cluster5 (Pwork_a)	Cluster6 (Hbound)	Cluster7 (Pwork_b)
Cluster Size (%)		23.92	21.14	17.01	13.75	10.18	7.19	6.80
Day 1	Hdur1(min.)	1259.59	792.71	775.61	799.82	812.93	1305.55	1143.11
	Sdur1 (min.)	0.00	443.10	524.33	564.53	240.05	0.00	0.28
	Nsdur1 (min.)	120.17	91.32	49.66	1.48	280.93	91.69	191.07
	Ttime1 (min.)	60.23	112.87	90.40	74.17	106.09	42.76	105.53
	Finhome1	2.49	2.69	2.49	2.08	2.46	1.84	2.57
	Fsub1	0.00	1.91	1.62	1.36	1.12	0.00	0.01
	Fnsub1	2.78	2.24	1.81	0.27	2.67	1.94	3.82
Day 2	Hdur2 (min.)	1227.70	783.03	794.91	810.57	1021.12	1439.73	957.30
	Sdur2 (min.)	0.03	417.69	523.41	555.88	0.03	0.00	296.25
	Nsdur2 (min.)	142.08	123.76	38.24	1.01	337.86	0.19	102.03
	Ttime2 (min.)	70.20	115.52	83.44	72.54	80.98	0.07	84.42
	Finhome2	2.57	2.68	2.42	2.06	2.32	1.02	2.60
	Fsub2	0.00	1.74	1.63	1.37	0.01	0.00	1.33
	Fnsub2	2.99	2.41	1.62	0.26	3.11	0.02	2.24
Number of cases: 1480					BIC (based on LL): 160289.54			
Number of parameters (Npar): 226					AIC (based on LL): 159091.78			
Log-likelihood (LL): -79319.89					CAIC (based on LL): 160515.54			

The first and largest cluster contains 23.9 percent of the sample and appears to be the non-workers cluster. This group has the second longest time at home (22-22.5 hours per day), no subsistence activity time, and a high frequency of non-subsistence activity episodes in both days. The second, third, and fourth clusters appear to be regular workers/students clusters with 21.1 percent, 17.0 percent, and 13.8 percent of the sample, respectively. Although all these groups have a consistent activity-travel pattern between the two days, they have different levels of activity participation patterns. The second cluster (worker_a) and the fourth cluster (worker_c) show two different ends of activity-travel behavior for regular workers/ students, the third cluster (worker_b) is the "middle" between these two behaviors. In other words, among the three groups, worker_a group has the shortest time in subsistence activity but the longest time in non-subsistence activity and traveling in both days. This group is also characterized by high frequency of episodes in all activity types. On the other hand, worker_c group has the longest time in subsistence activity and in-home activity but the shortest time in non-subsistence activity and traveling. Worker_c group is characterized by low frequency of all activity episodes. The sixth cluster (hbound) with 7.2 percent of the sample is characterized by their home bound activity behavior in both days. This group spends the majority of time on in-home activity and a very short time on out-of-home activity and traveling. The other clusters (pwork_a and pwork_b) have different time use patterns in in-home and subsistence activity between the two days.

Table 8-5 provides further insights about these groups. The unemployed persons have the highest probability of belonging to cluster 1, while the employed persons are more likely to belong to clusters 2, 3, or 4 (especially cluster 2). Age is also a useful explanatory variable for clustering activity patterns of people. Young people (age 15-24) have the highest probability of belonging to Cluster 1 but very low probability to be in clusters 3 and 6, while older people (age 65-98) are more likely to belong to cluster 1. As people are getting older the probability of belonging to cluster 2 or 4 is generally decreasing, but the probability of belonging to cluster 3 is initially increasing and then decreasing with a peak at age 45-64.

These seven clusters map completely activity and travel behavior of the survey respondents in wave 7 (1997) and they are used to represent past behavior. To do this membership to each cluster is used as the explanatory variable in the structural equations model.

Table 8-5 Average Membership Probabilities for Activity and Travel Clusters

Covariates		Cluster1 (Nworker)	Cluster2 (Worker_a)	Cluster3 (Worker_b)	Cluster4 (Worker_c)	Cluster5 (Pwork_a)	Cluster6 (Hbound)	Cluster7 (Pwork_b)	Total
Employ	Yes	0.0289	0.3013	0.2897	0.2184	0.0808	0.0116	0.0692	1.0000
	No	0.5300	0.0870	0.0047	0.0258	0.1309	0.1553	0.0664	1.0000
Gender	Male	0.2009	0.2306	0.1830	0.2012	0.0845	0.0584	0.0415	1.0000
	Female	0.2729	0.1945	0.1587	0.0815	0.1171	0.0838	0.0914	1.0000
Age	15-17	0.0000	0.6447	0.0008	0.2744	0.0800	0.0000	0.0000	1.0000
	18-24	0.1304	0.4866	0.0006	0.2954	0.0451	0.0000	0.0418	1.0000
	25-34	0.1313	0.2655	0.2045	0.2163	0.0486	0.0500	0.0836	1.0000
	35-44	0.1198	0.2990	0.2336	0.1495	0.1310	0.0167	0.0504	1.0000
	45-54	0.0987	0.2562	0.2614	0.1997	0.0713	0.0318	0.0808	1.0000
	55-64	0.2969	0.1733	0.1512	0.1225	0.1094	0.1093	0.0375	1.0000
	65-98	0.5387	0.0366	0.0274	0.0122	0.1327	0.1569	0.0955	1.0000
Residence County	King	0.2241	0.2189	0.1882	0.1393	0.0976	0.0546	0.0773	1.0000
	Kitsap	0.2539	0.2437	0.1062	0.0849	0.0942	0.1244	0.0927	1.0000
	Pierce	0.2943	0.1760	0.1396	0.1454	0.0895	0.0969	0.0582	1.0000
	Snohomish	0.2084	0.2116	0.1956	0.1560	0.1311	0.0574	0.0398	1.0000

8.4.2 Cross-sectional Effects

Figure 8-2 and Table 8-6 provide an overview of the complex relationships found among the amount of time allocated to activities and travel in 24-hour framework in each day by each person and the number of activity episodes in the year 2000 (wave 9) of PSTP. Trip frequency is also implicitly included in the model, because the number of trips is also the frequency of activity episodes that involve the change of an activity location. Therefore, there is a relationship between the number of trips and the number of activity episodes in our variables: The total number of trips = Sum of the number of activity episodes – 1. In the section with label “goodness-of-fit indices” we see that every indicator shows a model with excellent fit to the data.

