6-16-2015

On the Impacts of Telecommuting over Daily Activity/Travel Behavior: A Comprehensive Investigation through Different Telecommuting Patterns

Hamidreza Asgari
Florida International University, hasga001@fiu.edu

DOI: 10.25148/etd.FIDC000118

FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

ON THE IMPACTS OF TELECOMMUTING OVER DAILY ACTIVITY/TRAVEL BEHAVIOR: A COMPREHENSIVE INVESTIGATION THROUGH DIFFERENT TELECOMMUTING PATTERNS

A dissertation submitted in partial fulfillment of

the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

CIVIL ENGINEERING

by

Hamidreza Asgari

2015

To: Dean Amir Mirmiran
College of Engineering and Computing

This dissertation, written by Hamidreza Asgari, and entitled On the Impacts of Telecommuting over Daily Activity/Travel Behavior: A Comprehensive Analysis through Different Telecommuting Patterns, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Zhenmin Chen

Albert Gan

Mohammed Hadi

L. David Shen

Xia Jin, Major Professor

Date of Defense: June 16, 2015

The dissertation of Hamidreza Asgari is approved.

Dean Amir Mirmiran
College of Engineering and Computing

Dean Lakshmi N. Reddi
University Graduate School

Florida International University, 2015

DEDICATION

This dissertation is dedicated to my parents, Zahra Golzarkashi and Hossein Asgari, for their endless love, encouragement, and support.

ACKNOWLEDGMENTS

I would like to take this opportunity to acknowledge everyone who helped me realize my dream of achieving a doctoral degree in Transportation Engineering. First and foremost, I would like to express my deepest gratitude toward my major advisor, Dr. Xia Jin, for her support, guidance, and encouragement at every stage of this dissertation, which provided me with a tremendous atmosphere for research work. Along my journey to accomplish this dissertation, I have always been impressed by her thoughtful insights and comments, which make me feel fortunate to be her first Ph.D. student in her academic career.

I would like to thank my dissertation committee members, Dr. Albert Gan, Dr. Mohammed Hadi, Dr. L. David Shen, and Dr. Zhenmin Chen, for serving on my committee and for their invaluable comments, suggestions, and interest in my research.

A special note of appreciation is due to my co-researchers, Mr. Sakoat Hossan, Mr. Kollol Shams, Mr. Fengjiang Hu, and Mrs. Nishat Zaman. Their hard work, collaboration, and companionship has made me proud of being part of this research group during all these years.

Finally, I am especially indebted to the University Graduate School at the Florida International University for providing the financial support for this dissertation research through a Dissertation Year Fellowship.

ABSTRACT OF THE DISSERTATION

ON THE IMPACTS OF TELECOMMUTING OVER DAILY ACTIVITY/TRAVEL BEHAVIOR: A COMPREHENSIVE INVESTIGATION THROUGH DIFFERENT TELECOMMUTING PATTERNS

by

Hamidreza Asgari

Florida International University, 2015

Miami, Florida

Professor Xia Jin, Major Professor

The interest in telecommuting stems from the potential benefits in alleviating traffic congestion, decreasing vehicle miles traveled (VMT), and improving air quality by reducing the necessity for travel between home and the workplace. Despite the potential economic, environmental, and social benefits, telecommuting has not been widely adopted, and there is little consensus on the actual impacts of telecommuting. One of the major hurdles is lack of a sound instrument to quantify the impacts of telecommuting on individuals' travel behavior. As a result, the telecommuting phenomenon has not received proper attention in most transportation planning and investment decisions, if not completely ignored.

This dissertation addresses the knowledge gap in telecommuting studies by examining several factors. First, it proposes a comprehensive outline to reveal and represent the complexity in telecommuting patterns. There are various types of telecommuting engagement, with different impacts on travel outcomes. It is necessary to identify and distinguish between those people for whom telecommuting involves a

substitution of work travel and those for whom telecommuting is an ancillary activity. Secondly, it enhances the current modeling framework by supplementing the choice/frequency approach with daily telework dimensions, since the traditional approach fails to recognize the randomness of telecommuting engagement in a daily context.

A multi-stage modeling structure is developed, which incorporates choice, frequency, engagement, and commute, as the fundamental dimensions of telecommuting activity. One pioneering perspective of this methodology is that it identifies non-regular telecommuters, who represent a significant share of daily telecommuters. Lastly, advanced statistical modeling techniques are employed to measure the actual impacts of each telecommuting arrangement on travelers' daily activity-travel behavior, focusing on time-use analysis and work trip departure times. This research provides a systematic and sound instrument that advances the understanding of the benefits and potentials of telecommuting and impacts on travel outcomes. It is expected to facilitate policy and decision makers with higher accuracy and contribute to the better design and analysis of transportation investment decisions.

CONTENTS

CHAPTER PAGE

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1. Background

The concept of telecommuting gained attention in the late 20th century, following the advent of personal computers and sophisticated communication technologies. In 1974, the term "telecommute" or "telework" was applied for the very first time in a report from the University of Southern California that focused on a rush-hour traffic elimination project funded by the National Science Foundation (Nilles et al., 1974). Later in the 1980s, pilot telework programs were initiated across the United States and by the 1990s, many states, local governments, and private sector corporations had implemented telework arrangements. Enabled by the development of information technologies and encouraged by the global business competition, more and more organizations tend to incorporate telework into their layout. A 2001 study by the International Telework Association and Council (ITAC) reported 28.8 million teleworkers in the United States. This showed a 17% increase compared to the prior year, and almost equates to one out of every five U.S. workers. The United States Bureau of Transportation Statistics in 2006 showed that 30% of the U.S. labor force work at home for at least part of the week (Mello, 2007). According to the "Global workplace analytics & telework research network," regular telecommuting grew by 79.7% between 2005 and 2012, and with no growth acceleration, it is estimated that regular telecommuters will reach a total of 3.9 million by 2016, reflecting a 21% increase from the 2012 level of 3.22 million in 2012.

The definition of telecommuting has been subject to fundamental evolution since its first introduction 40 years ago. A quick review of what a telecommuting background

entails reveals a plethora of definitions for the concept, which depend on the inclusion or exclusion of any of the following attributes: 1) alternative workplace, which leads to savings in time/physical distance ("tele"), 2) partial or total substitution of daily commute ("commute"), 3) intensity of the telecommuting activity, and 4) availability of information and intercommunication technologies. Nilles, also known as the father of telecommuting, defined telecommuting as "the phenomenon that employees can access information in the workplace through technologies without physically being there" (Nilles, 1994). Some researchers made the definition more detailed by emphasizing the use of electronic devices such as computers, cellular phones, emails and online database services (Crimando and Godley, 1985; De Marco, 1995; Handy and Mokhtarian 1995). Teo et al. (1998) described telecommuting as "performing a job task away from the regular work site at least one to two days per week." It is also important to recognize that telecommuting does not necessarily involve working at home, but it can also include the use of a telework center, located at some point between an individual's home and workplace. In a survey in 2001, The International Telework Association and Council ITAC-2, found that telecommuting may be performed at home, on the road, at a customer location, or at a satellite office. In addition, many studies have agreed that telecommuting leads to a total or partial substitution of daily commutes (Nilles, 1988; Mokhtarian, 1991; Sampath et al., 1991; Handy & Mokhtarian, 1995; Walls & Safirova, 2004). Despite the general consensus about the basic components of telecommuting in academia, the definition of telecommuting on a professional level may be slightly different from place to place or from one survey to another. Surveys reflect the needs and biases of data collection bureaus; hence, the bureaus

follow their own pattern when it comes to the definition of telecommuting. This is the main reason why reported telecommuting statistics from different agencies are inconsistent.

In order to come up with a concise, consistent definition of telecommuting, the following general description is applied in this research: "Telecommuting is defined as working at home or at a location close to home instead of commuting to a conventional work location. It may or may not lead to commute removal or displacement." It should be noted that this study only focuses on home-based telecommuting.

Like any other type of development, implementation of telecommuting is followed by a number of benefits and costs. Literature reveals that there are a host of advantages for participants of a telecommuting program, including employers, employees and community (Fitzgerald and Halliday, Inc., 2001; Turnbull et al., 1996; Shafizadeh et al., 2000; Grippaldi, 2002; PVPC, 2011). Employer benefits include increased productivity, morale and commitment improvement, cost savings through office and parking spaces, etc. Employees also benefit from the reduction of stress, the general cost of daily commuting, an increase in job satisfaction and productivity, and the expansion of job flexibility, which results in a balance of job and family responsibilities. General public advantages include reduced emissions and improved air quality, reduction of vehicle miles traveled (VMT), an increased rate of employment, global competitiveness, etc. Above all, policy makers believe that telecommuting is an easy-to-implement strategy that does not require long-term planning and could be applied at any time at a low cost, compared to other management strategies (Sampath et al., 1991). However, telecommuters might be discouraged by a number of drawbacks (Gil Gordon Associates, 1995; Piskurich, 1996; Teo et al., 1998). Such disadvantages mainly include the emotional or mental effects of

telecommuting on individuals. Employees may feel lonely or isolated for fear of being left out of office culture. In addition, some jobs are not classified as being intrinsically suitable for telecommuting.

While there is a lot to discuss about the background of telecommuting, including its pros and cons, certain attention is drawn to exploring the concept from a forecasting perspective. In terms of travel demand analysis and behavioral models, there is an overall emphasis on the importance of work schedule and labor force participation, mainly in activity-based models (ABM), which are increasingly being deployed in practice. In this respect, work, as the primary activity of the majority, implies time-space constraints on individuals' activity patterns, restricting the degree of freedom to pursue other maintenance or discretionary activities. Hence, work activities and commute-related trips are scheduled first, and non-work activities and non-mandatory travel are scheduled around work activities. Therefore, any changes in work arrangements are expected to significantly affect the general daily activity pattern of individuals. Developing a framework that provides an accurate and reliable estimate of telecommuting rates will therefore improve the general transportation planning framework.

Several attempts have been made in the past two decades that focus on prediction of telecommuting behavior. The main idea is to develop forecasting frameworks using statistical tools at a disaggregate level, which will predict employees' behaviors about telecommuting. Models usually rely on various types of personal, household and job-related attributes, and follow specific statistical distributions. As the models have gradually evolved, a variety of telecommuting facets are recognized, and dimensions such as "Adoption" of telecommuting, Telecommuting "Option," telecommuting "Choice" and

"Frequency" of Telecommuting have been introduced. Inferences have been made about significant variables and their respective effects on telecommuting estimation. Regardless of the applied methodology, there is a general agreement that the decision to telecommute is complex and is governed by a host of demographic, occupational, and attitudinal factors (Yen & Mahmassani, 1994; Popuri & Bhat, 2003).

1.2. Research Needs and Problem Statement

Researchers' interest in telecommuting has been continuous and growing since its first implementation as a part of public policy to address transportation congestion in 1988 in California. In view of practical studies, two major topics are of the essence: 1) telecommuting estimation, and 2) telecommuting impacts. There is a close relationship between these two topics as impact studies rely on the number of telecommuters (telecommuting rate), which in turn is derived from the outcomes of estimation studies. This section focuses on the existing deficiencies and research needs, with an emphasis on any of the two aforementioned topics.

While there is an extensive body of literature on estimating telecommuting decisions, some aspects are yet unexplored. The approach centered on "Option, Choice, and Frequency" provides insight on who, among those that have the option, may choose to telecommute and at what frequency level. This approach considers telecommuting as part of the lifestyle arrangement, or in other words, a long-term choice (i.e., the decision of whether to own a car or use a transit pass). However, owning a car or a transit pass does not mean the traveler is driving or using transit for every trip by default, instead, car/transit pass ownership is seen as critical determinant factors in mode choice models. Similarly,

the knowledge surrounding the long-term telecommuting decision needs to be translated into daily decisions.

There are two important reasons to extend modeling efforts into the daily framework. First, the abovementioned approach can only capture "regular telecommuters" that have added telecommuting to their lifestyles and have more or less settled into their daily activity arrangements. Yet, there are other workers that have not chosen to telecommute regularly but may telecommute on a random day, which is referred to as "non-regular telecommuters." Based on a New York regional household travel survey, 22% of workers that telecommuted on a random day were non-regular telecommuters (Jin and Wu, 2012). This percentage is too significant to ignore, but it cannot be addressed unless a daily level decision is introduced where any worker could be a potential telecommuter regardless of his/her long-term "choice."

Secondly, telecommuting can be implemented in a variety of ways. It could involve a *full-day* engagement, where the daily commute is completely removed and telecommuting serves as a substitution effect, or it could be a *part-day* assignment where the commute may or may not be displaced temporally and telecommuting serves as a supplementary effect It is clear that full-day and part-day telecommuting have different impacts on workers' travel activity schedules, which is well recognized in existing literature (Mokhtarian, 1998; Shafizadeh et al., 2001; Lyons et al., 2006; Lyons and Haddad, 2008; Haddad et al., 2009; Nilles, 1988; Mokhtarian, 1991; Sampath et al., 1991; U.S. DOT report, 1993; Handy and Mokhtarian, 1995; Walls and Safirova, 2004). However, the current choice/frequency approach remains at the long-term level, which does not reflect an employee's daily decision whether or not to telecommute on a specific

day, and which type of telecommuting to engage in. Therefore, the actual impacts of different types of telecommuting on travel outcomes cannot be fully addressed. On a technical note, a majority of previous household travel surveys, including the National Household Travel Survey (NHTS), did not provide details about in-home activities, which made it impossible to differentiate telecommuting from other in-home activities. Hence, it was not feasible to extend the telecommuting estimation framework to a daily basis.

Consequently, there appears to be no comprehensive planning structure that appropriately encompasses all of the following issues. First, the planning structure should include the ability to identify all possible forms of telecommuting engagements (e.g., full-time, part-time, regular, non-regular, full-day, and part-day) based on simple and comprehensible definitions. Second, the structure should include appropriate modeling structures in order to predict respective shares of each type of telecommuting in the market. Third, it should incorporate the types of telecommuting into a daily activity pattern or tour generation model in order to explore the final impacts of telecommuting at a disaggregate level.

1.3. Goals and Objectives

Considering the prevailing deficiencies, this study contributes to the literature by developing a comprehensive planning module that focuses mainly on estimation of telecommuting forms, along with their respective influences over individuals' daily activity/travel scheduling. The current planning framework relatively tracks the following well-known pattern: The procedure usually starts with a population synthesis, which categorizes the individuals based on a variety of their attributes, including socio-economic, demographic, land-use, professional and job-related characteristics, etc. Such information

is usually obtained from several sources at the national or regional level, such as the National Household Travel Survey (NHTS) or Regional Household Travel Survey (RHTS), which inclusively record the travel behavior of individuals, along with their personal and household data. The American Time Use Survey (ATUS), is another informative source that examines how American individuals allocate their daily time budget into different types of activities.

The next step is to plug each individual into daily activity scheduling models. This step helps the analyst forecast how individuals plan their respective daily activity schedule and subsequently, predicts their trip (tour) generation behavior. Several structures were proposed in terms of daily activity schedule and tour generation (Bowman, 1995 & 1998; Bhat & Misra, 1999; Doherty, 2000; Kulkarny & McNally, 2000; Mohammadian & Doherty, 2005; Cynthia & Mokhtarian, 2006; Erica et al., 2009; Auld & Mohammadian, 2009). The outcome of this stage usually includes major daily activities, number of generated tours and tour type (simple or complex). This may further be examined by taking into account the different temporal and spatial characteristics of a single tour, including time of day, mode choice, and destination. Finally, any of the various existing algorithms might be applied to assign the predicted traffic volumes into the transportation network.

This research work attempts to enhance the current planning framework by adding a sub-procedure (module) to the context. The major objective of this additional module is to estimate and classify telecommuting engagement behavior based on individuals' attributes (Figure 1-1). This aspect of telecommuting indicates whether or not a certain worker telecommutes, and if so, indicates the type of "telecommuter." This attribute will then be used as an independent variable in the next step to account for the influence of

telecommuting on daily activity patterns. The major assumption in this study is that "Telecommuting is anticipated to reflect significant impacts on individuals' activity scheduling and trip/tour characteristics. Moreover, it is important to distinguish various forms of telecommuting as the impacts of telecommuting engagement forms will probably be different from one another."

Herein, the study will encompass the following phases and steps:

Phase I

1. Identify the main types of telecommuting engagement by exploring the dataset and analyze various aspects of telecommuting adoption. This step also provides simple and straightforward definitions and algorithms in order to categorize employees based on different types of telecommuting behavior.
2. Develop appropriate statistical models in order to predict market shares of different types of telecommuting behavior. This step requires a comprehensive literature review in order to capture a fundamental grasp of statistical methodologies applied in telecommuting literature, respective pros and cons, and to find the best possible structure.
3. Investigate the results and compare how different socio-economic, demographic, job-related, or land-use variables play significant roles in telecommuting behavior.

Phase II

1. Incorporate the outcomes of the first phase into the activity/tour generation model. More precisely, this step includes adding the "telecommuting form" as an exogenous variable into the modeling structure.

2. Explore the model outcomes, which will further enable the researcher to make reasonable inferences. This sheds light on how telecommuting, as a new work arrangement, will impact daily activity or tour generation patterns.

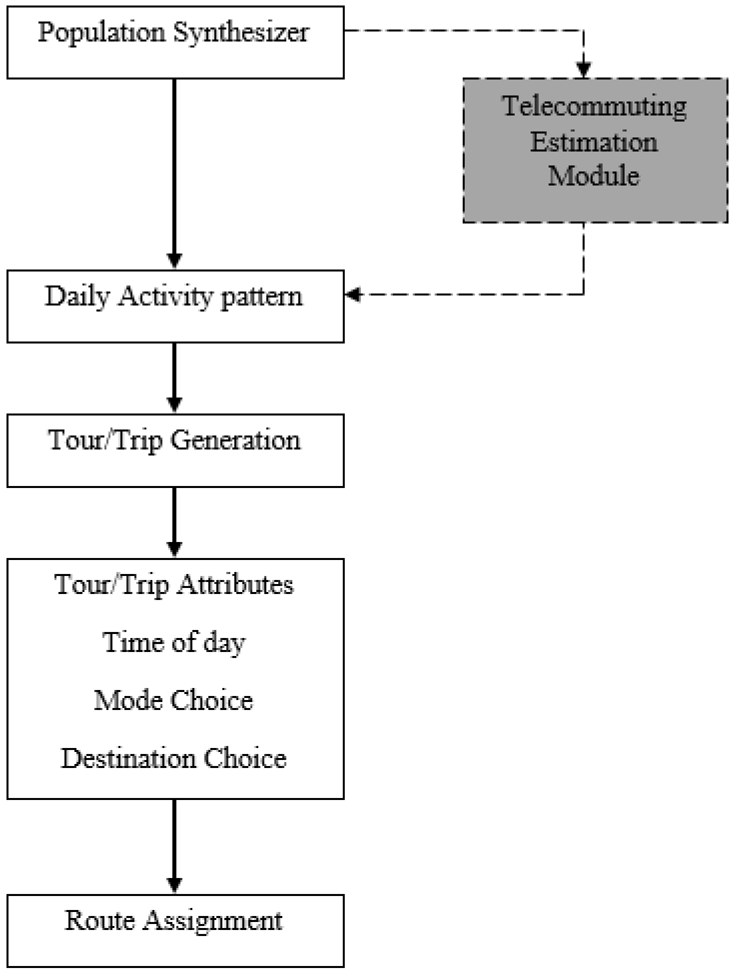

Figure 1-1 Modification of the General Planning Framework

1.4. Dissertation Organization

The rest of this dissertation is organized as follows: Chapter 2 will provide a nearly comprehensive review of the conducted research efforts in the field of telecommuting, with

an emphasis on telecommuting forecast, along with impact analysis. Chapter 3 focuses on research methodology, which presents a general telecommuting estimation framework, in addition to statistical tools and modeling structures. Moreover, appropriate modeling tools are investigated for estimating telecommuting impacts. Chapter 4 presents the results of Phase 1, which explores different dimensions of telecommuting activity. Chapter 5 uses the outcomes of Phase 1 in order to estimate the impacts of telecommuting in terms of time-use analysis and commute departure times. Finally, Chapter 6 provides general conclusions and further research opportunities.