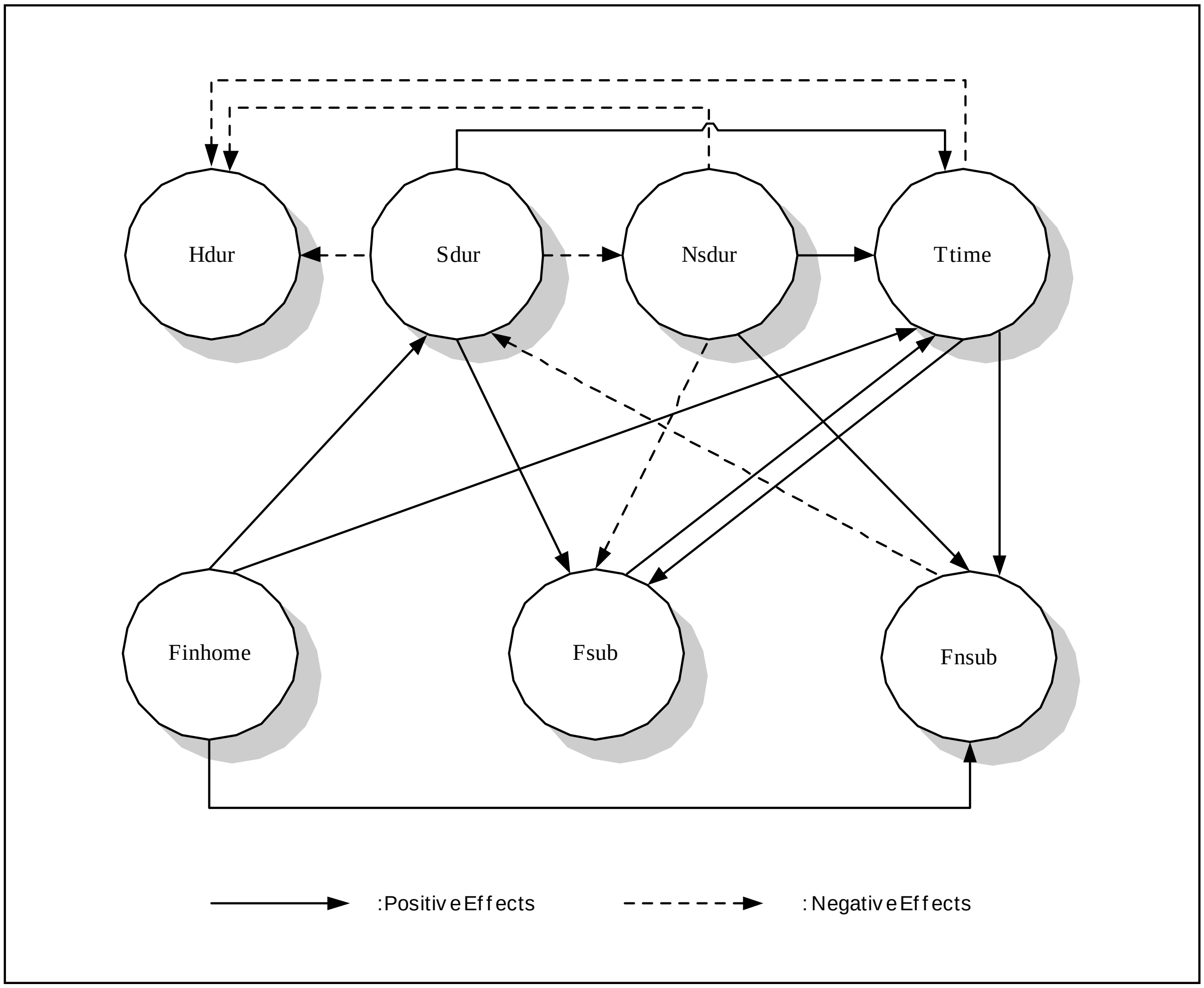


Figure 8-2 Path Diagram Among Endogenous Variables Based on Direct Effects

Table 8-6 Total, Direct, and Indirect Effects among Endogenous Variables

Causal Endogenous Variables		Resulting Endogenous Variables						
		hdur	sdur	nsdur	ttime	finhome	fsub	fnsub
sdur	total	-0.834	0.004	-0.194	0.024	0.000	0.002	0.000
	direct	-1.000	0.000	-0.193	0.029	0.000	0.002	0.000
	Indirect	0.166	0.004	-0.001	-0.004	0.000	0.000	0.000
nsdur	total	-1.022	-0.064	0.012	0.074	0.000	0.000	0.003
	direct	-1.000	0.000	0.000	0.076	0.000	-0.000	0.002
	Indirect	-0.022	-0.064	0.012	-0.002	0.000	0.000	0.001
ttime	total	-0.843	-0.215	0.042	0.017	0.000	0.004	0.010
	direct	-1.000	0.000	0.000	0.000	0.000	0.004	0.010
	Indirect	0.156	-0.215	0.042	0.017	0.000	0.000	0.000
finhome	total	-19.627	-6.667	1.289	25.018	0.000	0.083	1.337
	direct	0.000	22.025	0.000	24.628	0.000	0.000	1.090
	Indirect	-19.627	-28.692	1.289	0.390	0.000	0.083	0.247
fsub	total	-4.907	-1.252	0.242	5.921	0.000	0.020	0.058
	direct	0.000	0.000	0.000	5.821	0.000	0.000	0.000
	Indirect	-4.907	-1.252	0.242	0.100	0.000	0.020	0.058
fnsub	total	17.901	-21.545	4.164	-0.518	0.000	-0.037	0.004
	direct	0.000	-21.456	0.000	0.000	0.000	0.000	0.000
	Indirect	17.901	-0.089	4.164	-0.518	0.000	-0.037	0.004
Goodness-of–fit Indices		Chi-Square =224.535, d.f.=308, P-value=1.000 Chi-Square/d.f =0.729 NFI=0.998 TLI =1.007 CFI =1.000 RMSEA =0.000, 90 Percent C.I. of RMSEA=(0.000 0.000), Probability(RMSEA <=0.05) =1.000						

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 95% level. However, the values of –0.000 or +0.000 indicate that the effects are less than 0.0005 in magnitude, but significant at 95 % level.
All are significant at 95% level

Turning to the effects among endogenous variables, in-home duration does not influence any other variable and therefore it is implicitly treated as the outcome of all the other indicators. One way of looking at the relationships among daily in-home duration (hdur), daily out-of-home subsistence duration (sdur), daily out-of-home non-subsistence duration (nsdur), and daily travel time (ttime) is to consider the possible effect of a minute more in one type of activity on another. Table 8-6 shows clear trade-off relationships among the time use indicators. Persons that work/study longer are more likely to spent less time in in-home (-0.834) and non-subsistence (-0.194). This is evidence of time budgeting by individuals and their households. However, with information on respondents' time use between their first trips and last trips in a day, Goulias, Kilgren, and Kim (2003) find that there is extreme variation in “budgeting” and the existence of multiple groups with very different budgets. As expected, persons that spend more time working/studying are more likely to travel longer (0.024). Note that the coefficient of the direct effect of subsistence on in-home is one, implying a perfect trade-off between subsistence and in-home durations. Non-subsistence duration has also a perfect substitution effect on time expenditure on in-home activity (-1.022), while it has a very negative and small effect (-0.064) on subsistence. Persons that have longer non-subsistence are also more likely to travel longer (0.074), but the effect of non-subsistence is larger than the effect of subsistence before. The total effect of travel on in-home is also negative and very large (-0.843). Therefore, the large effects of subsistence, non-subsistence, and travel on in-home activity indicate the existence of almost perfect substitutions in time use between in-home activity and the other activities and travel.

Moving to the effects of daily activity durations on the number of activity episodes, we observed the overall lack of influence of time allocation on the number of activity episodes. It is more likely that the number of episodes determine activity duration and not the other way around confirming a similar finding in the previous chapter. Persons with longer durations in subsistence and non-subsistence are more likely to have more episodes of subsistence and non-subsistence, respectively. In addition, longer travel time appears to have a positive effect on subsistence and non-subsistence episodes, but the effects on subsistence episodes is smaller than those on non-subsistence episodes.

When we consider the effect of the number of activity episodes on time allocation we find some interesting relationships. The frequency of in-home episodes are accompanied by a negative effect on the amount of time allocated to in-home (-19.6 minutes) and subsistence (-6.7 minutes), but a positive effect on non-subsistence (1.3 minutes) and travel time (25.0 minutes) as expected. It is because the higher frequency of in-home activities means more trip chains, which is more likely resulting in more non-subsistence activity involvement and traveling. The frequency of subsistence episodes has also a similar but much smaller effect on all activity durations (its effect on all activity durations are between 1/4 to 1/5 that of subsistence episode). However, non-subsistence episode is accompanied by longer daily allocations to in-home and non-subsistence, but not subsistence and travel. The large difference between direct and total effect of in-home episodes on in-home and subsistence durations is a justification of using structural equation models for a better understanding of the effect one variable has on another. Overall, the effect of activity episodes on the activity durations appears to be much stronger than the effect of activity durations on the activity episodes.

Moving to the effects among the frequency of activity episodes, in-home episodes have a positive and small effect (0.08) on subsistence episodes but a positive and large effect (1.34) on non-subsistence episodes, as expected. Subsistence episodes have a positive and small effect (0.02) on non-subsistence episodes, while non-subsistence episodes on subsistence episodes have a negative and small effect (-0.04).

Due to PSTP’s double stratification sampling, we include as explanatory variables factors used in the stratifications (e.g., household classification with respect to usual mode and county of residence). Table 8-7 shows that the inclusion of these variables explains some of the variation in the endogenous variables and, as expected, there are large differences among the segments that reside in different counties.

Table 8-7 Total and Direct Effects of Cross-sectional Household-level Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables						
		hdur	sdur	nsdur	ttime	finhome	fsub	fnsub
carpool	total	3.546	-4.268	0.825	-0.103	0.000	-0.007	0.199
	direct	0.000	0.000	0.000	0.000	0.000	0.000	0.198*
transit	total	-8.551	-5.767	1.115	13.210	0.073	0.185	0.344
	direct	0.000	0.000	0.000	10.420	0.073*	0.145	0.133*
kitsap	total	-27.050	23.588	-4.559	8.022	0.000	0.291	0.300
	direct	0.000	30.017	0.000	5.996	0.000	0.223	0.231
snoho	total	-8.564	1.256	-0.243	7.681	0.000	0.031	-0.059
	direct	0.127	0.000	0.000	7.484	0.000	0.000	-0.133*
totadult	total	12.003	-14.447	2.792	-0.347	0.000	-0.025	-0.185
	direct	0.000	-18.409	0.000	0.000	0.000	0.000	-0.187
tot6_17	total	-2.471	-3.642	0.704	5.412	0.218	0.014	0.394
	direct	0.000	0.000	0.000	0.000	0.218	0.000	0.102
tot1_5	total	3.672	-7.547	1.459	2.418	0.103	-0.003	0.458
	direct	0.000	0.000	0.000	0.000	0.103*	0.000	0.318
midinc	total	-38.141	9.392	19.028	9.726	0.127	0.044	0.275
	direct	0.000	12.507	20.843	4.648	0.127	0.000	0.000
highinc	total	-36.961	-3.313	33.111	7.167	0.174	0.082	0.333
	direct	0.000	0.000	32.471	0.000	0.174	0.073*	0.000
mhinc	total	-42.131	-2.618	41.723	3.028	0.000	-0.009	0.122
	direct	0.000	0.000	41.217	0.000	0.000	0.000	0.000
dkinc	total	-50.709	1.932	38.162	10.621	0.000	0.028	-0.090
	direct	0.000	0.000	38.536	7.516	0.000	0.000	-0.278
car2	total	-1.423	-0.483	0.093	1.814	0.073	0.006	0.097
	direct	0.000	0.000	0.000	0.000	0.073	0.000	0.000
car3_	total	-14.729	-0.915	14.586	1.059	0.000	-0.003	0.043
	direct	0.000	0.000	14.410*	0.000	0.000	0.000	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

In the same table, we see some interesting household composition effects. In general households with more children spend less time engaging in subsistence but more time in non-subsistence and travel. The effect on the number of in-home and non-subsistence episodes is positive for persons in households with children in the age group of 1 to 17. However, children in the age group of 1 to 5 and in the age group of 6 to 17 have different effects on in-home duration and the number of subsistence episodes. Households with more children in the age group of 6 to 17 have a negative effect on in-home durations and a positive effect on the number of subsistence episodes, while households with more children in the age group of 1 to 5 have the opposite effects on the two variables. In addition, as expected, the person in a household with more adults spends more time engaging in in-home and non-subsistence and less time in subsistence and travel. The number of subsistence and non-subsistence episodes is lower for persons in households with more adults. The household income indicators show that in general wealth is accompanied with spending more time in non-subsistence and travel and less time in in-home activity. The persons in a household with \$35,000-\$75,000 annual income spend more time engaging in subsistence activity than the other income groups. The number of activity episodes is higher for persons with higher household income, indicating that wealthy people are more active in their time allocation and activity participation.

Table 8-8 shows the effect of person-level and time-related variables. As expected, working more than 5 times a week and attending a school or college are the two largest factors on subsistence activity durations. Males are also an important positive factor on subsistence duration. Persons in the age group of 18-34 with a driver's license spend more time on non-subsistence than any other age group. Additionally, having a driver's license or bus pass are the largest contributors to total travel time in a day. Since in-home activity durations are determined by other activity and travel durations, all the factors that have large positive effects on other activity and travel durations, have negative effects on in-home activity durations. People have different patterns of time use within the various occupation types. For example, people having a professional position spend less time on in-home but more on travel than those in other occupations. On the other hand, people who are in secretarial occupations are engaged less in subsistence and more in non-subsistence activities. The sales person travels more than any other occupation as expected.