CHAPTER 2

LITERATURE REVIEW

2.1. Introduction

This section focuses on reviewing the empirical literature on telecommuting concepts. Considering that the literature on telecommuting is extensive and has been growing rapidly in recent years, such review may not be considered exhaustive by any means. However, it attempts to cover the major studies and publications in the telecommuting field for the past twenty to thirty years.

According to Walls and Safirova (2004), telecommuting literature could well be classified based on emphasis on one of the following categories:

1. General telecommuting trends and statistics
2. Studies over telecommuting forecasts and modeling frameworks
3. Estimation of telecommuting impacts

These three separate categories are explicitly investigated in this chapter. Before stepping into details, it seems useful to provide a general overview of the evolution of telecommuting literature, including the drawbacks, improvements, and overall trends since the early 1990s. The general movement in the development of telecommuting literature can be viewed from various angles, including the following:

1. Data**:** Early telecommuting studies were usually based on stated preference (SP) data (Bernardino et al., 1993; Mahmassani et al., 1993; Mokhtarian and Salomon, 1995). However, since the mid-1990s, one may observe an overall shift toward revealed preference (RP) data (Mannering and Mokhtarian, 1995; Mokhtarian and Salomon, 1997; Drucker and Khattak, 2000; Popuri and Bhat, 2003). Such change

stems from the observed inconsistencies between the findings from SP-based and RP-based analyses. Those inconsistencies originated from the existing gap between telecommuting preference and actual telecommuting behavior. As Mokhtarian and Salomon (1995) discussed in their California case study, although 88 percent of 628 respondents preferred to telecommute, only 13 percent actually did.

Another common disadvantage among early empirical studies is data limitation, which could be viewed in terms of sample size or technical definition. Initially, studies were usually based on small samples from a limited number of specific organizations (Sullivan et al., 1993; Bernardino et al., 1993; Mokhtarian & Salomon, 1994, 1996a, 1996b, 1997; Mannering & Mokhtarian, 1995; Mokhtarian et al., 1998; Wells et al., 2001). Although such organization-specific datasets are capable of providing detailed job-related information and attitudinal behaviors of both employers and employees, they hinder the generalization of the study's outcomes and question model transferability.

Furthermore**,** initial studies seldom offered standard and coherent definitions of telecommuters or telecommuting intensity. The intensity (frequency) of telecommuting, for instance, was initially based on defining discrete categories (Mannering & Mokhtarian, 1995; Mokhtarian et al., 1997; and Walls et al., 2006). Thresholds, however, used to be study-specific, i.e., they were different from one study to another, which led to confusion when it came to a comparison of the results. In order to resolve this issue, some researchers suggested using the number of telecommuting days (either per week or per month) as a frequency index rather than ad hoc discrete categories (Popuri & Bhat, 2003; Sener & Bhat, 2011; Singh

et al., 2012). Also, researchers did not distinguish between home-based workers (those who do not have or need a conventional office rather than home) and real telecommuters (those who have a fixed office but telecommute regularly). Hence, application of large sample sizes, usually at the national or statewide level (Drucker & Khattak, 2000; Yen, 2000; Popuri & Bhat, 2003; Wernick, 2004; Walls et al., 2006; Zhou, 2008; Sener & Bhat, 2011; Singh et al., 2012), along with providing clear definitions of telecommuters and their subcategories, could be named as major enhancements of models in the research background.

2. Telecommuting dimensions: One fundamental improvement in the modeling methodology refers to obtaining the knowledge that telecommuting is a multidimensional concept and should be analyzed from several perspectives. Early studies mainly focused on either "preference" or actual "choice" (Sullivan et al., 1993; Bernardino et al., 1993; Mokhtarian & Salomon, 1994, 1996a, 1996b, 1997; Mokhtarian et al., 1998; Belanger, 1999; Wells et al., 2001; Grippaldi, 2002), while aspects such as "frequency" or "option" were gradually added to the literature (Mannering & Mokhtarian, 1995; Yen, 2000; Drucker & Khattak, 2000; Peters et al., 2001; Popuri & Bhat, 2003; Wernick, 2004; Walls et al., 2006; Mamdoohi et al., 2006; Zhou, 2008; Vana et al., 2008; Haddad et al., 2009; Tang et al., 2011; Sener & Bhat, 2011; Singh et al., 2012).

3. Statistical modeling and technical issues: Unquestionably, there has been a remarkable tendency toward using more sophisticated and intricate statistical models in order to improve prediction accuracy. Having initially focused on descriptive statistics and basic models such as the Multinomial or binary logit,

telecommuting research history is enhanced through application of different econometric tools and methodologies, including nested logit structures, generalized ordered response models, multivariate distributions, Structural Equation Modeling (SEM), and instrumental variables. A detailed review is provided in Section 2.3.

4. Enhancement of variables: A quick review of the literature reveals that like any other behavioral models, the likelihood of telecommuting in any aspect may be explained based on individual and household characteristics, along with job-related attributes. In addition, when detailed information is available regarding telecommuting opportunities at work, organizational variables and managerial attitudes may well be added to the models in order to provide a better fit. However, this requires identification of different types of companies with respect to their reactions toward telecommuting implementation. Moreover, detailed surveys should be prepared and sent out separately to each company. As it is not plausible to do this at a national level and includes high expenses in terms of both time and money, such surveys usually lead to relatively small sample sizes, which counteract the models' reliability and transferability. Hence, research work that deals with large sample sizes are restricted to using general job-related variables, which are easily accessible from national or statewide surveys. In some cases, the impact of land-use and built environmental variables are also explored using geo-coded data. Likewise, detailed information will be discussed in Section 2.3.

2.2. General Telecommuting Trends and Statistics

References falling into this category could be summarized either as statistical reports and technical memorandums funded by the government (USDOT report, 1993;

ITAC-1, 2001; ITAC-2, 2001; USOPM report to the Congress, 2013), or discussion papers that provide theoretical analysis on the definition and measurement of telecommuting (Mokhtarian, 1991; Sampath et al., 1991; Nilles, 1994; Handy & Mokhtarian, 1995, 1996; Pratt, 2002; Balaker, 2005; Mello, 2007).

In terms of statistics, there is a general agreement that telecommuting popularity is increasing both among employers (option) and employees (adoption). According to the United States Office of Personnel Management's report (2013), there has been a significant increase toward telecommuting implementation in view of employees, employers, and using sophisticated approaches in telecommuting development.

Discussion papers mainly focused on how the concept of telecommuting has evolved and on the major theoretical deficiencies or noticeable issues at the time of the study. In a pioneering study in 1991, Mokhtarian explored the concept of telecommuting from a variety of aspects, including the definition, subforms, transportation impacts, and application of information technologies. Based on the definition, it was insisted that both concepts of "tele" and "commute" should be involved in order to consider a telecommuting option as an alternative work arrangement. In other words, the worker should be far from the conventional workplace (or from the supervisor), and the daily commute should be either removed or displaced. Secondly, telecommuting can be exercised in a variety of ways. If a worker telecommutes all five days per week and does not travel to the workplace on any of the workdays, he/she will be labeled as a *full-time* telecommuter; otherwise, he/she is a *part-time* telecommuter. This means that a part-time telecommuter may telecommute on some days and work at the regular workplace on other days. Mokhtarian showed that part-time telecommuters only telecommute an average of one or two days per

week. Even on a single day, telecommuting could be practiced differently, depending on whether or not the daily commute is removed. It could involve a *full-day* engagement, where the daily commute is completely removed and telecommuting serves as a substitution effect, or it could be a *part-day* assignment where the commute may or may not be displaced temporally and telecommuting plays a supplementary effect.

Handy and Mokhtarian (1995) discussed different approaches by which telecommuting is measured and also explained the problems involved in comparing estimates from different surveys. From a transportation-based perspective, the critical component of telecommuting definition is the elimination, or partial elimination, of daily commute trips. Therefore, telecommuting is commonly described as working at home or at a telework center (also known as a tele-center) as a substitute for travel to an employer's conventional workplace. Available data sources on telecommuting, however, have a variety of difficulties. First, many surveys do not address tele-centers at all, thereby leaving out workers who telecommute in this manner. Second, some workers may telecommute only for part of a day (i.e., they work in the office part-day as well), thus shifting the commute time but not removing the trip entirely. These workers may be captured as telecommuters in a survey but should probably not be grouped with full-day telecommuters. Third, many surveys ask about working at home, thus possibly capturing a group of workers based in their homes. These categories, such as home-based businesses, should not be considered telecommuters.

Aside from the issues associated with the definition of telecommuter, there are multiple ways to analyze the survey data in order to provide information about the magnitude of telecommuting. The authors here distinguish between the percentage of

workers that telecommute, labeled as telecommuting *penetration,* and the number of telecommuting *occasions*, or the number of days an employee works entirely at home. While both statistics can be useful, it is the latter that is crucial for evaluating the effects of telecommuting, including VMT, congestion, emissions, etc.

Handy and Mokhtarian (1995) also explored the findings from four studies that provide information on telecommuting penetration. The national survey done by the Census Bureau discovered that approximately 1% of California workers in occupations that are conducive to telecommuting report that they "usually" work at home. In an annual national survey, a private firm, Link Resources, reported that between 1.88% and 3.34% of U.S. workers telecommute. Two California surveys, one in Los Angeles and one in the San Francisco Bay area focused only on full-time workers that worked outside home. Accordingly, around 9% of Los Angeles workers "sometimes" telecommute compared to 9.8% in San Francisco. These percentages are higher because of the option for occasional telecommuting (as opposed to "usually" in the Census survey), and also because only full-time workers are examined. These pilot studies also suggest that there is a high variation observed in telecommuting frequency. The range varies from 0.8 days a week to 3 days a week. Finally, looking at the proportion of workers that telecommute on any given day, telecommuting penetration ranges from less than 1% up to 2.1%; that is, on any given day of the week, between 1% and 2% of workers actually telecommute. Handy and Mokhtarian applied a Caltrans survey to summarize the final estimate of the percentage of telecommuting workers. It found that on any given day, 1.47% of people in the workforce telecommute, 1.98% of people working on that particular day telecommute, and 2.01% of commute trips are replaced by telecommuting.

Pratt (2002) placed an effort on summarizing statistics from questions added to several national surveys, including the Federal Highway Administration's Nationwide Personal Transportation Survey (NPTS) and the Census Bureau's American Housing Survey and Current Population Survey. Some of the results are unanimous with the issues identified by Handy and Mokhtarian. More specifically, the magnitude of telecommuting varies across studies because the sample of workers is often different. Whether or not the sample includes self-employed, independent contractors, part-time workers, or workers with multiple jobs, the percentage of the telecommuting workforce tends to differ. Samples including self-employed workers or workers with multiple jobs often show higher telecommuting rates. However, it should be noted that these people are not necessarily making fewer vehicle trips or traveling fewer miles. According to the Nationwide Personal Transportation Survey (NPTS) data, 15% of individuals that reported working from home within the past two months were holding two or more jobs. Furthermore, 22% of workers with multiple jobs telework, which is a much higher percentage than what most studies report for total workers or workers with one job. Pratt also reported that the work-at-home group contained 68% employees, 19% home-based business owners, and 11% non-home-based self-employed people.

Comparing numbers and trends, Pratt found that as expected, including self-employed workers in the sample leads to overestimation of telecommuters. The actual number of telecommuters as a fraction of commuting employees is far lower. Overall, Pratt reported that different surveys agree that telecommuting has been holding steady, with about 16% to 17% of total employees working at home some of the time.

In 2005, Mokhtarian et al. criticized what they called "lack of consensus" among different telecommuting statistics in the existing literature. Five major data sources were taken into account: U.S. Census Bureau, American Housing Survey (AHS), Current Population Survey (CPS) of the Bureau of Labor Statistics (BLS), market research firms and the trade association-sponsored Telework America surveys. Evaluating these data sources regarding their usefulness and reliability toward telecommuting estimates, authors came up with three major dimensions that can cause further uncertainty in data: definition, quality, and quantity. In terms of definition, several aspects should be carefully considered, including types of workers being counted or the frequency threshold applied as the telecommuting criteria. In addition, issues such as overtime work, misinterpretation of paid work, and confusion of home-based workers with telecommuters might lead to further statistical inconsistencies. Clearly, more workers fall into the category of telecommuters if the criterion is shifted from "at least three days a week" to "at least once a month." On the other hand, when it comes to the quality and quantity of telecommuting data, technical aspects should be carefully considered and applied. These include sample size, and whether the data is drawn properly (unbiased) and weighted in order to correctly represent the whole population. The analysis in this paper indicates that a great deal of uncertainty surrounds estimates of the number of telecommuters and frequency of telecommuting. Obviously, the answers greatly depend on the questions asked, and also that framing the phenomenon of interest is central to framing the questions. Though data quality may well be maintained through appropriate statistical techniques, it is yet unlikely to achieve consensus on the "best" definition of telecommuting. This can be justified considering its multifaceted nature and the variety of perspectives from which people approach the subject.

2.3. Telecommuting Forecasts and Modeling Frameworks

From a planning perspective, it is crucial to figure out reliable estimates of how telecommuting impacts the transportation system performance or urban area characteristics. Such impacts will not be assessed unless there is a sound framework that captures and quantifies the popularity (intensity) of telecommuting adoption among workers. In other words, it is inevitable to come up with a systematic procedure that provides reliable answers to the following key questions: Among the workers' sample, who telecommutes? To what extent? What are the underlying factors that contribute to workers' decisions toward telecommuting adoption?

Based on such understanding, it is essential to forecast how much telecommuting will occur and how sensitive this demand is to structural changes or policies. At a disaggregate level, this calls for a behavioral modeling approach for telecommuting adoption. This section sheds light on some of the major publications that focus on telecommuting forecast and modeling frameworks.

Handy and Mokhtarian (1996) provided an exploration of methodologies and research needs in order to forecast telecommuting. Four alternative methodologies were introduced, along with their respective advantages and disadvantages. Moreover, researchers discussed the type of data that is required for each methodology. These methodologies include: 1) Trend extrapolation, which relies on growth factors and curves of technological substitution; 2) Analysis of telecommuter characteristics versus non-telecommuters, which is based on descriptive statistics and the correlation between the choice to telecommute and several individual, household or job-related characteristics; 3) Analysis of telecommuting choice, which estimates the probability that an individual with

certain characteristics and in a specific situation will telecommute; and 4) Incorporating telecommuting into traditional transportation forecast models, which may be done in any of the generation, distribution or mode choice steps. Table 2-1 summarizes the pros and cons of any of the aforementioned methodologies.

Table 2-1 Summary of Forecasting Methodologies

Methodology	Advantages	Disadvantages	Data and Research Needs
Trend extrapolation	Requires minimal data and analysis	Ignores trends in underlying factors that might alter currently observed relationships.	Time-series data on telecommuters and telecommuting frequency. Analysis of probable maximum adoption.
Analysis of telecommuter characteristics	Accounts for underlying trends. Relatively simple models required.	Based on correlations and does not reflect causal relationships.	Time series data on characteristics of telecommuters, especially occupation. Forecasts workforce characteristics.
Analysis of factors affecting the choice to telecommute	Accounts for causal factors at the individual level.	Models give probability of individuals choosing telecommuting but do not directly provide an aggregate telecommuting forecast.	Research on factors affecting the choice to telecommute. Forecasts of choice factors. Development of method for aggregating results.
Transportation forecasting models	Incorporates telecommuting into widely used planning models. Accounts for trade-offs between telecommuting and other travel choices.	Telecommuting represented as a simple alternative to other possible choices. Wide margins of error and insensitivities in models.	Travel surveys designed to identify telecommuting. Development of choice models.

This section mainly focuses on methodology types two and three, which explores the factors that contribute to telecommuting adoption either in terms of descriptive statistical analysis or developing modeling structures. A summary of the research background is highlighted in Table 2-2.

Using a cost neutral scenario, Sullivan et al. (1993) developed a multinomial logit model of employees' stated preference toward telecommuting. The scenario was basically defined as if all of the telecommuting costs were incurred by the employer, and the employees' salary would remain unchanged. The major idea was to investigate the impacts of individual and household characteristics, work-related attributes and individuals' travel behavior. Consequently, researchers concluded that as the round-trip commute time increases, workers show a higher tendency to prefer full-time telecommuting, especially when the total commute time is greater than or equal to 20 minutes. In addition, the number of commute stops employees make has a positive impact over their telecommuting preference. This might be due to their need for a flexible schedule in order to combine their daily activities. As far as job characteristics are concerned, employees with higher experience (five years or more) are less likely to prefer telecommuting. Likewise, tasks that include several daily face-to-face contacts with customers or supervisors decrease the telecommuting preference. On the contrary, technology improvements, such as computer-related tasks increase employees' propensity toward full-time telecommuting. In terms of individual and household variables, results indicate that females with young children, along with males from low-income households, are more likely to prefer telecommuting.