Table 8-8 Total and Direct Effects of Cross-sectional Person-level and Time-related Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables						
		hdur	sdur	nsdur	ttime	finhome	fsub	fnsub
male	total	-34.349	32.317	-6.246	8.279	0.000	0.084	-0.204
	direct	0.000	27.943	0.000	7.338	0.000	0.000	-0.271
young	total	-79.784	-4.957	79.012	5.735	0.000	-0.017	0.231
	direct	0.000	0.000	78.054	0.000	0.000	0.000	0.000
midage	total	-29.728	-5.496	30.083	5.145	0.123	-0.001	0.383
	direct	0.000	0.000	29.020	0.000	0.123	0.000	0.131
prof	total	-6.075	-1.550	0.300	7.329	0.000	0.025	0.072
	direct	0.000	0.000	0.000	7.205	0.000	0.000	0.000
manag	total	-2.154	-0.732	0.141	2.746	0.110	0.009	0.147
	direct	0.000	0.000	0.000	0.000	0.110*	0.000	0.000
secre	total	-4.303	-1.462	0.283	5.485	0.219	0.018	0.293
	direct	0.000	0.000	0.000	0.000	0.219	0.000	0.000
Sales	total	38.561	-56.543	10.928	7.062	0.335	-0.066	0.458
	direct	0.000	-54.088	0.000	0.000	0.335	0.000	0.000
wk5	total	-127.124	151.003	-29.185	5.294	0.000	0.547	-0.510
	direct	0.000	140.064	0.000	0.000	0.000	0.280	-0.497
dpupil	total	-2.306	71.073	-66.526	-2.250	0.000	0.128	-0.934
	direct	0.000	51.044	-52.790	0.000	0.000	0.000	-0.764
Dlicen	total	-54.384	-5.723	46.049	14.067	0.430	0.026	0.708
	direct	0.000	0.000	44.943	0.000	0.430	0.000	0.000
dbpass	total	-30.121	18.681	-3.610	15.208	0.083	0.196	0.232
	direct	0.151	21.810	0.000	11.753	0.083*	0.108	0.000
day2	total	10.796	-12.994	2.511	-0.312	0.000	-0.022	0.003
	direct	0.000	-12.940	0.000	0.000	0.000	0.000	0.000
Tue	total	1.070	-3.109	0.601	1.439	0.060	0.000	0.207
	direct	0.000	0.000	0.000	0.000	0.060	0.000	0.126
Wed	total	-4.350	-1.132	0.219	5.351	0.000	0.018	0.053
	direct	0.086*	0.000	0.000	5.261	0.000	0.000	0.000
Thu	total	-24.364	22.791	-4.405	5.979	0.000	0.060	0.049
	direct	0.000	23.834	0.000	5.312	0.000	0.000	0.000
Fri	total	-5.181	-1.322	0.256	6.251	0.000	0.021	0.062
	direct	0.000	0.000	0.000	6.146	0.000	0.000	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

In terms of the frequency of activity episodes, the number of non-subsistence episodes is lower for males, full-time workers, and students, but higher for persons in the age of 35-64, persons having a sales occupation, and people having a driver's license. Full-time workers, students, and persons having a bus pass have an expectedly positive effect on the number of subsistence episodes.

Time related variables in the bottom of Table 8-8 confirm the existence of daily and weekly variability in people's time allocation patterns. For example, the activity participation pattern on Friday is quite different from the other weekdays. On Thursday, people spend the longest time on subsistence and spend the least time on in-home and non-subsistence. In terms of time allocation and activity episodes, there are similarities between Wednesday and Friday. Monday is used as the reference day and Saturdays and Sundays are absent from this database.

8.4.3 Longitudinal Effects

Unlike cross-sectional data, panel data enable us to measure change in a variable and concomitant effect on another. From an activity-travel behavior viewpoint it is also interesting and useful to know if there is behavioral symmetry when the changes happen in opposite directions. For example, is the difference in activity participation the same when a person looses a job and when s/he gains a job? Or what is the effect of socio-demographic changes in the household (that is, an increase or a decrease in the number of children in the household)?

The variables reported in Table 8-9 aim to describe the difference in activity and travel behavior among households and individuals that experienced diametrically opposed events such as increase in employed persons versus a decrease in employed persons, increase in household cars versus a decrease in household cars, as well as personal changes such as change in employment status.

As seen in Table 8-9, in all the events, the effects of personal and household changes on time allocation to activity and travel and the number of activity episodes are not symmetrical.

Table 8-9 Total and Direct Effects of Household-level & Person-level Change Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables						
		hdur	sdur	nsdur	ttime	finhome	fsub	fnsub
inadult	total	-2.837	-0.852	0.165	3.196	0.128	0.011	0.171
	direct	-0.330	0.000	0.000	0.000	0.128	0.000	0.000
dnadult	total	-9.342	-2.697	0.521	11.523	0.189	0.039	0.320
	direct	0.000	0.000	0.000	6.682	0.189	0.000	0.000
inkid	total	-3.686	4.436	-0.857	0.107	0.000	0.008	-0.207
	direct	0.000	0.000	0.000	0.000	0.000	0.000	-0.206*
dnkid	total	-20.819	34.928	-6.751	-7.062	0.000	0.031	-0.084
	direct	0.303	33.127	0.000	-7.729	0.000	0.000	0.000
inbaby	total	-30.287	11.491	32.716	-13.927	-0.246	-0.047	-0.788
	direct	0.000	0.000	34.937*	-10.403*	-0.246	0.000	-0.456
dnbaby	total	5.972	1.524	-0.295	-7.206	0.000	0.087	-0.071
	direct	0.000	0.000	0.000	-7.732	0.000	0.111*	0.000
inlicen	total	-17.644	30.293	-5.855	-6.631	-0.292	0.025	-0.396
	direct	0.170	28.227	0.000	0.000	-0.292	0.000	0.000
dnlicen	total	-23.684	28.505	-5.509	0.685	0.000	0.049	-0.006
	direct	0.000	28.387	0.000	0.000	0.000	0.000	0.000
inbpass	total	12.606	3.217	-0.622	-15.209	0.000	-0.052	-0.150
	direct	0.000	0.000	0.000	-14.952	0.000	0.000	0.000
inemp	total	-1.601	-0.588	0.114	2.076	0.109	-0.101	0.139
	direct	0.000	0.000	0.000	0.000	0.109	-0.108	0.000
dnemp	total	3.032	1.030	-0.199	-3.864	-0.155	-0.013	-0.207
	direct	0.000	0.000	0.000	0.000	-0.155	0.000	0.000
inveh	total	32.075	1.234	-35.273	2.111	0.000	0.024	-0.058
	direct	0.147	0.000	-35.035	4.606*	0.000	0.000	0.000
dnveh	total	21.952	1.889	-19.990	-3.855	-0.096	-0.004	-0.187
	direct	0.000	0.000	-19.624	0.000	-0.096	0.000	0.000
expemp	total	-123.074	188.917	-69.568	3.707	0.000	0.612	-0.514
	direct	0.000	177.888	-33.055	0.000	0.000	0.276	-0.396
novemp	total	-68.121	79.069	-15.282	4.329	0.000	0.554	0.008
	direct	0.000	79.250	0.000	0.000	0.000	0.408	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

8.4.4 Longitudinal Effects of ICT

Table 8-10 reports the effects of ICT on time allocations and activity frequencies giving evidence of lack of symmetry and linearity in the effects when gaining a technology and losing a technology. Although the effects are not exactly symmetrical in most cases, they often have the opposite patterns. For example, new computer users at work spend more time on subsistence and less time on in-home and non-subsistence while past computer users at work have the opposite behaviors in those activities. One interesting fact is, however, that the effects of the past computer users at work are almost symmetrical to those of the experienced computer users, not the new computer users, on in-home, subsistence, and non-subsistence activity durations (i.e., they have different signs but similar coefficients in magnitude). In case of cellular phones, however, the effects of new users and past users are roughly symmetrical on all activity and travel durations.

Experienced and new users of ICT, except for the laptop, generally show a similar pattern in time use and episode frequency by activity. In the case of laptop, the experienced users and new users show quite different effects on all the activity and traveling indicators (different signs or quite different coefficients in magnitude), except for non-subsistence episode frequency.

In the period of 1997-2000, we observed a rapid increase in computer and Internet users at home. These two rapidly growing technologies seem to have different effects on people’s behavior. The new computer users at home spend less time on in-home activity and more time traveling, while the new Internet users at home spend more time on in-home activity and less time in traveling. In addition, these two groups have the opposite effects on the number of subsistence and non-subsistence episodes.

Table 8-10 Total and Direct Effects of ICT Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables						
		hdur	sdur	nsdur	ttime	finhome	fsub	fnsub
expcw	total	-43.367	58.044	-11.218	-3.466	-0.193	0.082	-0.517
	direct	0.000	51.205	0.000	0.000	-0.193	0.000	-0.248
novcw	total	-23.632	32.152	-6.214	-2.310	-0.123	0.044	-0.398
	direct	0.000	26.316	0.000	0.000	-0.123	0.000	-0.228
quitcw	total	56.910	-56.452	10.911	-11.368	0.000	-0.336	-0.087
	direct	0.000	-58.316	0.000	-8.624	0.000	-0.201	0.000
expnw	total	-37.708	35.124	-6.789	9.374	0.000	-0.019	0.077
	direct	0.000	36.766	0.000	8.990	0.000	-0.111	0.000
novnw	total	-16.175	19.468	-3.763	0.468	0.000	0.034	0.145
	direct	0.000	22.569	0.000	0.000	0.000	0.000	0.148*
expch	total	-6.138	-1.567	0.303	7.406	0.000	0.025	0.073
	direct	0.000	0.000	0.000	7.281	0.000	0.000	0.000
novch	total	-23.512	14.110	-2.727	12.133	0.000	0.069	0.113
	direct	0.000	16.523	0.000	11.536	0.000	0.000	0.000
novnh	total	6.820	1.741	-0.336	-8.228	0.000	-0.028	-0.081
	direct	0.000	0.000	0.000	-8.089	0.000	0.000	0.000
quitnh	total	-1.307	-0.334	0.065	1.577	0.000	0.272	0.016
	direct	0.000	0.000	0.000	0.000	0.000	0.266	0.000
expcel	total	-46.140	11.381	24.639	10.124	-0.074	0.132	0.073
	direct	0.000	14.574	26.838	8.980	-0.074	0.085	0.000
novcel	total	-21.768	-2.154	17.653	6.273	0.000	0.013	0.100
	direct	0.000	0.000	17.237	4.922	0.000	0.000	0.000
quitcel	total	33.245	3.128	-29.385	-6.992	-0.195	-0.010	-0.346
	direct	0.000	0.000	-28.781*	0.000	-0.195*	0.000	0.000
exppag	total	39.070	-46.488	8.985	-1.118	0.000	-0.080	0.009
	direct	0.446	-46.295	0.000	0.000	0.000	0.000	0.000
explap	total	-71.356	46.193	33.190	-8.034	-0.441	-0.172	-0.486
	direct	0.000	45.486	42.118*	0.000	-0.441	-0.202	0.000
novlap	total	34.995	11.920	-44.073	-2.846	0.000	0.025	-0.556
	direct	0.000	0.000	-41.769	0.000	0.000	0.000	-0.430
quitlap	total	-71.217	-4.425	70.527	5.119	0.000	-0.015	0.206
	direct	0.000	0.000	69.672	0.000	0.000	0.000	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

Using the coefficients in Tables 8-7, 8-8, 8-9, and 8-10, we performed some additional calculations. Regression coefficients defined for a group of indicators are relative to the excluded group (implicitly assumed to have a zero coefficient). Based on the coefficients, two different comparisons are possible. The first is cross-sectional variation (comparison between different persons in 2000) and the second is longitudinal change (comparison between 1997 and 2000 for the same person). For example, let's assume a woman in a young couple finds a professional job working 5 days per week, thus increasing the combined household income from low to mid income. From this situation, we can compute how much more time she spends on subsistence activity in a day than a woman who does not work in a similar couple with low income. This would be computed as follows: (9.39-1.55+151.00) = 158.84, which means that on average, the employed woman spends 158.84 minutes more on subsistence activity than an unemployed woman. This is a result of a combination of an increase in income (9.39 more minutes in Table 10-7), professional occupation (1.55 less minutes in Table 8-8), working 5 days in a week (151.00 more minutes in Table 8-8). Similar calculations lead to 171.34 minutes less on in-home activity, 9.86 minutes less on non-subsistence activity, and 22.35 minutes more on traveling, 0.62 more subsistence episodes, and 0.16 less non-subsistence episodes than any other unemployed woman in similar households with low income. Note that the sum of the differences in time allocation between employed women and unemployed women is equal to zero (158.84-171.34+9.86+22.34=0). It shows different time allocation patterns between the two groups of women within the 24-hour time budget.

As an example about longitudinal change, suppose a woman that did not work in 1997 is newly employed in 2000, thus getting a computer and Internet at work, a cell phone, and a laptop. Due to her new employment and ICT use, she spends 139.87 (-0.59+79.07+32.15+19.47-2.15+11.92) minutes more on subsistence activity than her previous status, resulting from an increase in the number of employed persons in the household (-0.589 in Table 8-9), new employment (79.069 in Table 8-9), starting using a computer and Internet at work (32.15 and 19.47 in Table 8-10, respectively), starting using a cellular phone (-2.15 in Table 8-10), and starting using a laptop (11.92 in Table 8-10). Similarly, it turns out that she spends 96.30 minutes less on in-home activity, 51.57 minutes less on non-subsistence activity, and 7.99 minutes more on traveling than before. Again, the sum of changes in time allocation is equal to zero (139.87-96.30-

51.57+7.99=0) showing how the time reallocation (trade-off among activities and travel) occurs with a limited time budget after her employment. Similar calculations applied to the number of activity episodes lead to 0.57 more subsistence episodes and 0.56 less non-subsistence episodes than her previous status.