Table 2-2 Major Studies in Telecommuting Forecast

Research Work	Methodology Applied	Data	Sample Size	Dimensions
Sullivan et al. 1993	Multinomial Logit (MNL) Model	Survey in three cities in Texas	554	Preference
Bernardino et al. 1993	Ordered Response Probit Model	Survey in three cities in Texas	554	Preference
Mokhtarian & Salomon 1994	Descriptive statistics & Correlation Analysis	San Diego data	628	Preference & Choice
Mokhtarian & Salomon 1995	Binary Logit Model	San Diego data	628	Preference & Choice
Mannering & Mokhtarian 1995	Multinomial Logit Model	Three agencies in California	809	Frequency
Mokhtarian et al. 1997	Binary Logit Model	San Diego data	628	Preference
Mokhtarian et al. 1998	Correlation Analysis, Hypothesis testing	San Diego data	628	Preference
Belanger 1999	Correlation Analysis, Hypothesis testing	Two high-technology firms	71	Choice
Yen 2000	Ordered Probit Model	Survey In Taipei, Taiwan	2715	Choice & Frequency
Drucker & Khattak 2000	Ordered Logit, Ordered probit, Multinomial Logit	1995 nationwide transportation survey	29,994	Choice & Frequency
Peters et al. 2001	Binary Logit Model	Sample of Dutch labor force	849	Option, preference & choice
Wells et al. 2001	Correlation Analysis, Hypothesis testing	Two firms in Minnesota	797	Preference
Grippaldi 2002	Correlation Analysis, Factor Analysis	Random sample from GFOA	400	Preference
Popuri & Bhat 2003	Joint Sample Selection Model (Binary & Ordered Bivariate Probit)	1997/98 RT-HIS survey	6532	Choice & Frequency
Wernick 2004	Binary & Ordered Logit Model	2001 NHTS	23451	Choice & Frequency

Table 2-2 Major Studies in Telecommuting Forecast (continued)

Research Work	Methodology Applied	Data	Sample Size	Dimensions
Walls et al. 2006	Two- Staged Model (Binary & Ordered Probit)	202 SCAG dataset	2448	Choice & Frequency
Mamdoohi et al. 2006	Nested Logit, Multinomial Logit	Survey in Tehran, Iran	245	Option
Zhou 2008	Generalized Ordered Logit Model	Washington State CTR 2005	92'321	Choice & Frequency
Haddad et al. 2009	Ordered Probit Model	GFK NOP survey 2007	570	Choice & Frequency
Tang et al. 2011	Nested Logit, MN, Two-staged	Survey in North California 2003	1064	Choice & Frequency
Sener & Bhat 2011	Copula Based Joint Sample Selection Model (Binary & ordered bivariate probit)	CRHTI 2008	9624	Choice & Frequency
Singh et al. 2012	Joint Sample Selection Model (Binary & Ordered Probit)	NHTS 2009	2563	Option, Choice & Frequency

Bernardino et al. (1993) improved the model structure by developing different scenarios. Each scenario is represented by a combination of salary, costs, schedule flexibility, telecommuting frequency, and available equipment. Respondents stated that their preferences were measured on an arbitrary scale from one (definitely would not telecommute) to five (would definitely telecommute). Considering the ordered nature of the dependent variable, an ordered-response probit model was developed to describe individuals' stated preference to telecommute. According to their results, researchers found that parents with children under 18 are more likely to prefer telecommuting. Moreover, employees who were not offered a telecommuting opportunity showed a higher tendency to participate in telecommuting, which may well indicate a policy bias. Surprisingly,

variables such as gender, commute time, and years of employment had no significant impact on the model. As expected, the telecommuting preference will decrease if employees are forced to provide a computer or accept their extra work-related payments, such as telephone bills.

Yen and Mahmassani (1994) proposed a conceptual framework with the objective to explore the interactions between telecommuting adoption and travel behavior, as well as to develop statistical models for telecommuting adoption. The framework divides telecommuting into two major dimensions: the employer and the employee. Data used in this study come from a survey of employees and employers in selected organizations from three cities in Texas: Austin, Houston, and Dallas. The final sample includes 694 employees and 83 employers. An explanatory analysis of stated preference data indicated that employee attitudes and preferences toward telecommuting were significantly affected by personal and household characteristics such as gender, job attributes, computer proficiency, number of children under 16, and personal computers at home, as well as commuting attributes. Factors that influence employer attitudes and preferences include management concerns such as productivity, morale, absenteeism, and data security. A comparison of the two categories reveals that employers are more reluctant to adopt telecommuting than employees.

Two separate generalized ordinal probit models were developed, one for employees and one for employers. In terms of employees, results confirm most of the previous exploratory findings, namely that employee participation in telecommuting is primarily influenced by five groups of attributes: 1) economic implications of program design, 2) personal and household characteristics, 3) job characteristics, 4) commuting attributes, and

5) attitudes toward telecommuting. Moreover, estimated coefficients of variables point out that both changes in employee salary and the costs incurred by telecommuters significantly influence employee telecommuting adoption, with the salary changes having a stronger effect. Furthermore, the effect of salary decrease is stronger than salary increase. In terms of employers, as expected, estimation results indicate that employers are not likely to support any program that increases telecommuter salary. On the other hand, they do not consider that telecommuters should incur a decrease in salary, which is one of the main concerns of employee adoption. Results also confirm that management issues are the major obstacle to employer support, as widely speculated in the literature.

Mokhtarian and Salomon (1994) presented a conceptual framework for individuals' decision-making toward telecommuting. The key elements of the model include constraints, facilitators, and drives. A constraint is defined as a factor that prevents or hinders any change (in this case, the choice to telecommute) if it is present. Facilitator or enabler is a factor that allows change (telecommuting), or makes the change easier or more effective, if it is present. The same basic factor may be either a facilitator or a constraint, depending on whether it is present in a positive sense or a negative one. Drive or motivator is a factor that actually motivates a person to consider a change (begin to telecommute). Authors explain that these concepts may be applied to any type of change, which is telecommuting in this case. Thus, one may consider the following scenario where a person is not telecommuting. He/she is driven toward telecommuting by one or more factors. Given the initial drive, the presence of facilitators increases the probability that telecommuting will be adopted (or the amount that he/she chooses to telecommute). Without that drive, facilitators are assumed to have no effect on the adoption of

telecommuting. On the other hand, the presence of constraints decreases the likelihood of adoption (or the amount of telecommuting) and, if sufficient, will preclude adoption.

Two major types of constraints are categorized and introduced: External factors that are subject to change (for example by company or public policy) and internal factors that are less amenable to external change due to their internal nature. External factors are related to awareness, the organization, and the job, while internal constraints usually include psychological factors. Furthermore, it is important to notice that constraints or facilitators do not tell the whole story. A person does not telecommute simply because the technology is available or because the supervisor agrees to that. Those factors facilitate telecommuting but do not drive it. Five major types of drives are introduced in this context including: Work-related, family-related, leisure-related, ideology-related and travel-related. Given the presence of one or more drives, the probability of the choice to telecommute will increase with the number and strength of drives and facilitators, and decrease with the number and strength of constraints.

While a conceptual framework was developed in their earlier studies, researchers presented the descriptive statistical results from the empirical data of 628 employees in San Diego, California. Three different aspects of telecommuting including possibility, preference and choice were explored and their relationships were examined. The data for this study come from a 14-page self-administered questionnaire that includes questions about: respondents' awareness and experience with telecommuting, job characteristics, ability to telecommute, advantages and disadvantages of telecommuting, socio-demographics, attitudes and lifestyle drives. A total of 1428 surveys were sent out, of which 628 were returned, yielding an effective response rate of 44%.

Regarding the dependent variable, authors discussed various possible dimensions that may be considered. Whether the individuals' preference or actual behavior is considered remains an important issue. In addition, one might consider the application of binary or nominal variables. While the binary variable focuses on "whether or not to telecommute," a nominal variable simultaneously considers the "frequency" aspect. For the purpose of their research work, a binary variable is adopted.

Constraints are categorized into "dichotomous" or "continuous". Three major dichotomous constraints are identified: "Lack of awareness" is active for 4%, "job unsuitability" is active for 44%, and "manager disapproval" for 51% of the sample. It is assumed that if any of the constraints is active for a person, he/she will not have the possibility of telecommuting. This occurs for 68% of the sample. However, even in the absence of dichotomous constraints, most people do not choose telecommuting, which is probably due to continuous constraints. According to the questionnaires, five major reasons were reported as significant including: lack of resources, being content with the present situation, etc. Only a small portion of the whole sample (11%) find telecommuting as being possible, preferred, and chosen. One key finding is the existence of a large share of the people (57%) for whom telecommuting is a preferred, impossible alternative, i.e., they prefer to telecommute but are prevented by at least one of the constraints.

In 1995, Mokhtarian and Salomon operationalized their previously published conceptual model. Using survey data from the City of San Diego, hypothesized drives to telecommute and constraints on facilitators of telecommuting are measured. A binary logit model of the preference to telecommute from home is estimated, which shows a ρ^2 value of 0.68. The explanatory variables include attitudinal and factual information. Factor

analysis is performed on two groups of attitudinal questions, identifying a total of 17 (oblique) factors that can be classified as drives and constraints. Additional measures are created from other data in the survey, usually objective socio-demographic characteristics. Variables representing at least four of the five hypothesized drives (work, family, independence/leisure, and travel) are found to be significant in the final model. Variables from four of the ten groups of constraints (job suitability, social/professional and household interaction concerns, and a perceived benefit of commuting) are significant, primarily representing internal rather than external constraints. The results clearly demonstrate the importance of attitudinal measures over socio-demographic ones, as the same demographic characteristics (such as the presence of children and commute time) will have different effects on preference for different people.

The results for the preference model seemed statistically sound and reasonably justified. However, it should be noted that there is a wide gap between preference and actual choice. Eighty eight percent of the entire sample prefers telecommuting, while only 13% actually telecommute. Researchers therefore enhanced their modeling structure by shifting the dependent variable from "preference" to "actual choice." Preference is then added to the model as a binary independent variable. In addition, constraints are treated and evaluated in two intrinsically different approaches: In the first approach, constraints are directly incorporated into the model. In the second approach, constraints are applied to define and limit the choice set. Results indicate that models developed through the first approach are statistically superior in this analysis. Significant variables include work and travel drives, awareness, manager support, technology, job suitability, and discipline constraints.

One advantage of the first approach is that it enables the analyst to explore how any of the existing constraints will impact the telecommuting rate in the population. Based on the results, when unawareness, lack of manager support and job unsuitability constraints are relaxed, 28% of the PIA (preferred impossible alternative) categories adopt telecommuting.

Considering its richness in terms of variables and its compatibility to the telecommuting framework, the San Diego survey data was popularly used for some further studies. Mannering and Mokhtarian (1995) explored individuals' telecommuting frequency as a function of demographic, travel, work and attitudinal factors. Three different datasets were used to develop three separate multinomial logit models. These include data collected from the Franchise Tax Board in Sacramento (90 individuals), data from the Public Utilities Commission in San Francisco (90 individuals) and data from the City of San Diego survey (629), all of which form a total sample of 809 workers.

Three alternatives were considered for telecommuting frequency: Never telecommute, infrequently telecommute (less than once a week) and frequently telecommute (at least once a week). Moreover, it was discussed whether ordered or un-ordered response models should be considered for frequency. The most critical disadvantage discussed by the authors was that ordered response models assumed monotonic increase of desirability for each explanatory variable. It means this modeling approach cannot accommodate variables that favor mid-range alternatives over high- or low-range alternatives. Therefore, multinomial logit models were preferred and applied to the data.

One important conclusion is the apparent lack of transferability of the models, which raises the need to identify organization-specific attributes, i.e., attitudes which differentiate one organization from another. This includes size, geographic location, managerial structure, age and industry. Moreover, degree of empirical experience with telecommuting seems to play an important role in telecommuting frequency. Among the significant variables, one can mention the presence of small children, number of household members, respondent's gender, number of household vehicles, supervisory status of respondent, and family orientation.

Mokhtarian et al. (1997) examined three models of individual preference for home-based or center-based telecommuting. Different aspects of dependent variable were discussed including: 1) binary (choice/preference) versus multinomial (frequency), 2) telecommuting type (home, center or both), and 3) whether preference or actual choice should be considered.

As there were not enough data available for center-based telecommuting adoption, preference was addressed as the main dependent variable. One major problem was that the three alternatives of home, center and regular workplace were not mutually exclusive. It means a person may be attracted to all three options over a course of a week. In order to resolve this issue, six different choices were offered for each of home- or center-based telecommuting: not at all, less than once a month, about 1 to 3 days a month, one to two days a week, three to four days a week and five days a week. A matrix was then formed with the rows indicating home-based preference and he columns indicating center-based preference. Therefore, 581 individuals were divided into four categories: 61 people who do not prefer any type of telecommuting, 245 individuals falling on the matrix diagonal

(which prefer either of the telecommuting options), 31 workers falling above the diagonal (who prefer center-based over home-based), and 244 individuals who prefer home-based telecommuting over center-based.

Two binary logit models were presented, one on the preference of center-based telecommuting versus other options ($\rho^2 = 0.24$), and the other on the preference of center-based telecommuting over home-based telecommuting ($\rho^2 = 0.64$). A nested logit model was also developed, including two tiers: the first tier includes three alternatives of no preference, strict preference and indifference. The strict preference is further divided into home- or center-based telecommuting.

The results of the models confirmed the importance of attitudinal measures in measuring an individual's preference to telecommute. Oblique factor scores representing workplace interaction, stress, workaholism, internal control, and commute stress were statistically significant in some or all of the models. Other explanatory variables that were found to be consistently significant were education, job suitability, and age. Most respondents preferred either to telecommute from home or were indifferent between either form of telecommuting, which raises the question as to whether there really is a sizeable market position to be filled by telecommuting centers, and whether they may make a significant contribution to transportation demand reduction.

In another relevant study, Mokhtarian et al. (1998) used the San Diego data to explicitly target how gender, occupation, and presence of children (as the most important demographics) influence individuals' perception of motivations or constraints. Exploratory statistical analyses were carried out on the data. Eleven disadvantages of telecommuting, also known as "internal constraints" were identified, which were later classified into four

different classes: Workplace interaction, management visibility, office discipline and commute benefit. Seventeen recognized advantages were also further stratified into five new groups: Personal benefits, stress, family, disability/parental leave and relocation. External constraints consist of a variety of issues such as lack of awareness, job unsuitability, supervisor unwillingness, etc. In order to compare these variables among different categories of gender, occupation, and presence of children, several statistical tests were applied. These include ANOVA, the "t" test, and Pearson chi square. Several detailed results were obtained that may further be used to inform policies intended to support telecommuting. For instance, women were more likely than men to consider family, personal benefits and stress reduction as potential incentives toward telecommuting. They were also more prone to take supervisor unwillingness, risk aversion and lack of visibility to the manager as the major constraints. Among different occupation categories, while managers were mostly concerned about reduced professional interactions or household distractions, clerical workers were mostly affected by misunderstanding, supervisor unwillingness and job unsuitability. One interesting outcome was that lack of awareness, cost and lack of technology did not differ significantly by gender or occupation. In addition, respondents with children considered stress reduction and family benefits as their main motivations towards telecommuting.

Belanger (1999) carried out an empirical study over workers' propensity to telecommute. The data applied in this study came from a survey in two large work groups working for a high technology organization during the spring and summer of 1997. The final sample consists of 76 workers out of 168, reflecting an acceptable return rate of 46%. The major motivation was to answer the following two questions about the concept of

telecommuting: First, what are the underlying factors and determinants which affect individual's decision whether or not to telecommute? And, once telecommuting is selected, what are the consequent differences in their job-related outcomes?

Different types of individual characteristics were applied and tested including age, gender, job category, years with the organization and technical skills. Four different outcomes were considered, namely productivity, performance, personal control and satisfaction. A number of statistical hypotheses were made and tested between the two categories of telecommuters and non-telecommuters. Two-sample t test, Chi-square and one way ANOVA were applied as the most prevalent statistical tools. Among the variables, job category and gender showed significant differences between telecommuters and non-telecommuters. As far as outcomes are concerned, only personal control and productivity were statistically different between the two categories at the 0.05 significance level. The need to share information with co-workers, more productivity at office environment and the need to socialize with colleagues were the three most often mentioned reasons for choosing not to telecommute.

Yen (2000) explored the concept of telecommuting adoption from an economic perspective. The study was based on the assumption that telecommuting adoption may be viewed as a trade-off among several constituents including the price of telecommuting itself, substitutes and complements as well as generalized income and situational constraints incurred by the employee. A survey was done in Taipei, Taiwan where workers were offered 11 different financial scenarios comprised by variations in their salaries versus the prices imposed by adoption of telecommuting. They were then asked about their favorite telecommuting frequency for each scenario. 8890 questionnaires were sent out and

460 usable ones were received which reflected a return rate of 5.2%. Six different frequency alternatives including 0 to 5 days per week were considered. An ordered probit model was further developed where scenarios were incorporated into the model as dummy variables. In general, five types of variables including prices of telecommuting, substitutes, complements, social status of employees and situational constraints were tested. In addition to arguing the impacts of variables in the model, elasticity of variables were carefully analyzed. Results indicated that the elasticity with respect to the prices imposed on the telecommuter was the largest one and the elasticity of the living space at home is the second one. In addition, all the elasticities calculated for the auto driver commuters were found to be larger than the ones regarding transit riders.

Drucker and Khattak (2000) analyzed the effects of socio-economic, household, locational and accessibility variables on workers' telecommuting behavior. Using the 1995 Nationwide Personal Transportation Survey (NPTS), they developed ordered logit, ordered probit and MNL structures. The NPTS focuses on general travel behavior and vehicle ownership and also collects a host of socio-demographic data and asks respondents how often they had worked from home in the previous two months. The choices available were two or more times per week, about once per week, once or twice per month, less than once a month, or never. One major shortcoming of the NPTS is the absence of job or employer data. Being primarily a travel survey, it focuses on questions related to vehicle ownership and driving, and does not survey people about their jobs. It does, however, include a wealth of socioeconomic and demographic information and is one of the few large national samples available for study. Researchers found that age and level of education reflected positive impacts on more frequent telecommuting. Men were more likely to work at home

than females, and people with children under the age of six showed higher tendencies to work at home. Likelihood of telecommuting was positively correlated with household income but the marginal effects were relatively small. Rural residents, workers who had to pay to park at work and those with less access to transit were more prone to telecommute. A somewhat surprising finding was that commute distance was negatively associated with working at home– that is, the farther individuals live from their job, the less likely they are to work at home. This usually rises from the endogeneity effect between telecommuting and residential location which will further be discussed and clarified in the next section. Considering the absence of job-related variables as well as employer characteristics, some of the individual attributes in their model are probably proxying for other factors. For example, the gender, age, education, and income variables may all substitute for things like job tenure and organizational position.

Using a representative employee sample (N=849) in Netherlands, Peters et al. (2001) investigated three aspects of telecommuting: Telecommuting opportunity, preference and actual practice. The data came from the computer designed "Work & IT"-2001 survey. Statistical analysis revealed that 24% of the sample, were given the opportunity to telecommute, 55% had preferences for telecommuting while 25% actually telecommuted. These were higher than the average rates obtained from previous studies as this research only considered those employees using a personal computer at work.

Four clusters of variables were being focused on, including organizational, job, household and individual characteristics. Regarding any of the clusters, initial hypotheses were expressed by the researchers based on the literature. A binary logit model was then developed for each of the aforementioned dimensions. In addition to facilitating them to

test the pre-established hypotheses, careful analysis of the results provided the researchers with several interesting outcomes. In terms of organizational characteristics, possession of more business localities induces a large positive impact on telecommuting adoption. While management literature suggests telecommuting as an outcome of modern management principles, the results hardly support this assumption. As expected, the absence of a supervisor increases the likelihood of telecommuting opportunity. Regarding job characteristics, higher education levels and IT skills encourage both telecommuting opportunity and practices. Considering household attributes, presence of children under the age of 4 increases telecommuting preference. A one-way commute length of more than an hour or desire for a quiet workplace urges workers to adopt telecommuting. Results also indicate that gender has no impact on the model.

Wells et al. (2001) explored the relationship between telecommuting and travel behavior, and the potential effects of travel outcomes for community systems. Data were collected in the Minneapolis St. Paul area from two intrinsically different types of companies: a large private high-technology firm and a public agency. A multiple methodology design was applied in order to access all the possibly required information. This includes a cross-sectional survey among non-telecommuters, a census survey of telecommuters and detailed interviews with telecommuters, their colleagues and managers. The surveys focused on travel behavior exploration, telecommuting constraints, telecommuting facilitators and implementation variables and demographic attributes. The final sample consists of 797 individuals, 43 percent of which involved in telecommuting. In order to have a more in-depth exploration of the data, 50 individuals were selected for a follow-up interview. Several statistical inferences can be made based on a two-sample t

test between telecommuters and non-telecommuters. In particular, telecommuters were more likely to be women, married, and have children. Findings also confirm that job suitability is an important factor in telecommuting ability. When it comes to frequency, public agency participants engaged in a significantly higher number of days than did the private workers. Private firm workers were more prone to telecommute on Mondays and Fridays while public agency employees did not show any significant differences. In addition, both survey and interview showed that “long commute” is a primary reason of telecommuting engagement.

Grippaldi (2002) evaluated attitudes towards telecommuting among finance employees who were employed by special district governments in the United States. Original data was collected by using a self-administered mail survey sent to 400 special district government finance employees who are members of the Government Finance Officers Association (GFOA) of the United States and Canada. Variables such as employees’ support for telecommuting, the likelihood of employees working away from the office, and the number of days employees wish to telecommute were investigated. A factor analysis was employed to determine if patterns of correlation within the set of 16 observed attitudinal variables (directly obtained from survey questions) could be explained by underlying factors. The results revealed that four main factors exist. These included how telecommuting impacts organizational attitudes, personal attitudes, job satisfaction, and the relationship between job stress and saving money. Overall, women were more likely than men to express positive attitudes towards telework. Individuals who were married or provided childcare expressed positive attitudes towards telework more often than singles or employees not caring for children.

Popuri and Bhat (2003) contributed to the telecommuting literature by examining revealed preference data to analyze the choice as well as frequency of home-based telecommuting. Their empirical analysis was based on a sample of 14’441 households from the Regional Transportation Household Interview Survey (RT-HIS) conducted by the New York Metropolitan Transportation Council (NYMTC) and the North Jersey Transportation Planning Authority (NJTPA). According to the researchers, there are several compelling reasons to consider the RTHIS as an appropriate dataset for telecommuting analysis. First, the survey collects information on workers’ actual behavior rather than stated preferences. Second, the survey reduces the prevalent confusion between home-based telecommuting and home-based business by asking if home was the primary/main workplace. Negative responses are regarded as home based telecommuters, while individuals with a home-based business would respond positively. Third, in addition to whether or not a person is telecommuting, the survey also collected information on telecommuting frequency. Fourth, the RT-HIS collected data form a wide variety of individuals, hence representing a variety of demographic and occupational characteristics. This enables the consideration of a multitude of elements contributing to telecommuting decisions. Last but not least, the RT-HIS provides a fairly large sample compared to most other surveys used for telecommuting analysis, offering the opportunity for a rigorous analysis of telecommuting choice and frequency.

A joint model of home-based telecommuting choice and weekly telecommuting frequency was proposed. Such approach uses two equations, a binary-response for telecommuting choice and an ordered- response for the number of telecommuting days per week. The distinctive aspect of their methodology is that it accounts for the correlation in

error terms between the two equations by considering a joint bivariate normal distribution of the two decision-making factors. That is, it accounts for the potential presence of unobserved individual that influences both the telecommuting participation decision as well as the frequency decision (such as an overall preference for less travel). It is assumed that skipping such common unobserved factors can lead to the inflation of error terms, inconsistent parameter estimates and, therefore, misleading estimations of telecommuting magnitude. Results indicate that individual demographics, work related attributes and household characteristics are significant determinants of telecommuting adoption and frequency. For instance, having college education, being a licensed driver, being married, part-time working and private employment encourage both choice and frequency of telecommuting. Moreover, females with children are more prone to telecommute and also, do it more frequently. One drawback of this study is the lack of some job-related variables which may have potentially significant impacts on the model.

In a similar effort, Walls et al. (2006) used the SCAG 2002 telework survey to analyze individuals' behavior towards teleworking. Based on a sample of 499 observations, a two stage model was developed for propensity and frequency. While propensity was modeled as a binary probit model, an ordered structure was applied for telecommuting frequency based on number of telecommuting days per week. Three levels of telecommuting frequency were considered: Infrequent (zero or one day per week), Medium (two or three days per week) and High (four or five days per week). Using a weekly diary for workers is a distinguishing aspect of this study which researchers believed would remove any bias or substantial errors due to lack of memory or respondents' quick response.

Results indicated that the two decision-making factors came from different underlying procedures. While age and education significantly encouraged both telecommuting aspects, no other demographic variable affected telecommuting frequency. Unlike the propensity model, industry, occupation or company size had no significant effect on telecommuting frequency. Factors such as employers' formal telecommuting program, multiple jobs and longer commute times also led to more frequent telecommuting.

Mamdoohi et al. (2006) introduced a new approach in order to consider suitability of any job for telecommuting implementation. Accordingly, adoption of telecommuting usually depends on the interaction among three different components: 1) Job suitability, 2) employers' attitudes and 3) employees' attitudes. While this research work focuses on the first aspect, the main hypothesis is that the conventional job title or job category does not reveal that much about the suitability for telecommuting. Instead, one should notice the structure, components and tasks that a job comprises. This leads to a pioneering approach introduced herein as the "abstract job". By using this term, researchers imply the fact that every job is considered as a vector of their elements and constituents whose distribution in the overall time allocation will play the major role in telecommuting suitability. As the concept of abstract job highly depends on identification of job-related tasks, the following characteristics have been specifically paid attention to regarding the relationship between tasks and telecommuting: a) Independence from a particular location, b) independence from colleagues or supervisors and c) dependence on modern communication technology. Six major tasks are identified and categorized including: reading or writing reports,

working with pc, talking on the phone, talking with clients and colleagues, teamwork, and mission out of the office.

The sample data came from a survey carried out in 2003 in Tehran, Iran, and included 245 employees coming from seven different companies and departments. Four different categories of job suitability in terms of “frequency” were considered: not suitable, one, two, and three days per week. Researchers considered both nested and multinomial logit structures, however the nested structure proved to be inappropriate. Using multinomial logit as the preferred structure, two different models were developed, one for supervisors and one for employees. Results indicate that among the 6 different tasks primarily defined, 5 of them proved to have significant influence on the model (except for reading/writing). Working with a pc, talking on the phone and teamwork showed positive impacts while mission out of the office and conversing with clients and colleagues were accompanied with discouraging effects over telecommuting suitability.

Wernik (2004) developed a modeling framework for telecommuting with an emphasis on technology accessibility, innovations in telecommunication, and geographical influence. Using the NHTS 2001 data, binary and ordinal logit models were estimated to respectively predict telecommuting choice and frequency. The representative sample included 25’432 American workers, age 16 and over from the whole nation. In order to consider the impact of geographical variables, data was collected for 18 different metropolitan areas known as Consolidated Metropolitan Statistical Areas (CMSA). The results are therefore expected to be applicable to the working population at a national level. For each of the two dependent variables, two separate models were estimated: The constituent effect model and the interaction effect model. The latter takes into account the

interaction between internet access and variables such as CMSA, rail access, education, gender and full time work. Three classes of frequency were applied in the model: Frequent (including responses of almost every day or once a week or more), Infrequent (responses of once a month or more and a few times a year) and never. Results indicated that several key variables such as income, age, commute distance, access to internet both at home and work; household cellular phones and number of land lines all showed positive impacts on telecommuting. Regarding metropolitan areas, San Francisco and Denver exhibited higher likelihoods of telecommuting. In terms of interaction variables, Dallas is a likely place for telecommuting as residents will have more access to the internet.

As part of his Ph.D. dissertation focusing on TDM policies, Zhou (2008) explored the Washington State Commute Trip Reduction (WA CTR) data to analyze telecommuting participation trends and choice modeling. Based on a unique dataset which included more than 90,000 observations, he developed a generalized ordered logit model, predicting workers telecommuting option into either of the following categories: Non-telecommuting, one day, two days, three or more days per two weeks. One major aspect of this study is that the researcher shifts from an ordered logit model into a generalized ordered logit structure. This rises from the violation of "parallel slopes" or "proportional odds" assumption, which is the basic hypothesis in regular ordered-response models. An ordered logit model was estimated at the very first step. Relevant statistical tests including Wald tests were carried out and as the "parallel slopes" assumption was violated, the researcher applied a generalized logit structure which allowed the incorporation of different coefficients for different alternatives. Results indicated that variables such as commute distance, job type, travel pattern, time flexibility and years of telecommuting implementation played a

significant role in telecommuting model. Employees commuting longer distances were more likely to make the transition from not telecommuting to telecommuting and from telecommuting one day to two days and from two days to three or more days per two weeks. Compared with commuters who use the driving alone mode, employees using single mode of transit and shared ride were more likely to not telecommute or telecommute fewer days. It is interesting to see that people working on compressed week schedule were less likely to work on telecommuting. Workers living in an area with higher property values were significantly more prone to telecommute. This may suggest that telecommuting is more appropriate for high-end jobs. Among different job titles included in the model, administrative support, production/labor, and customer services reflected discouraging effects on telecommuting, which may well be justified by their nature. While management occupations had positive signs, they were not statistically significant for frequent telecommuting choices. This reveals their desire to shift into telecommuting but only for low frequencies which seems reasonable taking their job characteristics into account.

Tang et al. (2011) investigated the effect of residential neighborhood built environmental (BE) factors on telecommuting. The data used in this study came from a self-administered survey mailed in two rounds in late 2003 to households in eight neighborhoods in Northern California. The final sample dataset consists of 1246 workers. Focusing on the two decision-making factors (choice and frequency), they explored several structures including the single level multinomial logit, nested logit and two staged models. Based on the statistical results, an MNL structure was preferred. Five different categories were identified for frequencies: “zero days”, “one day”, “two to four days”, “five to eight days”, and “nine or more days” per month. Including zero days as a separate alternative in

the MNL model reveals that choice and frequency are modeled simultaneously. Four types of explanatory variables were included in the model: Commute trip attributes, BE characteristics and neighborhood preferences, travel attitudes and socio-demographics. While many publications question the causality effect of telecommuting on residential relocation, this paper assumed that telecommuting did not motivate individuals to move.

Results generally confirmed the expected influence of commute time, work status, household income, and education level on adoption and frequency decisions. Moreover, results reflected that several subjective and objective BE characteristics were significant for at least one of the frequency categories. Individuals who perceived high regional accessibility for their neighborhood tended to work at home either very little (perhaps due to less burdensome commuting) or a great deal (possibly because they operate a well-positioned home-based business). Two measures of density, the number of eating-out places and the number of institutional establishments within 400 meters of the residence, showed counteracting effects. Greater densities of eating-out places in the neighborhood resulted in higher frequencies of working at home for two to four days a month (compared to lower and higher frequencies), whereas higher densities of institutions (such as churches, libraries, and banks) led to lower the propensity to work at home at all.

Vana et al. (2008) used the 1992 San Diego data and explored three distinct dimensions of work-related choices in a joint structure. These dimensions include: work-hour arrangement, location and telecommuting frequency. Among several structures tested namely multinomial logit (MNL), nested logit (NL) and mixed multinomial logit (MMNL), the multinomial logit turned out to fit best. The dependent variable comprised all the possible combinations of the three aforementioned dimensions: work arrangement choices

include “conventional” versus “unconventional”, location included “exclusively home”, “home or center” or “neither”, and telecommuting frequency consists of “not at all”, “less than once a month”, “about one to three days a month”, “one or two days a week”, “three or four days a week”, “five days a week”, and “occasional partial days”. A rich set of socioeconomic, demographic, job-related and attitudinal attributes were applied to the model. Results of the model were investigated from different aspects. Household attributes reflect complex impacts over telecommuting. As household size increases, employers are willing to telecommute more frequently. However, they are less likely to choose exclusive home-based telecommuting options. Regarding job-related characteristics, it is interesting to notice that when managerial employees prefer to telecommute exclusively from home, they prefer lower frequencies (low or medium). Logically, employees who perceive daily commute as being troublesome are more likely to prefer both home or center-based telecommuting and that, in terms of frequency they are willing to do it more frequently. Furthermore, the model delves into some attitudinal measures of employees. For example, workers who are “willing to spend more time with family” are more inclined towards exclusively home-based telecommuting. Or workers who consider themselves as “not self-disciplined” are less likely to adopt unconventional work hour arrangement or prefer home-based telecommuting. From a technical perspective, researchers believe that the joint choice model is of superior descriptive power and clarity compared to standalone models as it captures the combined effects of the correlated dimensions and helps clarify the complex underlying behavioral procedure.

Haddad et al. (2009) focused on part-day homeworking, also recognized as VST (Varied Spatio-Temporal) working. VST is defined when “at least 30 minutes of

continuous work takes place at home and also in the usual workplace on any given day". This is compared to "whole-day homeworking" which is the term used instead of the traditional phrase "full-day telecommuting" in this paper. Two key aspects of each pattern are investigated: desire and frequency. Socio-economic factors along with attitudinal characteristics are the main parameters tested as independent variables in this study. Workday arrangements were classified into seven different patterns: 1) worked at workplace only (W), 2) worked at home only (H), 3) work at home then workplace (H_W), 4) (W_H), 5) (H_W_H), 6) not worked today, 7) other workday patterns. Patterns three, four, and five represent VST while pattern two symbolizes whole-day homeworking. In addition, the commute-related details for each person were captured through various sets of questions. In addition, a subsequent set of 16 belief statements was included in the survey which was used to obtain individuals' attitudinal determinants over any of the pre-selected working patterns.

Analyzing the data from the third wave of a national longitudinal survey carried out in UK in March 2007, researchers came up with a final sample size of 1015 full time paid employers aged 18 to 64. Ordered probit models were developed for each of the dependent variables. For each model, two successive stages were adopted. First, only SED variables were applied to the model. Second, attitudinal factors were added to the calibration process. The second stage was systematically selective where the variables were added provided that they were either significant or increased the model overall goodness-of-fit. Results indicate that avoiding interruptions at work, avoiding wasted time in traffic, appreciation of other household members and working longer hours are among the most significant attitudinal factors regarding the desire to both VST and H. In terms of frequency, employer

support is relevant to both patterns. While VST frequency is more associated with avoiding work interruptions, frequency of H pattern is better explained by commute struggle. As far as SED attributes are concerned, variables such as age, gender, one-way commute distance and etc. play important roles in both models. The better performance of H models compared to VST models perhaps explains the fact that VST relies on other factors which are yet to be identified.

Sener and Bhat (2011) contributed to telecommuting literature by proposing a joint structure for propensity and frequency of telecommuting among workers. The distinctive aspect of this paper is using a sophisticated statistical bivariate methodology known as Copula. Copula is defined as a device that generates a stochastic dependence among random variables with pre-specified marginal distributions. Once developed, it allows generation of a joint bivariate distribution functions with specified marginal. The data used in this study are drawn from the 2008 Chicago Regional Household Travel Inventory (CRHTI) and the final dataset contains 9624 employees of which 1534 individuals are telecommuters (15.9% of overall sample). Binary and ordered structures were respectively used for choice and frequency. 5 categories were considered for telecommuting frequency: "once a year", "a few times a year", "once a month or more", "once a week or more" and "almost every day". The modeling structure is very similar to Bhat and Popuri (2003). However the final bivariate distribution function is based on a dependency parameter which is incorporated into a copula function. This allows testing of several types of dependency structures between choice and frequency behavioral processes.

Results clearly reflected the different underlying processes of the two decision-making factors. As an example, although gender does not show a significant impact on

telecommuting frequency, it plays an important role in choice decision as women are less likely to telecommute compared to men. While full time employees are more prone to have a telecommuting arrangement, they tend to show less telecommuting frequency compared to part-time workers. In general, results indicate that demographics and work-related attributes have significant contribution to both choice and frequency.

Singh et al. (2012) expanded the telecommuting modeling framework by incorporating three decision-making factors: Option, choice and frequency. “Option” considers whether the employers provide their employees with telecommuting opportunities or not. “Choice” reflects employees’ reaction towards telecommuting program, i.e., to accept it or not. “Frequency” provides the analyst with a quantitative value, measuring to what extent telecommuters engage in telecommuting activity. Compared to the previous works, this study combines some unique features including the consideration of “option to telecommute” as a significant factor or applying the actual number of telecommuting days per month instead of using broad discrete intervals. Furthermore, the joint structure helps the analyst take into account the presence of unobserved factors, which may simultaneously impact all three types of decision-making. The NHTS 2009 data was used for this analysis and the final sample consists of 2563 workers. Four different categories of variables were identified and applied into the model including: Individual demographics, work characteristics, household demographics and built environment (BE) measures. Based on the results, women are less likely to be offered the telecommuting option, but are more prone to choose it if they have the opportunity. Age reflects significant impacts on both option and frequency. Middle-aged workers are more prone to have telecommuting option but less likely to do it frequently. Moreover, highly educated

individuals have higher opportunities to have the option and adopt telecommuting. Among household variables, presence of young children and belonging to high-income category will encourage telecommuting option and choice dimensions. The impact of BE measures on telecommuting are also explored. Neighborhoods with high household density are less likely to have the telecommuting option while highly populated areas show less inclination towards telecommuting. On the contrary, workers residing in areas with a high employment density are more likely to have the telecommuting option. In terms of accessibility measures, high ease of access to several facilities and different types of land-use encourages telecommuting. One major finding which is logically acceptable is that accessibility has no significant impact on telecommuting option.