In addition, men spend on average 34.35 minutes less on in-home activity, 32.32 minutes more on subsistence activity, 6.25 minutes less on non-subsistence activity, and 8.28 minutes on traveling, and have 0.08 more subsistence episodes and 0.20 less non-subsistence episodes than women.

8.4.5 State Dependence Effects

Turning to the effects of state dependence on activity and travel behavior summarized in Table 8-11, each group has almost identical patterns of time use and activity frequency to those in the year 1997 (Table 8-4) derived from the LC cluster analysis. For example, the home-bound group (Hbound) spends more time on in-home and less time on non-subsistence and traveling than any other group. Additionally, this group has the lowest number of activity episodes in all activity types. Among "regular" worker groups (worker_a, worker_b, and worker_c) worker_c group spends the most time on subsistence and the least time on in-home, non-subsistence, and traveling, and it has the least activity episodes in all activity types. On the other hand, worker_a group has the exact opposite position, except for in-home duration. In other words, this group spends the least time on subsistence and the most time on non-subsistence and traveling among the three groups, and it has the most activity episodes in all activity types. The time use and activity frequency of worker_b group are in the middle of worker_a and worker_c, except for a little less time on in-home than both worker_a and worker_c. These identical patterns of activity and travel behavior among the groups over the 3 year period of 1997-2000, confirm people's strong habit persistence in activity and travel behavior.

Table 8-11 Total and Direct Effects of State Dependence on Endogenous Variables

Exogenous Variables		Endogenous Variables						
		hdur	sdur	nsdur	ttime	finhome	fsub	fnsub
hbound	total	28.876	9.401	-24.783	-13.502	-0.477	-0.026	-0.928
	direct	0.000	0.000	-22.966*	0.000	-0.477	0.000	-0.221
worker_a	total	-80.633	51.461	14.761	14.413	0.000	0.361	-0.022
	direct	0.000	50.989	24.707	9.723	0.000	0.232	-0.196
worker_b	total	-69.917	86.376	-16.694	0.227	-0.115	0.316	-0.160
	direct	0.000	85.474	0.000	0.000	-0.115	0.174	0.000
worker_c	total	-82.066	104.559	-20.209	-2.296	-0.191	0.162	-0.726
	direct	0.000	93.186	0.000	0.000	-0.191	0.000	-0.451
pwork_a	total	-58.759	21.470	35.449	1.839	-0.091	0.134	-0.003
	direct	0.000	23.417	39.599	0.000	-0.091*	0.107	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

8.5 Summary

In this chapter, using PSTP data complex relationships among the activity and travel indicators were studied. The system of equations defined here includes as dependent variables the amount of time allocated to in-home, out-of-home subsistence, out-of-home non-subsistence, and travel, as well as the total number of episodes by activity type. The model system is designed to extend and parallel other past studies and builds on the model system of chapter 7 with some important differences and new insights.

In order to get a clear trade-off relationship in time use among different activities and traveling within a limited 24-hour time budget, in-home duration is extracted and included in the model system. This allows us to take into account a fixed time budget explicitly in the models and detect the existence of very strong substitutional and complementary relationships in time use among different activities and travel. It also enables us to uncover how persons reallocate their time when they experience a change in their life and they need to change their activity and travel behavior. The changes we study are changes in socioeconomic, demographic, and technology ownership and availability. Out-of-home activity (subsistence and non-subsistence) duration and travel time have very large substitutional effects (-0.834 to -1.022) on in-home activity duration, while out-of-home activity duration has complementary effects on travel time (0.024 to 0.074).

Using information on changes in social and economic circumstances between 1997 and 2000, a number of change variables are defined and included in the model as explanatory variables to test if there is behavioral symmetry when opposite events take place. It is found that most social and economic changes have asymmetric effects.

In addition, the effects of different levels of ICT ownership and use on activity and travel behavior are examined jointly with all the other determinants of activity and travel behavior. The overall "technology" effect seems to depend on the location and type of technology. It is also found that the technology effects are differentiated depending on the levels of ICT ownership and use.

In this application a new method to take into account the effects of state dependence on activity and travel behavior is also illustrated. Through latent class clustering analysis, seven homogenous groups in activity engagement and time use are first identified, and then the group indicators are included as explanatory variables in the model system. This method allows us to test if there is any habit persistence of individuals in activity and travel behavior, and at the same time, avoid many problems resulting from strong serial correlation in panel data. The model results confirm the existence of strong habit persistence in activity engagement and time use even in a relatively long period of time (3 years).

CHAPTER 9
CONCLUSIONS AND FUTURE WORK

This chapter summarizes the dissertation research conducted and presented herein along with conclusions and suggestions for future research.

9.1 Summary and Conclusions

This research aimed to develop models that identify groups that use these technology devices, and assess how ICT usage influences their activity and travel behavior. A comprehensive study investigating relationships between ICT ownership and use and people's activity and travel behaviors from a variety of viewpoints has been conducted and presented in this document. A variety of advanced analytical methods, such as Seemingly Unrelated Regression models, Multivariate Multilevel models, Latent Class Cluster Analysis, and Structural Equation models, were used to test the following hypotheses, while controlling for a variety of other factors influencing the relationship between ICT, activity participation, and travel:

- Examine if trends for each type of ICT ownership and use over time exist.
- Examine if there is heterogeneity in each type of ICT ownership and use among different situations in terms of age group, income, or occupation.
- Examine if there is a substitution or complementarity relationship between ICT and travel
- Examine if the effects of ICT ownership and use on activity and travel behavior depend on the length of technology ownership and use.
- Examine if there is symmetry in activity and travel behavior when people gain and lose ICT.

To accomplish the research objectives, the Puget Sound Transportation Panel (PSTP) data collected in Wave 7 (1997) and Wave 9 (2000) were used.

During the period of 1997-2000, there was a substantial increase in all ICT use, except for pagers. Home-based technology (computer and Internet at home) and cellular phones were the fastest growing technologies. Computers at work appear to be stabilizing at 50 percent of the sample. Laptop computers and personal digital assistants (PDA) are still used by a small portion of people.

Multivariate Multilevel technology choice models were developed to identify ICT user groups. The model confirmed that decisions of ICT ownership and usage are most likely to be joint decisions among members of the same household. It was found that income level, employment, and age, are important factors in ICT choice and usage. For example, the employed and persons with household income more than $75,000 are more likely to use most of ICT types. Old persons tend to make less use of the computer and the Internet than their young counterparts. In addition, the length of employment correlates positively with ICT usage.

Using structural equation models, a plethora of relationships among ICT, time use for a specific activity and travel, and mode choice were studied and identified. Dependent variables in a system of equations include the amount of time allocated to subsistence, maintenance, leisure, and travel, as well as the total number of trips by drive alone, car sharing, public transportation, walking, biking, and all other modes used. In addition, a large set of change (or experience) variables were defined to detect if the experience of a specific event can explain behavior and if its opposite event has symmetric effects (the same in magnitude but opposite sign) on behavior. The striking majority of social and economic changes have significant, many times substantial, and asymmetric effects.