2.4. Telecommuting Impacts

From a traditional perspective, early interest in the concept of telecommuting stemmed from the idea that in general, daily commute could well be replaced by telecommunications. As daily commute is considered a routine trip purpose performed in well-defined and predictable time periods, it seems very amenable to substitution by telecommunications. Earlier studies, which evaluated implementation of telework programs at an aggregate level, reflected several benefits due to net travel reduction in the network. A variety of performance measures including vehicle-miles traveled, vehicle-hours traveled, total network delay, number of crashes, and environmental pollution were tested in before-after scenarios to estimate the benefits gained from telecommuting implementation. However, there is growing awareness that on a macro scale, the travel benefits from telework may be limited. While studies focusing on short-term impacts of telecommuting agree on net travel reductions, long-term impacts are yet to be explored

(Niles, 1994; Mokhtarian and Salomon, 1997). It is evident that limiting the research to small-scale and short-term effects will lead to an overestimation of the impacts, while in reality, long-term system-wide impacts tend to be less positive. Mokhtarian (1998) explains that telecommuting impacts may easily be counteracted by either of the following scenarios:

- Time savings due to telecommuting adoption may fully or partially be allocated to out-of-home activities and therefore generate new travel.
- The fact that workers are capable of working full-time at home or commute less often can encourage them to move and reside further away from their workplace. This phenomenon, known as "residential relocation" can potentially increase the daily VMT even though individuals commute at lower frequencies.
- Any increase in the number of telecommuters will free up the transport capacity of the network. However, such vacancy can be fully or partially filled up by the latent demand from other network users. Thus, any savings in the network travel by telecommuters will be compensated for by non-telecommuters.
- From a general standpoint, any enhancement in technology and telecommunication is likely to generate more travel as there would be more contact and exchange of information among individuals.

Therefore, it seems evident that summarizing the impacts of telecommuting into a simple trip reduction rate (and its consequences) will not provide a convincing solution or a reliable tool for further planning. In order to capture impacts of telecommuting in a detailed texture, it is inevitable to consider how telecommuting impacts individuals' travel and activity patterns at disaggregate level. In other words, one should carefully notice that

telecommuting may alter any aspect of individuals' daily patterns, including activity scheduling, travel time, destination, mode, or any other trip attributes (Mokhtarian, 1998). To reach a more realistic correlation between telecommuting and travel behavior, it may be essential to broaden the analysis scope from single trips into activity and time-use pattern. The behavioral modeling framework must therefore be used to fully investigate the interaction between telecommuting and travel patterns.

The rest of this chapter will therefore continue in two separate subsections. First, a quick review of aggregate effects on the transportation network and relevant background is presented. Moreover, we focus on literature that emphasizes disaggregate impacts of telecommuting on individuals' travel behavior. A summary of these efforts along with some major attributes of each study are presented in Table 2-3.

2.4.1. Aggregate Studies

This subsection focuses on the studies which analyzed telecommuting impacts on the traffic network at aggregate level.

Schintler (2001) focused on the impacts that an increase in telecommuting activity can have on overall delay and congestion in the Washington, D.C. region. Estimates of delay, vehicle hours traveled, and vehicle miles traveled were generated using the Metropolitan Washington Council of Governments regional transportation planning model. Two different scenarios of 3% and 10% reduction in number of trips were considered, and the results were subsequently compared to a baseline scenario for 1999. Travel times used in this study were those experienced on major highway segments in the area and reported using SmarTraveler technology

Table 2-3 Telecommuting Impact Studies

Study	Data	Sample	Criteria and focus	Methodology
Schintler 2001	SmarTraveler data in Washington D.C.	1487 TAZs	Delay-Vehicle Miles Traveled-Vehicle Hours Traveled	MWCOG model
Choo et al. 2005	FHWA data 1966-1999	varies based on the applied dataset	Vehicle Miles Traveled	Multivariate time series analysis
Vu and Vandebona 2007a	Australian Bureau of Statistics (ABS), Road and Traffic Authority (RTA)	3,044,800 employees	Network travel time	Closed-form equation based on trip reduction factor
Vu and Vandebona 2007b	Australian Bureau of Statistics (ABS), Road and Traffic Authority (RTA)	3,044,800 employees	Vehicle Kilometers Traveled	Closed-form equation based on trip reduction factor
Vu and Vandebona 2007c	Australian Bureau of Statistics (ABS), Road and Traffic Authority (RTA)	3,044,800 employees	Environmental impacts/air and noise pollution	Closed-form equation based on trip reduction factor
Vu and Vandebona 2008	Australian Bureau of Statistics (ABS), Road and Traffic Authority (RTA)	3,044,800 employees	Traffic assignment	Closed-form equation based on trip reduction factor
Pirdavani et al. 2012	Flanders data in north Belgium	2200 TAZs	Safety Improvement/Vehicle Kilometers Traveled-Number of Crashes	Exploring O/D trip matrices under telecommuting and non-telecommuting scenarios
Pendyala 1991	State of California telecommuting pilot project	252 workers	Time-space analysis of telecommuters' travel behavior	Descriptive statistics and correlation analysis

Table 2-3 Telecommuting Impact Studies (continued)

Study	Data	Sample	Criteria and focus	Methodology
Mokhtarian and Salomon 1997	NA	NA	Partial or total commute substitution, non-commute trip generations, changes in mode choice, residential relocation or latent demand realization	Descriptive study
Wells et al. 2001	Survey in two companies in Minnesota	797 workers	Impacts of full-time and part-time telecommuting on mode choice, trip length, and trip chaining	Descriptive statistics, correlation analysis, and attitudinal factors
Mokhtarian 2003	NA	NA	Impacts of ICT on trip generation	Literature review
Mokhtarian et al. 2004	California state pilot program- 6 agencies	218 employees	commute distances and residential locations	Descriptive statistics
Helminen and Ristimaki 2007	Statistics Finland survey 2009	19000 employees	direct impacts of teleworking on commuting distance and frequency	Bivariate logistic regression
Jiang 2008	CPS 2001/PUMS 2000	29147 workers	Commute length and mode choice	Two-sample Instrumental Variable (TSIV)
Zhu 2011	NHTS 2001/2009	56198/101843 employees	personal one-way commute trips, daily total work trips and total non-work trips	Ordinary Least Square (OLS), two-stage Least Square (2SLS)
Mosa 2011	Cairo, Egypt	459 individuals/ 15395 activities	Impact of ICT on no-mandatory activity durations	Structural Equations Modeling (SEM)

The model projects that a 3% reduction in total work-related trips will lead to a 2.4% reduction in VMT, 6.4% in VHT and 10.0% reduction in total delay. For a 10% reduction in trips, respective estimated impacts are 8.0%, 20.8% and 30.0%.

Using the FHWA data from 1966 to 1999, Choo et al. (2005) examined the effect of telecommuting on passenger vehicle-miles traveled (VMT) at a national level. Their methodology was a multivariate time series analysis based on the Box-Jenkins approach. In this regard, dependent variable “VMT” was modeled as a function of explanatory variables. The independent variables applied were Economic activity, Transportation price, Transportation supply, and socio-demographic attributes. Subsequently, models were estimated to identify the impacts of telecommuting on the residual VMT after the impacts of the stage 1 variables were accounted for. The telecommuting variable applied was the natural logarithm of the number of home-based telecommuters and is obtained from four different published sources: U.S. Census Bureau, Market Research Firms, Current Population Survey and Telework America. However, authors insist that as these data are based on small samples, it is likely that they overestimate the true number of telecommuters. The second stage models were applied to data from 1988 to 1998. Results indicated a reduction of 44 to 66 miles per telecommuting occasion for different scenarios, which seemed unrealistically high compared to the benchmark data on average daily VMT. Therefore, authors proposed using a certain confidence level based on statistical distribution. Results of the analysis revealed that assuming the models to be correct, we can be 90% confident that telecommuting reduces VMT (by an amount as little as 0.34% in 1998). However, at a 95% confidence level, there was not enough evidence to accept that telecommuting might reduce VMT.

In a series of studies about telecommuting impacts in Australia, VU and Vandebona (2007) explored network travel time savings as the major impact of telecommuting. The network travel time is considered the total daily travel time for the work purposes by all workers, on both highway and rail network. Vu and Vandebona developed a computation model to evaluate both the reduction in number of trips and the resultant reduction in travel time. One chief aspect of this methodology is to differentiate between telecommuting types and their impacts, including the full-day and part-day telecommuting. The total reduction in number of trips could be calculated based on the number of employed people, proportion of telecommuters, frequency of each telecommuting type and different mode shares. As stated before, full-time and part-time telecommuting situations were accounted for separately.

Seven different scenarios were applied by making different assumptions about the model input, examining the effect of variables like telecommuting proportion, frequency, mode share, etc. Growth factors were applied for a study period of 20 years (from 2001 to 2021). The plausible input values are obtained from several sources such as the Australian Bureau of Statistics (ABS) and Road and Traffic Authority (RTA). Generally, it was inferred that telecommuting proportion and frequency had strong influences on network travel time. The influence of individual commuting travel time and mode share was also remarkable. Considering VOT (value of time), it was also possible to demonstrate the potential economic benefit through network travel time reduction. Furthermore, the benefit increased rapidly as the proportion and frequency of telecommuting increases.

Vu and Vandebona (2007) expanded their formulations in a follow-up study. This time, network savings in terms of vehicle kilometers of travel was investigated and

formulated. Likewise, the proposed model accounted for a range of variables including employment, telecommuting proportion, telecommuting frequency, modal split and network performance measures. It is important to notice that only the drive alone mode affected savings of vehicle kilometers traveled. In addition, VKT was not affected by part-day telecommuters. The model was applied to four different scenarios in New South Wales. Outcomes revealed that savings of VKT would increase rapidly when telecommuting proportion and frequency were encouraged to increase.

In a successive effort, researchers focused on the environmental impacts of telecommuting in Australia. Following their previous studies, this specific study emphasized a quantitative methodology that computed the positive impacts of telecommuting on air and noise pollution. All of the calculations presented were based on the trip reduction formula extracted from the authors' previous papers. In terms of air pollution reduction, two different reductions were accounted for: start-up emission and running emission. The input data regarding start-up and running emissions for different types of gas were obtained from California's EMFAC emission model. For the traffic noise reduction, a 50% traffic noise formula was extracted from the Handbook of Acoustic Noise for speeds of 35-45 mph and distances greater than 20 feet. Four different scenarios were applied in New South Wales, for a 20-year period from 2001 to 2021. Results indicated a remarkable decrease in both air and noise pollution. Authors also shed light on some of the limitations of the model. For instance, the results were likely to underestimate the situation due to assumptions made about the combination of vehicle types in the traffic flow. Furthermore, the noise pollution model is only applicable to a specific roadway evaluation and is not reliable for the whole network.

Finally, Vu and Vandebona (2008) investigated the impacts of telecommuting on trip assignment. They applied an elastic-demand network equilibrium model, which maximized the consumer surplus in the traffic network. A general optimization problem was formed and solved for the network considering two different scenarios, with and without telecommuting policy. For simplicity, a small network with three origin and destination pairs and six links was determined. Results indicated that when telecommuting was introduced, travel demand decreased by different amounts in different areas and on different paths of the transport network. This result redistributes trips in the network. In addition, the reduction of demand by telecommuting leads to a reduction of flows and travel time on roads. The reduction of travel time by telecommuting can change traffic flow distribution over the transport network when the travel time reduction is different on different paths of the network. The users on roads with greater travel times will consider switching routes to roads with less travel time, which pushes the network to a new equilibrium state with a new flow pattern. At this point, the combination of the demand function and the supply function enables us to solve the abovementioned interactions and to simultaneously determine demand and the redistribution of flow pattern.

One interesting issue noted by the authors for further research is the reduction in number of trips. While they uses a predetermined fraction of eliminated trips due to telecommuting, Vu and Vandebona (2008) believed that this factor could be determined by using the network equilibrium method. In other words, the reduction in number of trips would be expressed as a function of input variables such as travel distances and traffic status. This relationship is then embedded into the objective function and solved by

optimization techniques to determine both the reduction in number of trips and flow pattern simultaneously.

Pirdavani et al. (2012) investigated the impact of telecommuting on improvement of traffic safety. The major performance measure applied in this research is the Number of Crashes (NOC), which is directly associated with Number of Trips (NOT). The study area in this research is the Dutch-speaking region in northern Belgium known as Flanders, consisting of 2200 TAZs. The procedure could be categorized into two different steps: In the first step, the FEATHERS (Forecasting Evolutionary Activity-Travel of Households and their Environmental Repercussions) framework was developed to facilitate an activity-based model for transportation demand. The results of this step produced O-D matrices, which include number of trips by different traffic modes. This predicted demand would subsequently be assigned to the travel network by applying a user equilibrium algorithm. Two different scenarios were applied to the model: the null scenario and the telecommuting scenario. It was assumed that 5% of workers engage in teleworking.

In the second stage, Zonal Crash Prediction Models (ZCPMs) were estimated based on the outcomes of the first step. According to the model's outcomes, the telecommuting scenario resulted in a reduction of 1.46 billion VKT per year, almost 3.152% of the total annual VKT by cars. In addition, results also demonstrated a reduction in the total NOC, which varied from 2.13% to 2.84%, based on crash type and severity. The authors also pointed out some deficiencies of the model. First, the model is not transferable due to implementation of local parameters. Furthermore, this is a short-term analysis based on uniform telecommuting rates, and therefore does not consider temporal fluctuations of telecommuting behavior.

2.4.2. Disaggregate Studies

Pendyala et al. (1991) carried out a spatial and temporal analysis of the travel diary data collected during the State of California Telecommuting Pilot Project. Their objective was to determine the impacts of telecommuting on household travel behavior. The results confirmed the earlier finding that the Pilot Project telecommuters substantially reduced travel; on telecommuting days, the telecommuters made virtually no commute trips, reduced peak period trip making by 60%, vehicle miles traveled by 80%, and freeway use by 40%. The spatial analysis of the geocoded trip records showed that telecommuters were likely to choose non-work destinations located closer to home. Spatial shrinkage of activities were also observed after the introduction of telecommuting. More importantly, this contraction took place on both commuting and telecommuting days. Telecommuters were likely to distribute their trips during the day and avoid peak-period travel on telecommuting days. Non-work trips, however, showed similar patterns of temporal distribution on telecommuting days and commuting days. Non-work trips were usually made during the lunch period or late afternoon and evening hours. Telecommuter driving-age household members also exhibited contracted action spaces after the introduction of telecommuting. Interestingly, no significant increase was observed in automobile use after telecommuting commenced.

In a descriptive study, Mokhtarian and Salomon (1997) explored the relationships between telecommunications and travel patterns. Different types of telecommunications including telecommuting, teleconferencing, teleshopping and cell phones were considered, and their impacts on travel behavior were studied. In particular, in terms of telecommuting, researchers pointed out that considering work as a series of specific tasks carried out at

predefined periods of time, the performance of many work situations could easily be improved through the use of telecommunications. However, the quality of work activity usually extends beyond regular incentives, that is, earning money. For many individuals, it includes face-to-face communication, an opportunity to exit home, and socially interact with others, and so many other social and psychological gratifications. Therefore, while net substitution is the most expected and desired impact of telecommuting other employment-related issues should be taken into account. Depending on the importance of other work-related benefits or costs, the likelihood of travel substitution will be subject to reduction. In addition, researchers found that telecommuting may also lead to travel stimulation due to non-commute trip generations, changes in mode choice, residential relocation or latent demand realization.

In a case study of Minnesota, Wells et al. (2001) found that telecommuters may not be regarded as a homogenous category. Interview results suggested that different implementation strategies played an important role in how telecommuting impacts travel behavior. For instance, results indicated that personal errands timing and location was deeply affected by full-time or part-time teleworking options. In terms of travel behavior, driving alone increased on tele-days while bus, carpooling and vanpooling shares decreased. There was also a reduction in the number and length of daily trips. Furthermore, trip chaining and errand-running behavior showed a dramatic change in telecommuters reporting longer commutes. Telecommuters were also asked about how they use their time savings due to commute removal. Private firm telecommuters included a number of activities, including personal tasks, overwork or a combination of both. Public employees,

however, mentioned that they were largely unionized and maintained a standard 8-hour work schedule mandated by the company policies.

Mokhtarian (2003) made an effort to review the literature in terms of conceptual, theoretical and empirical evidence regarding the impacts of telecommunications on travel. Accordingly, she introduced four major relationships being discovered between physical travel and telecommunications: 1) Substitution (replacement or elimination): ICT usage leads to complete elimination of some of daily trips, resulting in a total reduction of daily trips. 2) Complementary (stimulation or generation): Telecommunication can in fact increase the number of trips. 3) Modification: One communication mode modifies something about the use of another mode. 4) Neutrality: In some circumstances, use of one mode may leave the use of other modes unaffected. Investigating the results of research works for a twenty-year period, the author concluded that although direct short-term studies have often found substitution effects, more comprehensive analyses usually reflect indirect complementary effects of telecommuting on travel. It was also inferred that if current trends continue, both telecommunications and travel will increase; however, faster growth of telecommunications will result in an increasing share of interactions falling into telecommunications. At this point, what can be said with confidence is that there is substantial evidence for net complementarity (although not definitive), but the empirical evidence for net substitution appears to be virtually nonexistent.

Mokhtarian et al. (2004) investigated commute distances and residential locations through comparing descriptive statistics between two categories, telecommuters versus non-telecommuters. The authors emphasized that previous research efforts had only focused on short-term impacts, within one to two years of adoption of telecommuting by

the individual or the organization. In order to explore the long-term effects, they analyzed retrospective data on the impacts of telecommuting and residential location changes over a ten-year period. Estimates of the total commute person-miles traveled of telecommuters and non-telecommuters were compared on a quarterly basis. The database contained 218 cases for which commute person-miles traveled could be computed in at least one of the 41 quarters studied. Key findings included the following: One-way commute distances were higher for telecommuters than for non-telecommuters, consistent with prior empirical evidence and with expectation. Average telecommuting frequency declined over time; several explanations were proposed, but cannot be properly tested with these data. The average quarterly per capita total commute distances were generally lower for telecommuters than for non-telecommuters, indicating that they telecommuted often enough to compensate for their longer one-way commutes. However, this study did not argue for any particular direction of causality. That is, on the basis of the analyses presented, one cannot discern whether longer commute distances encourage telecommuting or, conversely, whether the adoption of telecommuting facilitates residential relocations farther away from the workplace.

In a similar effort in Finland, Helminen and Ristimaki (2007) concentrated on the direct impacts of teleworking on commuting distance and frequency at an aggregate level. The empirical analyses were based on two major data sources: Aggregate national data from the “Population Register Center” and a labor force survey carried out by “Statistics Finland” in 2001. Statistical analyses implied that in terms of commute distance, three major thresholds were identified. The proportion of teleworkers did not change remarkably for commute distances below 80 kilometers (around 5%). Gradual increases were observed

between 80 to 100 kilometers. The proportion of teleworkers was highest (16%) among those whose commuting trip was between 100 and 150 kilometers. A bivariate logistic regression analysis was also developed to investigate the impact of commute distance (independent) on working at home (dependent). Results revealed a correspondent 25% increase in telework probability for an increase of 10 kilometers in commuting trips. Furthermore, a higher telecommuting percentage was observed in urban core areas rather than in surrounding municipalities. Results also indicated that teleworking reduced the total kilometers traveled in the country by 0.7%. In accordance with the lifestyle in Finland, 65% of commuters that spent at least two hours on a one-way commute had a second apartment near their workplace. Such second apartments decreased the total amount of commuting kilometers by 8%, which reflected a much stronger effect on long-distance commuting than teleworking.

Jiang (2008) applied a two-sample instrumental variable (TSIV) methodology to explore the impacts of telecommuting on commute length and mode choice. The data comes from the Current Population Survey (CPS) and Public Use Micro-data Series (PUMS). The researcher discussed that existing models are not capable of precisely addressing the impacts of telecommuting on commute length and travel mode as they neglect the endogeneity between telecommuting and travel behavior. Defining "percentage of workers who use internet at home" as the instrument, linear probability models were developed. Results showed that telecommuting increased a married female worker's one-way commute time by 9–12 minutes. The impact on commute mode choice was positive but statistically insignificant.

Zhu (2011) used the National Household Travel Survey (NHTS) 2001 and 2009 to explore the differences in travel patterns between telecommuters and non-telecommuters. In order to investigate the dissimilarities, personal one-way commute trips, daily total work trips and total non-work trips were thoroughly analyzed. For any of the trip purposes, three dimensions including duration, distance and frequency were considered independent variables and modeled as a function of demographic and socio-economic characteristics, locational attributes, transportation factors, weekend dummy and telecommuting dummy. Two different types of models were tested. As the starting point, OLS models were developed. However, problems might rise due to the endogeneity between the telecommuting variable and commute distance or duration. In other words, while telecommuting may result in workers choosing longer commutes, there is a probability for the opposite scenario, i.e., people with longer commutes are more willing to telecommute to avoid lengthy daily commutes. In order to address this endogeneity problem, two-staged least square models (2SLS) are developed through adding instrumental variables. In 2001, internet usage at home and the total number of phones available were used as instruments. Due to a slight change in the 2009 survey questionnaires, frequent use of the internet is used as the instrument variable.

Statistical tests suggested that 2SLS models were able to address the endogeneity problem as the telecommuting variable showed statistically significant coefficient estimates compared to those in the OLS models. Results also indicated that telecommuting had a positive impact on the one-day total work trip in both years in terms of all three measures. This reflected that telecommuters' lifestyles differed from non-telecommuters in significant ways, considering their total daily work trips: Holding all other factors

constant, telecommuters consistently had more frequent daily work trips than non-telecommuters. However, the difference had been decreasing in the past eight years. In addition, telecommuters showed longer commutes (distance and duration), and the differences had been growing in the study period. The same results were obtained in the case of non-work trips, where telecommuting also showed significant positive impacts on all three aspects of non-work trips. Finally, the authors infered that the complementary effect of telecommuting was significant, which questioned the effectiveness of telecommuting as a planning practice or policy to reduce traditional travel.

Mosa (2011) used an activity and travel communication diary survey in order to analyze the impacts of ICT on household members' daily activity travel patterns in Cairo, Egypt. The primary data source for this analysis came from the survey administered by three major academic and research institutions in Cairo and spans the period from December 2005 to January 2006. The final survey sample included 459 individuals from 150 households reporting a total number of 15,395 weekday and weekend activities. A Structural Equation Model (SEM) was developed using mandatory activities, along with household and individual SED attributes as exogenous variables and duration of non-mandatory activities, along with travel times and number of trips as endogenous variables. Moreover, in order to assess the relationship between ICT usage, activity participation and travel behavior, a latent variable, labeled "ICT use," was defined based on the frequency of landline calls, cellular phone calls and SMS. Several results can be inferred based on the model's outputs. For instance, the use of ICT increases trip-making propensity and induces more time spent on travel. Results confirm that ICT has substitution effects on the time-use for in-home and out-of-home physical maintenance activities. The strongest reason for

ICT usage stems from out-of-home recreational activities. There are also substitution relationships between virtual in-home and out-of-home activities. While the results have important implications on activity/travel estimation, one major drawback of this study should be carefully noted: the respondents were recruited from academic institutions only and may not be a good representative sample of the whole population.

2.5. Summary

This chapter provided a comprehensive review of telecommuting literature. In particular, two major directions were explored, namely telecommuting estimation and telecommuting impacts. In view of telecommuting estimation, the existing literature reveals a number of deficiencies with respect to sample size, modeling methodologies, and telecommuting dimensions. Although company-specific surveys provide highly detailed information about telecommuting opportunities and adoption, they usually involve small sample sizes, which hinder the models' transferability. In terms of dimensions, models stay at the choice/frequency level and rarely step into daily estimates of telecommuting activity. Lack of telecommuting reflection at the daily level is a major shortcoming that prevents practical classification of telecommuting engagement forms. This will directly affect impact analysis as different engagement forms are expected to have dissimilar impacts both at aggregate and disaggregate levels. Furthermore, when it comes to impact analysis, research backgrounds mainly focus on aggregate studies, which are based on trip reduction due to telecommuting implementation. This is questionable from various perspectives for the following reasons: First, trip reduction estimates, which are the foundations of impact studies, probably need to be revised since they overlook different engagement forms. Second, aggregate studies do not reflect a comprehensive analysis of telecommuting

impacts, as secondary effects, including total rescheduling of daily activity plans, are not accounted for. Such findings from the literature review form the major motivations for this study, which will be discussed in detail in the next chapter.

CHAPTER 3

METHODOLOGY AND DATA DESCRIPTION

3.1. Introduction

As mentioned before, this study focuses on how telecommuting affects individuals' daily activity/travel behavior. This initially requires a comprehensive decision-making framework, which helps identify and categorize different types of telecommuting arrangements and patterns. The fact that different telecommuting patterns will influence workers' travel behavior differently and result in dissimilar impacts on the transportation network is therefore a key issue in this research. The differences in telecommuting arrangements mainly arise from the answer to the following simple question: whether the daily commute is completely removed as a consequence of telecommuting engagement or it is still there but temporally shifted. In other words, the fact that telecommuting completely "substitutes" conventional commuting or simply has a "complementary" effect is expected to have a remarkably different influence on workers' daily behaviors, as well as in the transportation network. The following example may help shed light on the differences between the two scenarios.

Consider individual X being offered two different telecommuting scenarios. The first scenario is a full-day telecommuting engagement, which completely replaces their conventional daily commute to work. The second option is a combination of part-day telecommuting plus conventional commute, which may follow any sequence according to the employer's offered program. In the first scenario, the obligation to commute at a strictly pre-defined timetable is totally removed. In addition to the savings in time, fuel consumption, mileage, and general improvements in peak hour congestion, this also relaxes

many of the temporal and spatial constraints imposed on the individual due to mandatory work activity. Now, the worker has more freedom to completely reschedule daily activity plans, perhaps allocating more time to non-mandatory activities, generate new trip purposes, select new destinations, and other similar decision makings, which overall results in a more self-optimized daily activity schedule. In the second scenario, however, the conventional commute still exists, which means the total benefits due to network savings may not be as much as the previous scenario. Moreover, as work destination plays a major role in trip chaining and tour generation, there might still be a preference to include subsidiary activities in the work tour. To make it simple, if the worker preferred to shop in a center close to their workplace, he/she may still keep the same trend even after part-day telecommuting is implemented. This simply explains how various patterns of telecommuting may leave different footprints on individuals' daily activities and travel patterns. It is also noticeable that in the long run, individuals may adopt a combination of telecommuting patterns, which makes predictions even more complicated. In the aforementioned example, individual X might adopt a combination of the two scenarios over a monthly period. This reveals a major drawback in previous telecommuting estimation studies where researchers usually consider telecommuting patterns a monthly or annual arrangement. As a result, the fact that final impacts should be a function of a "daily telecommuting engagement" has been somewhat, if not completely, overlooked.

In order to fully address the existing issues, this section provides the theoretical concept of a comprehensive modeling framework in terms of telecommuting estimation and consequent impacts. The framework consists of two different phases: The first phase tries to classify various observed telecommuting forms and develop forecasting models

using sophisticated statistical tools and methodologies. The results of this stage are then used in the second phase to investigate the impacts of telecommuting on daily travel behavior at an aggregate level. The remainder of this chapter is therefore divided into the following subsections: The next section will explain different dimensions of telecommuting that are used as major components or identifiers of telecommuting engagement patterns. The next two sections will explicitly describe the two phases of the research work. The final section emphasizes the data used in this study.

3.2. Major Dimensions of Telecommuting Activity

A quick review of telecommuting literature in Chapter 2 provides helpful guidance towards telecommuting features in terms of forecasting and estimation. There is a general agreement that telecommuting is a multifaceted decision-making process that incorporates several sides such as job attributes, employer attitudes and employee characteristics. In addition, telecommuting adoption is not a single-level decision, but rather, consists of a hierarchy of integrated decision-making opportunities that take into account several long-term and short-term resolutions. Some of the prevalent dimensions applied in the literature are presented here along with their descriptions:

1. Option: is defined as “Whether the employer offers any telecommuting arrangement as an alternative to the employees”. Intrinsically, this depends on several factors including job suitability, types of tasks involved in any particular profession, management attitudes towards telecommuting, etc. Singh et al. (2012) applied “option” as a separate decision-making level in their modeling framework. Mamdoohi et al. (2006) described option as a vector of tasks which require less

face-to-face interactions or less physical attendance in the workplace, therefore providing the job with more suitability towards telecommuting adoption. Instead of a separate level, Mokhtarian and Salomon (1996) summarized telecommuting option in terms of job-related “drives” and “constraints” among their variables list.

2. Preference: reflects workers' desire towards telecommuting, usually in terms of their “stated preference” data rather than “revealed preference”. This was first introduced in the early 90s by Yan and Mahmassani (1993) and Mokhtarian and Salomon (1996). However, this aspect gradually diminished as further research revealed the wide gap between workers actual behavior and preference (Mokhtarian and Salomon 1996).
3. Choice: Based on a worker’s “revealed” observations, “choice” is a binary index that illustrates whether or not a worker chose telecommuting as an alternative work arrangement. The telecommuting choice is not treated as a daily or short-term alternative. In other words, it does not describe an individuals’ daily behavior. Instead, it focuses on an extended period time, whether it is a week, a month or a year. Survey questionnaires usually asked if the respondent had any telecommuting experience in a defined period of time, such as last month or last week. Any response other than “never” would be assigned a positive choice to engage in telecommuting.
4. Frequency: highlights how often the respondent participated in telecommuting activity during the pre-defined period of time. Accordingly, frequency must also be regarded as a long-term arrangement which provides useful average information

over an extended period of time, but yet does not provide any information at a daily level.

With the above dimensions being widely applied and analyzed in literature, this study adds two other dimensions to the analysis. These include:

1. Daily Engagement: while the literature stops at "frequency" level, this study goes one step further and analyzes workers daily behavior towards telecommuting. This is absolutely important as major travel-related decision-making is investigated and analyzed on a daily basis. Activity planning, trip generation models, tour-based models and all other relevant analyzes are usually investigated in a daily framework. Thus, in order to provide a reliable estimation of how telecommuting impacts travel behavior, a daily reflection of telecommuting participation is required. This is explained through a binary index labeled herein as "daily engagement". Accordingly, if the respondent had participated in any telecommuting activity on the day the survey was carried out, the engagement value would be assigned as one, otherwise zero.
2. Additional daily commute: with reference to the argument between total or partial substitution effects of telecommuting, it is important to see whether telecommuters made any work-related trips on the day they engaged in telecommuting. This will result in another binary decision-making opportunity that divides the telecommuters into two major subcategories: those with no daily commute that showed a total replacement or substitution effect, and those with one or more additional work-related commutes that reflected a partial substitution situation.

Based on the aforementioned dimensions, a decision-making framework can be constructed which helps identify and categorize different arrangements of telecommuting. The basics of such framework will be explicitly explained and investigated in the following subsection.

3.3. Phase I: Telecommuting Estimation

This section focuses on the details of the decision-making algorithm which leads to the final arrangement of telecommuters. As can be seen in Figure 3-1, all the decisions are based on the previously defined dimensions. Some specific key terms and definitions along with the details of each step are comprehensively investigated.

Being explicitly demonstrated in Figure 3-1, the algorithm starts with excluding home-based workers and home-based business owners from the dataset. In the next step, a binary decision-making, known as "telecommuting choice", is modeled which divides the workers' dataset into two major subsets: Regular telecommuters versus non-regular (potential) telecommuters. "Regular telecommuters" are actually those workers who reported positive hours of telecommuting (TCHRS) on a weekly basis, which reflects their long-term arrangement towards telecommuting. Potential ones, however, reported zero hours of telecommuting in their background. The reason why potential telecommuters are important in this study is that according to the observations, there are workers among the respondents who actually engaged in telecommuting on a random day, although they reported zero hours of regular telecommuting experience. This subcategory, labeled here as "non-regular telecommuters", have not been paid attention in the literature as the daily framework of telecommuting activity has never been analyzed.

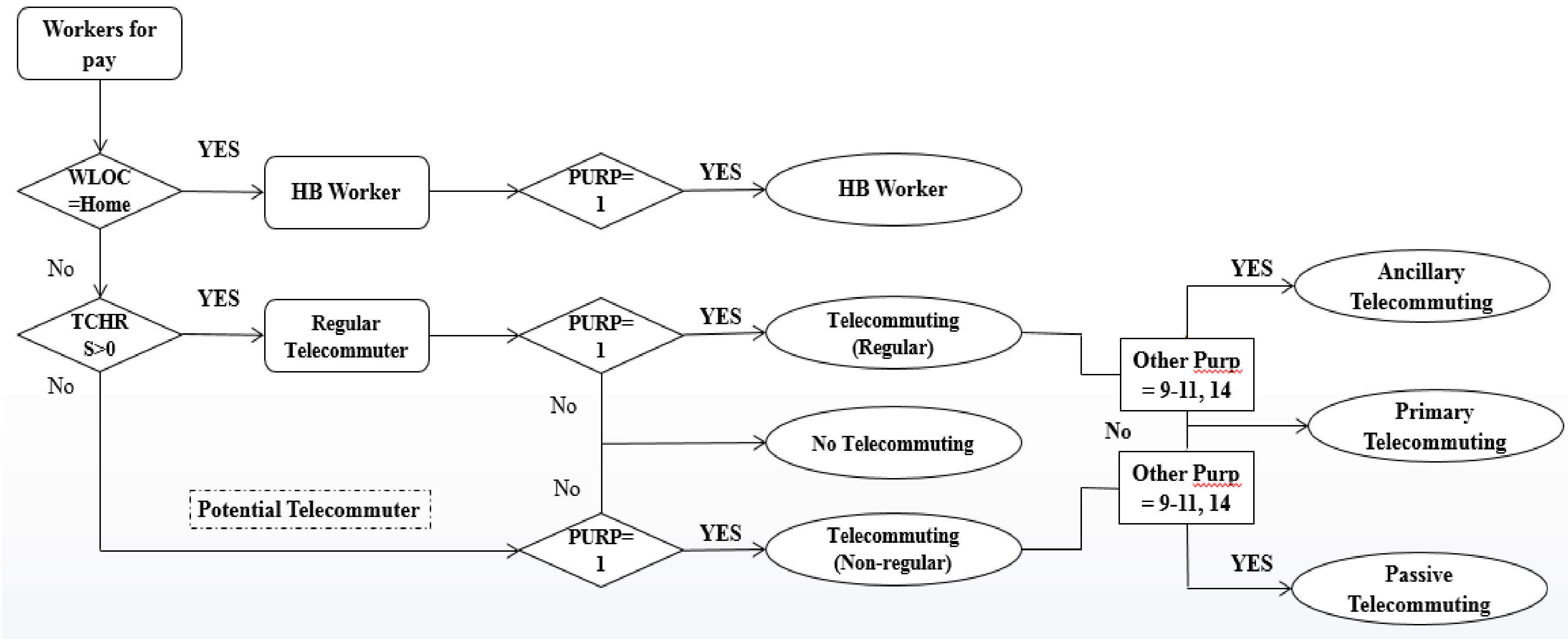

Figure 3-1 Telecommuting Estimation Framework

As the workers' dataset is divided into two sections, each section may be analyzed separately in terms of "daily engagement" and "additional daily commute". The latter two aspects are derived by analyzing daily trip purpose codes assigned to each person. Daily engagement is positive if the individual reported trip purpose code 1 which denotes "working from home". Consequently, other daily trips of his are explored to see whether or not any work-related trip exists in his diary. According to the dataset, work-related trips are identified by any of the following codes: 9, 10, 11 and 14.

Whether an individual participates in telecommuting or not along with making any other additional work-related trips is actually the basis of telecommuter stratification. Based on the combination of the two decision-making factors, four major categories of workers (with respect to telecommuting adoption) are recognized:

1. Primary telecommuters are actually workers that had positive results from their participation in telecommuting (daily engagement = one), while no additional daily commutes are observed on their daily diary (additional commute = zero). As reflected in the flowchart, primary telecommuters may be among regular or non-regular telecommuters based on their initial "telecommuting choice" decision.
2. Ancillary telecommuters are workers that had a positive "telecommuting choice," positive daily engagement, and additional daily commutes. In other words, they are regular telecommuters that participated in telecommuting on random days and reflected additional work-related trips on the same day.
3. Passive telecommuters: Non-regular telecommuters who had positive responses in terms of both daily engagement and additional commutes.

4. Non-telecommuters: Any negative response in terms of “daily engagement” is regarded as a “non-telecommuting” situation.

Table 3-1 demonstrates the details of telecommuting patterns based on the underlying dimensions. Having explained the concept of the framework and set the context, the next section provides the required foundation in order to empirically bring the theories into practice.

Table 3-1 Definition of Different Telecommuting Patterns

Choice	Daily Engagement	Additional Commute	Telecommuting Form
+ -	+	-	Primary
+ -	+	+	Ancillary Passive
+ -	-	NA	Non-telecommuter

3.3.1. Discrete Choice Models and Random Utility Theory

In order to operationalize the conceptual framework presented in the previous section, it is inevitable to look for possible statistical tools which facilitate the researcher to come up with reliable forecasting methods. A quick review of the literature sheds light on the importance of “Discrete Choice Models” which have been extensively used in the literature. Regardless of the telecommuting dimension being investigated, various structures of discrete choice models have proved themselves as powerful statistical equipment, providing a variety of useful analyzes over the variables. This section provides a brief introduction towards discrete choice models. Detailed formulas and in depth features will be discussed in the next chapter.

A discrete choice model is one in which decision makers choose among a set of alternatives. To fit within a discrete choice framework, the set of alternatives – the choice set – needs to exhibit three characteristics: 1) alternatives need to be mutually exclusive, 2) alternatives must be exhaustive, and 3) the number of alternatives must be finite.

In general, discrete choice models are usually derived in a random utility model (RUM) framework in which decision makers are assumed to be utility maximizers. The basic setup is the following: A decision maker, labeled n, faces a choice among J alternatives. The decision maker obtains a certain level of utility from each of the alternatives. The utility that decision maker n obtains from any alternative j is $U_{nj}, j = 1, 2, \ldots, J$.