The overall "technology" effect seems to depend on the location and type of technology. For example, the overall effect of computers and Internet at work shows an increase in subsistence participation and a decrease in leisure participation accompanied by less trip making, while use of computers and the Internet at home has the opposite effect on the two activities. In addition, the new computer users at home spend more time in all activities and travel more, while the new Internet users at home spend less time in activities and travel less. It was also found that the technology effects are differentiated depending on the levels of ICT ownership and use, although experienced and new users of ICT in general show a similar pattern (the same sign of the coefficients but different coefficients in magnitude) in time use and trip frequency by mode, except for the laptop computers. The substantial increase in Internet use at home between 1997 and 2000 seems to have desirable net effects (more leisure activity and less travel) at a small cost (a tiny increase in SOV trip) on the sample as a whole.

In order to identify a clear trade-off relationship in time use among different activities and traveling within a limited 24-hour time budget, in-home duration was extracted from the database and included in the last set of structural equation models. The system of equations includes as dependent variables the amount of time allocated to in-home, out-of-home subsistence, out-of-home non-subsistence, and travel, as well as the total number of episodes by activity type. This approach enables us not only to detect the existence of very strong substitutional and complementary relationships in time use among different activities and travel, but also uncover how persons reallocate their time when they experience a change in their life and they need to change their activity and travel behavior. Out-of-home activity duration and travel time have very large substitutional effects on in-home activity duration, while out-of-home activity duration has complementary effects on travel time.

In addition, to take into account the effects of state dependence on activity and travel behavior, seven homogenous groups with observed activity engagement and time use variables in 1997 are first identified through latent class cluster analysis, and then the group indicators are included as explanatory variables in the model system for activity engagement and time use in 2000. This method enables us to test if there is habit persistence of individuals in activity and travel behavior within the three year time interval, and at the same time, avoid many problems resulting from strong serial correlation in the panel data. The model results confirm the existence of strong habit persistence in activity engagement and time use even in a relatively long period of time.

The model system presented in this thesis proves to be a very powerful tool in understanding activity and travel behavior in a social and economic context and allows one to examine behavioral aspects in unprecedented detail for hypotheses testing.

9.2 Future Research

All these findings together provide a significant advancement in our knowledge about the interaction between ICT and activity and travel behaviors by individuals. However, there is still room for improvement and extensions.

First, although the structural equation models employed in this study are very useful to identify complex inter-relations among the dependent variables, this model system has also some limitations due to some fundamental assumptions. All the dependent variables were assumed to be multivariate normally distributed and continuous. This may influence the values of the effects and their significance (although testing and experimentation with single equation models lead to similar conclusions). For this reason one potential expansion of the work here is to use a limited dependent variable formulation for the time allocation indicators (to account for the large concentration of persons at zero minutes per day) and to use a count data regression formulation for the frequencies by mode or by activity.

Second, due to the market penetration of ICT into daily life, personal choices of activity and travel patterns become more intertwined with choices of ICT. In other words, activity and travel choices are a function of access to information technology for activity scheduling, while demands for ICT are probably a function of certain activity and travel patterns. This mutual causality can be captured by joint models of ICT ownership and activity and travel patterns. In the joint model system, cross-lag variables for activity and travel behavior need to be used as explanatory variables to assess the impact of activity and travel patterns in Wave 7 on demand for ICT in Wave 9.

Third, the analysis here focused more on the substitution and complementarity effects of ICT on activity participation and travel, but ICT effects are also more likely to influence the modification of activity and travel patterns. Therefore, the logical next analysis would be about temporal and spatial effects of ICT on activity and travel behavior such as trip timing, individual episode duration, and destination choice. In the long term, it is also interesting to investigate spatial impacts of ICT on residential location, office location, and urban form using Geographic Information Systems (GIS). Although the relationships are complicated, a better understanding of these relationships will greatly improve the accuracy of travel demand analysis and forecasting, and such understanding can be also used to test policy scenarios in a more comprehensive manner.

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APPENDIX

List of Explanatory Variables

Household level	SOV	Indicator, 1= household is sampled from SOV class; 0=otherwise
	CARPOOL	Indicator, 1= household is sampled from carpool class; 0=otherwise
	TRANSIT	Indicator, 1= household is sampled from public transit class; 0=otherwise
	KING	Indicator, 1= living in King County; 0=otherwise
	KITSAP	Indicator, 1= living in Kitsap County; 0=otherwise
	PIERCE	Indicator, 1= living in Pierce County; 0=otherwise
	SNOHO	Indicator, 1= living in Snohomish County; 0=otherwise
	HHSIZE	Number of people in the household
	TOT1_5	Number of children in the household who are less than 6 years old
	TOT6_17	Number of children in the household who are between 6 and 17 years old
	TOTADULT	Number of adults in the household who are 18 years old or older
	LOWINC	Indicator, 1= household income < $35,000; 0=otherwise
	MIDINC	Indicator, 1= $35,000 ≤ household income < $75,000; 0=otherwise
	HIGHINC	Indicator, 1= $75,000 ≤ household income; 0=otherwise
	MHINC	Indicator, 1= $35,000 ≤ household income; 0=otherwise
	DKINC	Indicator, 1=household income is unknown; 0=otherwise
	NUMVEH	Number of vehicles in the household
	CAR0	Indicator, 1= no car household; 0=otherwise
	CAR1	Indicator, 1= one car household; 0=otherwise
	CAR2	Indicator, 1= two car household; 0=otherwise
	CAR3_	Indicator, 1= three or more car household; 0=otherwise
	INBABY	Indicator, 1=an increase in the number of children < 6 years in the household between waves; 0=otherwise
	DNBABY	Indicator, 1= a decrease in the number of children < 6 years in the household between waves; 0=otherwise
	ENBABY	Indicator, 1= no change in the number of children < 6 years in the household between waves; 0=otherwise
	INKID	Indicator, 1= an increase in the number of kids whose age is 6-17 in the household between waves; 0=otherwise
	DNKID	Indicator, 1= a decrease in the number of kids whose age is 6-17 in the household between waves; 0=otherwise
	ENKID	Indicator, 1= no change in the number of kids whose age is 6-17 in the household between waves; 0=otherwise
	INADULT	Indicator, 1=an increase in the number of adults in the household between waves; 0=otherwise
	DNADULT	Indicator, 1=a decrease in the number of adults in the household between waves; 0=otherwise
	ENADULT	Indicator, 1= no change in the number of adults in the household between waves; 0=otherwise
	INLICEN	Indicator, 1=an increase in the number of drivers license holders between waves; 0=otherwise
	DNLICEN	Indicator, 1=a decrease in the number of drivers license holders between waves; 0=otherwise
	ENLICEN	Indicator, 1= no change in the number of drivers license holders between waves; 0=otherwise
	INBPASS	Indicator, 1=an increase in bus pass holders in the household between waves; 0=otherwise
	DNBPASS	Indicator, 1=a decrease in bus pass holders in the household between waves; 0=otherwise
	ENBPASS	Indicator, 1= no change in bus pass holders in the household between waves; 0=otherwise
	INVEH	Indicator, 1=an increase in the number of cars in the household between waves; 0=otherwise
	DNVEH	Indicator, 1=a decrease in the number of cars in the household between waves; 0=otherwise
	ENVEH	Indicator, 1= no change in the number of cars in the household between waves; 0=otherwise
	INEMP	Indicator, 1=an increase in the number of employed persons in household between waves; 0=otherwise
	DNEMP	Indicator, 1=a decrease in the number of employed persons in household between waves; 0=otherwise
	ENEMP	Indicator, 1=no change in the number of employed persons in household between waves; 0=otherwise
Person level	MALE	Indicator, 1=male; 0=female
	YOUNG	Indicator, 1=18≤ age ≤ 34; 0=otherwise
	MIDAGE	Indicator, 1=35≤ age ≤ 64; 0=otherwise
	OLD	Indicator, 1=65≤ age; 0=otherwise
	AGE1524	Indicator, 1=15≤ age ≤ 24; 0=otherwise
	AGE2544	Indicator, 1=25≤ age ≤ 44; 0=otherwise
	AGE4564	Indicator, 1=45≤ age ≤ 64; 0=otherwise
	AGE65_	Indicator, 1=65≤ age; 0=otherwise
	PROF	Indicator, 1=having professional occupation; 0=otherwise
	MANAG	Indicator, 1=having managerial occupation; 0=otherwise
	SECRE	Indicator, 1=having secretarial occupation; 0=otherwise
	SALES	Indicator, 1=having sales occupation; 0=otherwise
	UNEMP	Indicator, 1=unemployed; 0=otherwise
	WK5	Indicator, 1=working outside of home for 5+ times a week; 0=otherwise
	DPUPIL	Indicator, 1= student; 0=otherwise
	DLICEN	Indicator, 1= having driver's license; 0=otherwise
	DBPASS	Indicator, 1= having bus pass; 0=otherwise
	EXPEMP	Indicator, 1= employed outside home in both waves; 0=otherwise
	NOVEMP	Indicator, 1= started getting employed outside home after wave 7; 0=otherwise
	QUITEMP	Indicator, 1= employed outside home in wave 7 but not in wave 9;0=otherwise
	NOTEMP	Indicator, 1= unemployed in both waves; 0=otherwise