This utility is known to the decision maker but not the analyst. It is assumed that users decision rationally, that is the decision maker chooses the alternative with the highest utility: choose alternative i if and only if $U_{ni} > U_{nj}, \forall j \neq i$. The analyst cannot observe the decision maker's utility. However, the analyst can observe some attributes of the alternatives, labeled $X_{nj}, \forall j$ and some attributes of the decision maker, labeled S_n. The analyst can also specify a function that relates these observed factors to the decision maker's utility. This function is denoted $V_{nj} = V(X_{nj}, S_n), \forall j$ and is called representative utility. Because there are aspects of utility that the researcher does not or cannot observe, $U_{nj} \neq V_{nj}$. Instead, utility is decomposed as $U_{nj} = V_{nj} + \varepsilon_{nj}$, where ε_{nj} captures the factors that influence utility but that are not in V_{nj}. In effect, ε_{nj} is simply the difference between U_{nj} and V_{nj}. You can think of V_{nj} as the systematic component of a decision maker's utility and ε_{nj} as the stochastic component. The researcher does not know ε_{nj}, and

therefore treats these terms as random. The joint density of the random vector $\varepsilon_n = (\varepsilon_{n1}, \ldots, \varepsilon_{nj})$ is denoted $f(\varepsilon_{nj})$. With this density, the analyst can make probability statements about the choice of the decision maker. In other words, the probability that decision maker n chooses alternative i is simply:

$$P_{ni} = Prob\left(U_{ni} > U_{nj}, \forall\, i \neq j\right) = Prob\left(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}, \forall\, i \neq j\right) =$$

$$Prob(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}, \forall\, i \neq j) \tag{3-1}$$

This probability is a cumulative distribution, i.e., the probability that each random term $\varepsilon_{nj} - \varepsilon_{ni}$ is below the observed quantity $V_{ni} - V_{nj}$. Using the density function $f(\varepsilon_{nj})$, this cumulative probability can be written as:

$$P_{ni} = Prob\left(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}\right) = \int I(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}) f(\varepsilon_n)\, d\varepsilon_n \tag{3-2}$$

where *I* is the indicator function, which equals to 1 if the expression in parentheses is true and 0 otherwise.

As can be seen, this is a multidimensional integral over the density of the unobserved portion of utility, $f(\varepsilon_n)$. Note that different discrete choice models structures may be obtained depending on how you specify this density function, i.e., depending on what assumptions you make about the distribution about the unobserved portion of utility. The integral only takes a closed form solution for certain specifications of $f(\varepsilon_n)$. For example, logit and nested logit have closed form solutions; they are derived under the assumption that the unobserved portion of utility is distributed IID extreme value (logit) and a type of generalized extreme value (nested logit). Probit is derived under the assumption that $f(\varepsilon_n)$ is multivariate normal and mixed logit is derived under the assumption that the unobserved portion of utility comprises a part that follows any

distribution desired by the analyst and a part that is IID extreme value. With probit and mixed logit, the integral has no closed form solution and we have to evaluate it numerically through simulation.

3.3.2. Proposed Modeling Structure

As discussed in the previous sections, any telecommuting arrangement can be formed as the result of three interrelated decision-making levels: Telecommuting choice (regularity), daily engagement and additional commute (substitution effect). This can be summarized in the proposed modeling structure demonstrated in Figure 3-2.

The idea looks simple and straightforward. First a simultaneous model is developed in order to estimate both choice and frequency. While frequency is not a determinant factor in identifying telecommuting arrangements, it is used as a medium variable which is expected to deliver the impacts of long-term arrangements over short-term daily engagements. The hypothesis is that telecommuting frequency decisions are made as part of the household mobility arrangement beyond the daily choice framework, and once the frequency is known, telecommute engagement choices can be estimated with greater accuracy. This can be carried out using either a multinomial or ordered structure where an additional alternative of “zero” frequency is added to the existing frequency alternatives to account for choice as well as frequency dimensions (Tang et al., 2011; Mannering & Mokhtarian, 1995; Mamdoohi et al., 2006; and Yen, 2000) or a joint sample selection model where the frequency variable is observed only if the choice outcome is positive (Popury & Bhat, 2003; Singh et al., 2012; and Sener & Bhat, 2009). The results of this step will decompose the dataset into two different telecommuting subcategories: Regular and non-regular.

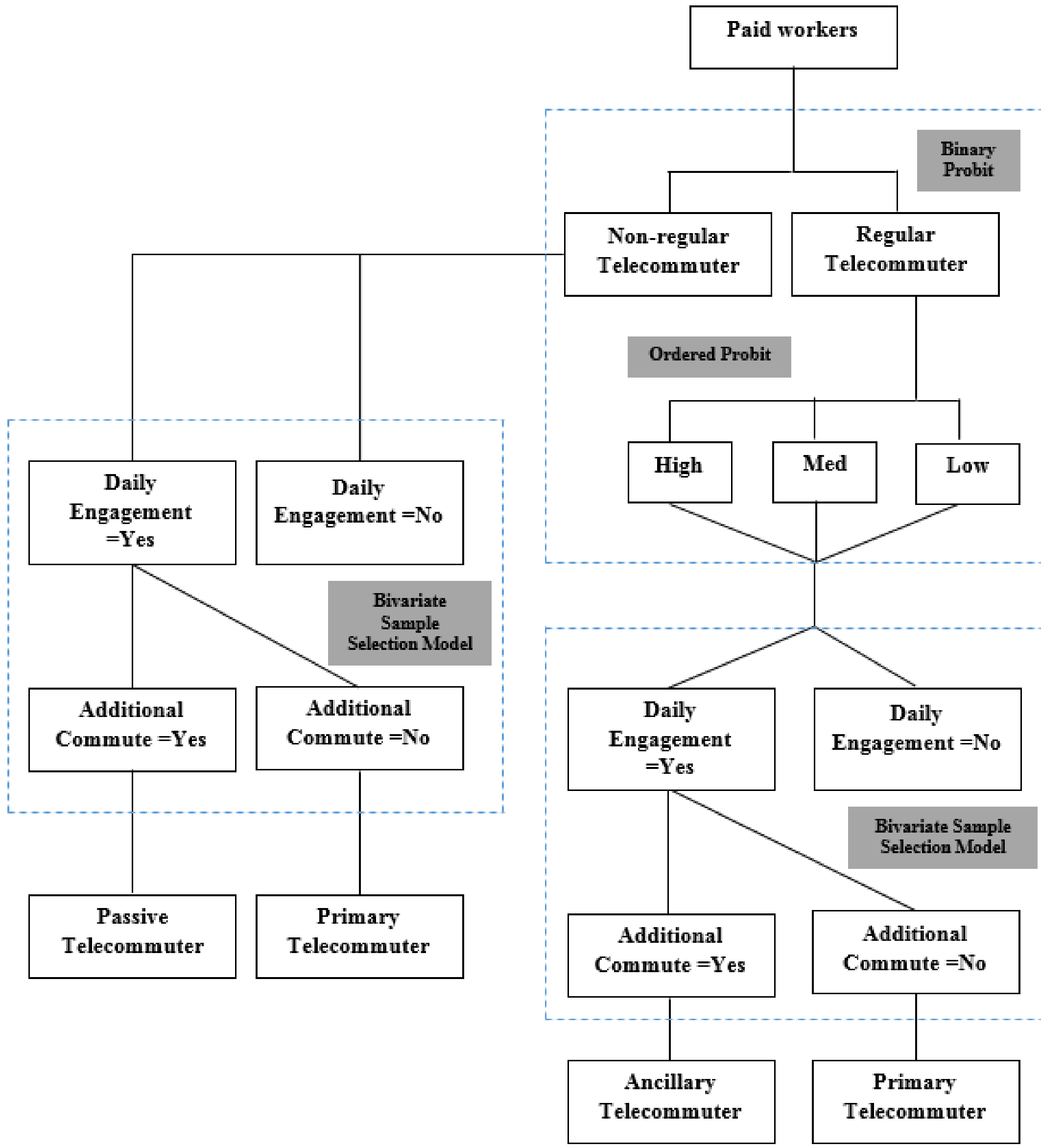

Figure 3-2 Phase I: Telecommuting Estimation Modeling

For each subcategory, the "daily engagement" and "additional commute" models will be developed and analyzed. Since the Additional commute variable is only observed when the daily engagement value equals 1, it is possible again to apply a sample selection

model using bivariate normal distribution. Further details will be discussed in Chapter 4. All the modeling efforts for this part will be accomplished using Statistical Analysis Software, SAS 9.3, and Nlogit 5.0. The details of each step are explained in the upcoming sections.

3.3.3. Choice/Frequency

The choice variable can be easily constructed as a binary variable based on the respondent's experience towards telecommuting on a weekly basis (Telecommuting hours, coded as TCHRS in the dataset). Accordingly, if a worker reported positive hours of telecommuting, he/she will be regarded as a Regular telecommuter (Choice =1), otherwise he/she will be assigned a Non-regular label (Choice=0). Considering the dichotomous nature of the choice variable, a binary structure (probit or logit) can be applied to estimate the probability. A binary probit model is finally selected. The binary model can be applied in any case where the client faces only two alternatives, yes or no, one or zero. Therefore it conforms to the binary nature of telecommuting choice. Moreover, assuming a normal distribution for the error term is consistent with the telecommuting literature. Walls et al. (2006) proposed a two-stage probit model based on a normal distribution, while Popuri and Bhat (2003) and Singh et al. (2012) considered normal bivariate distribution for joint structures.

Theoretically, a binary probit structure is based on the following formulas:

$$t_i^* = \gamma X_i + \varepsilon_i \qquad t_i = 1 \quad if \;\; t_i^* > 0, \text{otherwise } \; t_i = 0, \tag{3-3}$$

where,

X_i = vector of independent variables including, household, individual and job-related attributes, etc. for person i.

γ = coefficients of the explanatory variables.

The latent variable t_i^* is not observed directly. Instead, the decision on whether or not to participate in the activity is observed through the survey instrument, t_i . The probability that t_i equals one is

$$\Pr\,(t_i = 1|X_i) = \Pr\,(t_i^* \geq 0|X_i) = \Pr\,(\varepsilon \leq \gamma X_i|X_i\,) = \Phi(\gamma X_i) \tag{3-4}$$

where Φ is the cumulative function of a standard normal distribution.

This is a standard probit model that can be estimated by a maximum likelihood estimation technique.

According to the literature, frequency is usually modeled as an ordered response variable, reflecting the intensity of telecommuting in a predefined period of time. Several classifications of frequency categories are applied in the literature; however, they are barely based on solid statistical foundations. Such classifications may include incoherent definitions such as "Frequent" versus "Infrequent", or based on unexplained thresholds such as certain number of days per week. One innovative aspect of this study is the way frequency categories are defined. First, telecommuting intensity is based on the ratio of telecommuting hours rather than its absolute value, which is expected to provide a clearer

picture of relaxation of spatial/temporal constraints. Moreover, cluster analysis is applied in order to shed light on significant classes (boundaries) of the telecommuting intensity classes. This will lead to identification of three major frequency groups, labeled (in ascending order) as: Light, Medium, and Heavy telecommuters. This will be explained in details along with statistics in Chapter 4. Taking the ordered nature of the frequency variable, an ordered-response probit model is developed.

The basics of the ordered model are very similar to the binary model, with the dependent variable consisting of more than two classes. Each class j is defined by upper and lower thresholds, a_j and a_{j-1}.

$$N_i^* = \alpha Z_i + \eta_i \tag{3-5}$$

$$N_i = j \quad if \quad a_{j-1} < N_i^* < a_j \,, \ j = 1,2, \ \dots, J$$

where,

Z_i = exogenous variables,

α = vector of coefficients, and

a_j = threshold estimates.

Although, choice and frequency can be modeled separately in a sequential manner, there is a consensus in literature that these two decision-making factors are correlated and therefore, should be modeled simultaneously. In other words, there are common unobserved factors that affect both decision making factors, and that such correlation should be taken into account to improve the accuracy of the models. This is well explained through a joint sample selection structure. The sample selection structure takes the two decision-making factors jointly in a bivariate normal distribution with an unknown

correlation parameter. The second decision-making factor is only observed only if the choice decision is positive. Therefore, the probability function can be written as:

$$Prob\ (t_i = 1,\ N_i = j) = \Phi_2(a_j - \alpha Z_i;\ \gamma X_i;\ -\rho) \tag{3-6}$$

$$-\Phi_2(a_{j-1} - \alpha Z_i;\ \gamma X_i;\ -\rho)$$

where,

ρ = correlation between error terms ε_i and η_i, and

Φ_2 = cumulative standard bivariate normal function.

Using a maximum likelihood algorithm, the unknown parameters including the correlation factor can be estimated.

$$L_f = \prod_{i=1}^{I}[1 - \Phi(\gamma X_i)]^{1-t_i} \times \tag{3-7}$$

$$\left\{\prod_{j=1}^{J}\left[\Phi_2(a_j - \alpha Z_i;\ \gamma X_i;\ -\rho) - \Phi_2(a_{j-1} - \alpha Z_i;\ \gamma X_i;\ -\rho)\right]^{M_{ij}}\right\}^{t_i}$$

where

$$M_{ij} = 1\ \ if\ N_i = j,\ Otherwise\ M_{ij} = 0$$

3.3.4. Daily Engagement/Additional Commute

Upon identification of regular and non-regular telecommuters, the study expands to explore workers' daily telecommuting patterns in terms of the two aforementioned perspectives: whether the worker participates in telecommuting activity on a random day, and if they do, whether additional commutes also occur. Likewise, two different modeling approaches are employed to identify which one performs better given existing variables.

The first approach considers engagement and additional commute as two independent decisions which are modeled separately based on binary probit structures. While a binary

probit model conforms well to the binary nature of the dependent variables, once again the assumption of uncorrelated error terms between the two decision-makings may lead to erroneous results.

Given that the two decision-making opportunities may take place simultaneously in a daily framework, there could be a high probability toward the existence of unobserved factors that affect both decisions. The independent modeling approach ignores the presence of such factors and therefore may overestimate the magnitude of effects of independent variables on the second choice, i.e., additional commute model. As such, the second approach applies a “bivariate sample selection model” which considers a bivariate normal distribution for both decisions. As explained before, the advantage of the second approach is that it considers the correlation between the error terms and therefore is expected to provide more realistic outcomes. The bivariate sample selection model is based on the following Equations:

$$d_{i,1}^{*} = W_{i,1}^{\prime}\theta_1 + \varepsilon_{i,1}, \quad d_{i,1} = 1 \; if \; d_{i,1}^{*} > 0, 0 \; otherwise \tag{3-8}$$

$$d_{i,2}^{*} = W_{i,2}^{\prime}\theta_2 + \varepsilon_{i,2}, \quad d_{i,2} = 1 \; if \; d_{i,2}^{*} > 0, 0 \; otherwise, and \; if \; d_{i,1} = 1 \tag{3-9}$$

$$(\varepsilon_{i,1}, \varepsilon_{i,2}) \sim N_2[(0,0), (1,1), \rho] \tag{3-10}$$

where,

$d_{i,1}$, d_{i2} = utility functions for telecommuting engagement and additional commute, respectively,

θ_1 , θ_2 = coefficient estimates,

$W_{i,1}$, $W_{i,2}$ = vectors of exogenous variables, and

$\varepsilon_{i,1}$, $\varepsilon_{i,2}$ = error terms.

$d_{i,2}, W_{i,2}$ *are unobserved when* $d_{i,1} = 0$

The first decision serves as the "Selection Equation". Presence in the sample for observation of the second Equation is determined by the first, i.e., additional commute is applied if and only if the individual actually telecommuted. Estimation of this sample selection model is done by maximum likelihood in one step. The log likelihood is

$$\ln L = \sum_{d_{i,1}=0} \ln\Phi\left(-W_{i,1}^{'}\theta_1\right) + \sum_{d_{i,1}=1} \ln\Phi_2\left(W_{i,1}^{'}\theta_1, W_{i,2}^{'}\theta_2, \rho\right) \quad (3\text{-}11)$$

where,

Φ = the univariate normal cumulative distribution function,

Φ_2 = the bivariate normal cumulative distribution function, and

ρ = correlation parameter.

The parameters θ_1, θ_2, and ρ are estimated by maximizing the likelihood function. If the correlation between the error terms ρ is zero, the joint sample selection structure simplifies to two independent models, one for the binary telecommuting engagement choice and the other for the additional daily commute.

A wide range of demographic and work-related variables are tested in the models, to investigate whether and to what extent these factors may contribute to work arrangement choices, i.e., telecommuting engagement as well as additional commute. Both independent modeling and sample selection modeling approaches are applied to the two subsamples, regular and non-regular telecommuters, to examine whether and how their telecommuting behavior may differ.

Based on the results of the above modeling efforts, the propensity of workers towards any of the foresaid dimensions will be calculated and consequently, combining the

results will lead to formation of different telecommuting patterns (refer to Table 3-1 for more details). This will lead to introducing a new derived variable known as "telecommuting form," which labels each worker according to his/her behavior with respect to telecommuting behavior. This new variable will later be applied in the second phase to evaluate the impacts of any telecommuting form on an individual's activity/travel behavior.

3.4. Phase II: Analysis of Telecommuting Impacts

Upon completion of Phase I, which covers the estimation of different telecommuting patterns, it is time to observe and investigate the respective impact each telecommuting arrangement leaves on the individuals' travel behavior. In this regard, two major directions may be tracked and applied:

1. Trip/tour based approach: This has been the conventional approach in travel demand analysis for several years. The majority of transportation planning efforts in the United States and the rest of the world is based on the "Urban Transport Planning System, UTPS", which was originally developed in the 1950's and focuses on single trips as the basis of transportation decision-making. Perhaps the major drawbacks of the approach are that they overlook the temporal and spatial linkages between all trips and activities accomplished by an individual on a daily basis. In addition, most of these models see an individual as an isolated decision-maker, therefore disregarding the role of household context in daily travel decisions.

2. Activity-based modeling approach (ABM): Activity-based travel demand models view travel behavior as a derivative of activities. Therefore, by predicting which activities are performed at particular destinations and times, trips along with their timings and locations can well be forecasted in activity-based demand models. ABM models originally rely on a number of hypotheses including: 1) Travel is a derived demand from activity participation, 2) Activities are planned and executed in household context, 3) Activities are spread continuously over a 24-hour span, rather than discrete categories of "peak" and "off-peak", and 4) Travel choices are limited in time and space and personal constraints.

According to ABM principles, an activity can be defined as a physical engagement of an individual in something that satisfies his/his family needs. Activities are motivated by sociological, physical or economical needs. Activities can be grouped into various categories including work, shop, recreation, etc. Activities do not necessarily result in trips, i.e., some activities may be accomplished at home. A decision to engage in any activity therefore represents a complex interaction of household and individual roles and responsibilities, lifestyle choices, time, space and budget constraints.

Taking the above into consideration, the researcher believes that activity-based approach provides a rich and accurate framework in which travel is analyzed. Furthermore, it is also regarded as a daily pattern of behavior being related to and derived from different lifestyles and activity participation among individuals. Therefore, following the general tendency towards ABM approaches, the study herein puts an effort to track the impacts of telecommuting adoption using an activity-based framework of individuals' daily behavior. However, the analysis will not be complete unless the consequent impacts of

telecommuting on trip generation and mainly commute departure times are well accounted for. The impact analysis will therefore encompass two major aspects: First, a time-use analysis is carried out to explore the observed distinctions in telecommuters' time-use compared to regular workers. Second, for part-time telecommuters, it is necessary to explore commute departure times in order to provide a reliable estimate of congestion reduction during AM peak hours. This is done through a commute displacement analysis, which will be thoroughly explained in the upcoming sections.