Time related	PELAP	Time duration (No. of year) for person in panel
	PELAP2	Square of time duration for person in panel
	DAY1	Indicator, 1= the first diary day; 0=otherwise
	DAY2	Indicator, 1= the second diary day; 0=otherwise
	MON	Indicator, 1=diary on Monday; 0=otherwise
	TUE	Indicator, 1=diary on Tuesday; 0=otherwise
	WED	Indicator, 1=diary on Wednesday; 0=otherwise
	THU	Indicator, 1=diary on Thursday; 0=otherwise
	FRI	Indicator, 1=diary on Friday; 0=otherwise
Information and Communication Technology	CW	Indicator, 1=using a computer at work/school; 0=otherwise
	CH	Indicator, 1=using a computer at home; 0=otherwise
	NW	Indicator, 1=using the Internet at work/school; 0=otherwise
	NH	Indicator, 1=using the Internet at home; 0=otherwise
	INTERNET	Indicator, 1=using the Internet at work/school and home; 0=otherwise
	CELLULAR	Indicator, 1=using a cellular phone; 0=otherwise
	PAGER	Indicator, 1=using a pager; 0=otherwise
	LAPTOP	Indicator, 1=using a laptop; 0=otherwise
	PDA	Indicator, 1=using a PDA; 0=otherwise
	EXPCW	Indicator, 1= using a computer at work/school in both waves; 0=otherwise
	NOVCW	Indicator, 1= started using a computer at work/school after wave 7; 0=otherwise
	QUITCW	Indicator, 1= stopped using a computer at work/school after wave 7; 0=otherwise
	NOTCW	Indicator, 1= not using a computer at work/school in either wave; 0=otherwise
	EXPCH	Indicator, 1= using a computer at home in both waves; 0=otherwise
	NOVCH	Indicator, 1= started using a computer at home after wave 7; 0=otherwise
	QUITCH	Indicator, 1= stopped using a computer at home after wave 7; 0=otherwise
	NOTCH	Indicator, 1= not using a computer at home in either wave; 0=otherwise
	EXPNW	Indicator, 1= using the Internet at work/school in both waves; 0=otherwise
	NOVNW	Indicator, 1= started using the Internet at work/school after wave 7; 0=otherwise
	QUITNW	Indicator, 1= stopped the Internet at work/school after wave 7; 0=otherwise
	NOTNW	Indicator, 1= not using the Internet at work/school in either wave; 0=otherwise
	EXPNH	Indicator, 1= using the Internet at home in both waves; 0=otherwise
	NOVNH	Indicator, 1= started using the Internet at home after wave 7; 0=otherwise
	QUITNH	Indicator, 1= stopped using the Internet at home after wave 7; 0=otherwise
	NOTNH	Indicator, 1= not using the Internet at home in either wave; 0=otherwise
	EXPCEL	Indicator, 1= using a cellular phone in both waves; 0=otherwise
	NOVCEL	Indicator, 1= started using a cellular phone after wave 7; 0=otherwise
	QUITCEL	Indicator, 1= stopped using a cellular phone after wave 7; 0=otherwise
	NOTCEL	Indicator, 1= not using a cellular phone in either wave; 0=otherwise
	EXPPAG	Indicator, 1= using a pager in both waves; 0=otherwise
	NOVPAG	Indicator, 1= started using a pager after wave 7; 0=otherwise
	QUITPAG	Indicator, 1= stopped using a pager after wave 7; 0=otherwise
	NOTPAG	Indicator, 1= not using a pager in either wave; 0=otherwise
	EXPLAP	Indicator, 1= using a laptop computer in both waves; 0=otherwise
	NOVLAP	Indicator, 1= started using a laptop computer after wave 7; 0=otherwise
	QUITLAP	Indicator, 1= stopped using a laptop computer after wave 7; 0=otherwise
	NOTLAP	Indicator, 1= not using a laptop computer in either wave; 0=otherwise
	EXPPDA	Indicator, 1= using a PDA in both waves; 0=otherwise
	NOVPDA	Indicator, 1= started using a PDA after wave 7; 0=otherwise
	QUITPDA	Indicator, 1= stopped using a PDA after wave 7; 0=otherwise
	NOTPDA	Indicator, 1= not using a PDA in either wave; 0=otherwise

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- Ecosystems and Sustainable Development
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