3.4.1. Time-Use Analysis: SEM Theory and Principles

Several attempts have been carried out in terms of activity scheduling and engagement. In particular, efforts found that causal relationships among activity and travel behavior variables can be well represented in a Structural Equations Model (SEM) framework. (Lu & Pas, 1999; Golob & Meurs, 1987; Golob et al. 1996a; Golob et al., 1996b; Golob, 1998; Golob & McNally, 1997, Kuppam & Pendyala, 2001, Mosa et al., 2010; and Wenjing & Zhicai 2009). Structural Equations Models (SEM) have been applied extensively in the social sciences to study causal relationships. These techniques have seen increasing application in activity and travel behavior research over the past decade. Much of this research has shown that significant relationships exist among socio-demographics, activity participation, and travel behavior, and that travel behavior can be explained better by including activity participation variables in travel demand models.

Within the scope of this study, the researcher tries to explore the relationships among activity participation, time-use, and the socio-economic and demographic attributes

of individuals using Structural Equations framework. Specifically, the impacts of telecommuting arrangement scenarios will be discussed and addressed.

Structural Equation Models (SEM), also called simultaneous equation models, are multivariate (i.e., multi-equation) regression models. Unlike the more traditional multivariate linear models, the response variable in one regression equation in a SEM may appear as a predictor in another equation; indeed, variables in an SEM may influence one-another reciprocally, either directly or through other variables as intermediaries. These structural equations are meant to represent causal relationships among the variables in the model.

A typical structural equations model (with "*G*" endogenous variables) is defined by a matrix equation system as shown in Equation 3-12.

$$\begin{bmatrix} Y_1 \\ \vdots \\ Y_G \end{bmatrix} = \begin{bmatrix} \beta_{11} & \cdots & \beta_{1G} \\ \vdots & \ddots & \vdots \\ \beta_{G1} & \cdots & \beta_{GG} \end{bmatrix} \begin{bmatrix} Y_1 \\ \vdots \\ Y_G \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{1n} \\ \vdots & \ddots & \vdots \\ \gamma_{G1} & \cdots & \gamma_{Gn} \end{bmatrix} \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_G \end{bmatrix} \qquad (3\text{-}12)$$

Equation 3-12 can also be written as

$$Y = BY + \Gamma \mathrm{X} + \varepsilon \qquad (3\text{-}13)$$

Or

$$Y = (I - B)^{-1}(\Gamma \mathrm{X} + \varepsilon) \qquad (3\text{-}14)$$

where,

Y = column vector of endogenous variables,

B = $G \times G$ matrix of parameters associated with right-hand-side endogenous variables,

X = column vector of exogenous variables,

Γ = $G \times N$ matrix of parameters associated with exogenous variables, and

ε = column vector of error terms associated with the endogenous variables.

Structural Equations systems are estimated by covariance-based structural analysis, also called method of moments, in which the difference between the sample covariance and the model implied covariance matrices is minimized (Bollen 1989). The fundamental hypothesis for the covariance-based estimation procedures is that the covariance matrix of the observed variables is a function of a set of parameters as shown in Equation 3-15:

$$\sum = \sum \theta \tag{3-15}$$

where,

Σ = population covariance matrix of observed variables,

θ = vector that contains the model parameters, and

Σ(θ)= covariance matrix written as a function of θ.

The relation of Σ to Σ(θ) is basic to an understanding of identification, estimation, and assessments of model fit. The matrix Σ(θ) has three components, namely, the covariance matrix of *Y*, the covariance matrix of *X* with *Y*, and the covariance matrix of *X*.

Let Φ = covariance matrix of *X* and Ψ = covariance matrix of ε. Then, it can be shown that (Bollen 1989):

$$\sum \theta = \begin{bmatrix} (I-B)^{-1}\left(\Gamma\Phi\Gamma^{'}\right)(I-B)^{-1^{'}} & (I-B)^{-1}\Gamma\Phi \\ \Phi\Gamma^{'}(I-B)^{-1^{'}} & \Phi \end{bmatrix} \tag{3-16}$$

Before estimating model parameters, it is first necessary to ensure that the model is identified. Model identification in simultaneous Structural Equations systems is concerned with the ability to obtain unique estimates of the structural parameters. The identification

problem is typically resolved by using theoretical knowledge of the phenomenon under investigation to place restrictions on model parameters. The restrictions usually employed are zero restrictions where selected endogenous variables and certain exogenous variables do not appear on the right hand side of certain equations and selected error correlations are specified to be zero. There are several rules that can be used to check whether a SEM is identified. Detailed discussions on these identification rules may be found in Bollen (1989), Johnston & DiNardo (1997), Judge et al. (1985), and Koutsoyiannis (1972).

The unknown parameters B, Γ, Φ, and Ψ are estimated so that the implied covariance matrix, Σ is as close as possible to the sample covariance matrix, S. In order to achieve this, a fitting function $F(S, \Sigma(\theta))$ which is to be minimized, is defined. The fitting function has the properties of being a scalar, greater than or equal to zero, equal to zero if and only if $\Sigma(\theta) = S$, and continuous in S and $\Sigma(\theta)$. Available methods for parameter estimation include maximum likelihood (ML), un-weighted least squares (ULS), generalized least squares (GLS), scale free least squares (SLS), and asymptotically distribution-free (ADF). Each of these methods minimizes the fitting function and leads to consistent estimators of θ. The analysis is supposed to be accomplished using SPSS AMOS 22.0 software.

For ease of understanding and to provide more convenience for users, the results of SEM are usually depicted in a graphical scheme, usually referred to as the “path diagram”. The path diagram reflects different types of relationships including direct and indirect causal effects among different exogenous and endogenous variables. In view of that, all of the variables are represented by geometric shapes, e.g. rectangles or ovals, and each path

is represented by a straight line with an arrow head at one end. The predictor variables are joined by curved lines with arrow heads at both ends. The straight arrows are the paths, which indicate the causal effect, and the curved ones represent the correlations among the variables. The circle with an arrow pointing to the dependent variable is the error term, usually referred to as the disturbance term in Path Analysis (PA) and SEM, and is a part of every regression equation (and by extension, part of every PA and SEM diagram).

In PA and SEM, variables are barely labeled as “independent” and “dependent” ones. This rises from the underlying assumption that one variable can simultaneously be a predictor in one equation and also be predicted in another one. Instead, they are called "exogenous" and "endogenous" variables. To avoid confusion, we say that *an exogenous variable has paths coming from it and none leading to it*. Similarly, *an endogenous variable has at least one path leading to it*. All endogenous variables have an error term attached, which corresponds to the assumption in a multiple regression that the dependent variable is measured with some degree of error.

In view of a path diagram, two major types of causal relationships can be identified: Variable X has a “direct” effect on variable Y if and only if there is a unique arrow starting from X and ending on Y. An “indirect” effect is associated with any path starting from X and ending in Y that includes one or more intermediate variables. The mathematical summation of direct effect and all indirect effects will provide the “total” effect of X on Y (Figure 3-3).

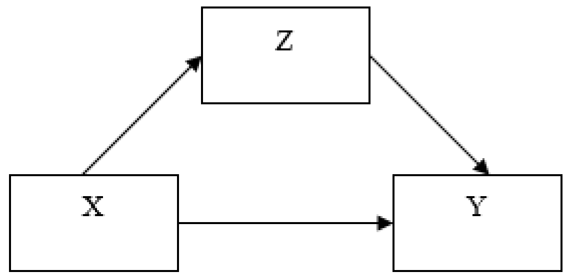

Figure 3-3 Direct and Indirect Effects

Path diagrams are divided into two major categories: "Recursive" and "Non-recursive". In a recursive structure all the arrows are in one direction, i.e., there are no loops. A non-recursive structure is the one that may consist of one or more loops. One specific result of a non-recursive model is that variables can have indirect impact on themselves. In addition, a non-recursive model can include “Direct Feedback Loops”. A direct feedback occurs when two variables have mutual direct impacts on one another, but in opposite directions. In other words, X causes Y and in return Y affects X (Figures 3-4).

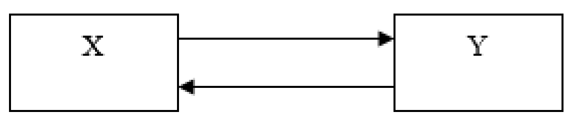

Figure 3-4 Direct Feedback Loop

In this specific case study, the path diagram is expected to approximately resemble Figure 3-5. Each arrow reflects a causal effect between the variables. Each arrow is accompanied with a coefficient value which represents the magnitude and the sign of the impact. Therefore, SEM provides a conceptual framework which enables us to explore the existing interrelationships among different attributes and activity scheduling behavio

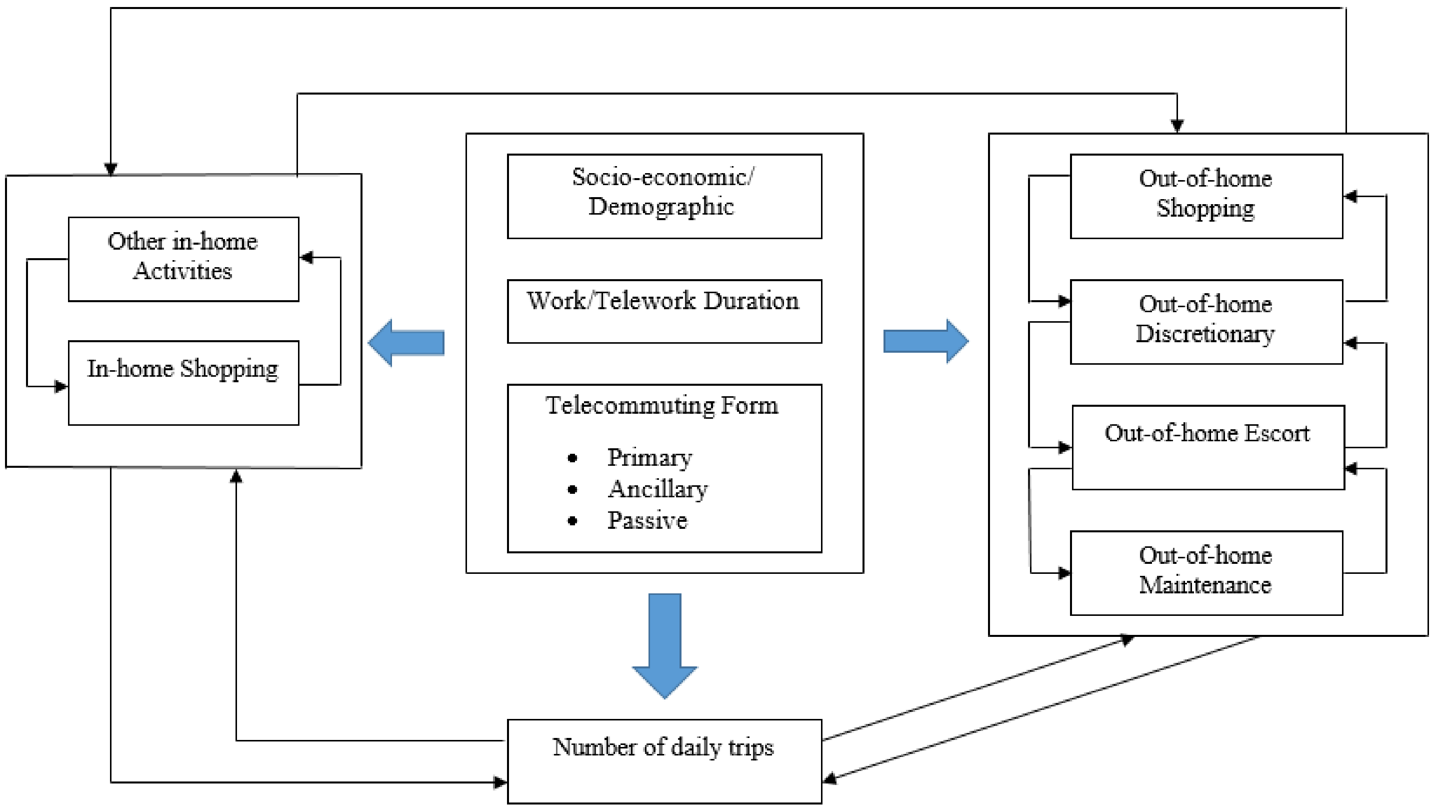

Figure 3-5 SEM Path Diagram for Daily Activity Schedule

In particular, the impact of telecommuting arrangements on daily activity/travel behavior can be investigated.

Like any other statistical model, Structural Equations frameworks are usually accompanied with a number of goodness-of-fit indices, which measure how well the estimated model predicts the observed data. Introduction and evaluation of such statistical indices have been the objective of many research efforts among statistical modelers. This section tries to provide a brief summary of some of the most useful statistical tests which provide helpful information about the model's performance. In general, SEM goodness-of-fit indices maybe categorized as one of the following: absolute fit indices, incremental fit indices, or parsimony fit indices.

"Absolute fit indices" determine how well an estimated model fits the sample data (McDonald and Ho, 2002) and therefore demonstrate which model reflects the most superior fit. Unlike incremental fit indices, their calculation does not rely on comparison with a baseline model but is instead a measure of how well the model fits in comparison to no model at all (Jöreskog and Sörbom, 1993). Included in this category are the Chi-Squared test, RMSEA, GFI, and AGFI.

The “Chi-Square” value is the traditional measure for evaluating overall model fit and assesses the magnitude of discrepancy between the sample and fitted covariance matrices (Hu and Bentler, 1999). Therefore, a good model fit would provide an insignificant result at a 0.05 threshold (Barrett, 2007). Although the Chi-Squared test remains as a popular fit statistic, there are a number of severe limitations in its application. Firstly, this test is based on multivariate normality assumption and severe deviations from normality may result in model rejections even when the model is properly specified

(McIntosh, 2006). Secondly, the Chi-Square statistic is sensitive to sample size, meaning that it nearly always rejects the model when large samples are used (Bentler and Bonnet, 1980; Jöreskog and Sörbom, 1993). Due to the limitations of the Chi-Square index, some alternatives have been introduced by researchers. One example of a widely used statistic that minimizes the impact of sample size is the "relative (or normed) chi-square" ($\chi2/df$). Although there is no consensus regarding an acceptable ratio for this statistic, recommendations range from as high as 5.0 (Wheaton et al., 1977) to as low as 2.0 (Tabachnick and Fidell, 2007).

The "Root Mean Square Error of Approximation (RMSEA)" tells us how well the model, with unknown but optimally chosen parameter estimates would fit the population's covariance matrix. It should be noticed that the RMSEA is sensitive to the number of estimated parameters in the model. In other words, it favors parsimony in that it will choose the model with the lesser number of parameters. Several recommendations have been made in the literature about the acceptable values. In general, values below 0.08 (or 0.06, to be more conservative) have been suggested.

The "Goodness-of-Fit Index (GFI)" can be considered as an alternative to the Chi-Square test and calculates the proportion of variance that is accounted for by the estimated population covariance (Tabachnick and Fidell, 2007). By looking at the variances and covariances accounted for by the model, it shows how closely the model comes to replicating the observed covariance matrix. Given the sensitivity of GFI towards sample size and number of parameters, its application has been under question in recent years and thus, has been replaced by "Adjusted Goodness-of-Fit Index (AGFI)", which takes into

account the degrees of freedom. Values for the AGFI also range between zero and one and it is generally accepted that values of 0.90 or greater indicate well-fitting models.

"Incremental (relative) fit indices" are a group of statistics that do not use the chi-square in its raw form but rather compare the chi-square value to a baseline model. "Normed Fit Index (NFI)", "Comparative Fit Index (CFI)", "Relative Fit Index (RFI)", "Incremental Fit Index (IFI)", and "Tucker-Lewis Index (TLI)" are some of the well-known statistics in this category. Recommended cut-values for these indices usually suggest values above 0.9 or 0.95 in more strict cases (Bentler and Hu 1999).

"Parsimony fit indices" are actually adjusted relative fit indices. The adjustments are applied in order to penalize models that are less parsimonious, so that simpler theoretical processes are favored over more complex ones. More complex models are therefore accompanied by lower parsimony indices. The parsimony concept is based on the fact that developing a nearly saturated, complex model indicates that the estimation process is dependent on the sample data. This will results in a less rigorous theoretical model that paradoxically produces better fit indices (Mulaik et al., 1989; Crowley and Fan, 1997). Parsimonious fit indices include "PGFI" (based on the GFI), and "PNFI" (based on the NFI). In general, no threshold values have been addressed for these indices. Some researchers however suggest parsimony fit indices within the 0.50 region while other indices achieve values over 0.90 (Mulaik et al. 1989).

3.4.2. Commute Displacement Analysis: Hazard Function

It was discussed earlier that telecommuting might be adopted in different forms and that assuming telecommuters as a homogeneous category will reduce the reliability of impact estimates. Thus, one major shortcoming observed in the existing literature pertains

to the hypothesis that when a worker is labeled as a telecommuter, it is automatically taken that he/she adopts a full-day telework schedule, i.e., the daily commute is totally removed. This will result in a computed trip reduction factor (Choo et al., 2005; Balaker, 2005; Vu & Vandebona, 2007a, 2007b, 2007c, 2008; and Lister & Harnish, 2010) which will probably need to be revised as the impact of part-time telecommuters is totally overlooked. Part-day teleworkers do not remove their daily commutes, but rather try to shift it temporally to avoid the peak hour congestion. Therefore, it is inevitable to explore the behavior of part-day telecommuters to obtain a more reliable estimate of their commute displacement behavior.

Studies of trip departure times have been of interest to researchers as they provide an understanding of temporal distribution of daily trips in a 24-hour span (Abkowitz, 1981; Small, 1982; McCafferty and Hall, 1982; Hendrickson and Plank, 1984; Bhat, 1998a, 1998b; Steed and Bhat, 2000; Bhat and Steed, 2002; Ettema and Timmermans, 2003; Jou, 2001; Jou et al., 2008; and Komma, 2008). Such studies are important for planning traffic control strategies, real-time operational information, and effectiveness of transportation demand management measures. While early studies usually focused on discrete time-of-day intervals, there has been a shift towards treating departure time as a continuous variable. Bhat and Steed discussed a number of disadvantages of discrete time-of-day modeling (Steed and Bhat, 2000; Bhat and Steed, 2002), including the unstable model results due to ad-hoc temporal partitioning of the day, inconsistencies of the results at interval boundaries, and impediments imposed on further applications of the model in real world time-dependent strategies. As a substitute, survival models based on hazard functions are introduced and applied.

Survival models consist of three basic characteristics: First, the dependent or response variable is the waiting time until the occurrence of a well-defined event, here regarded as the commute departure time. Second, observations might be censored, in the sense that for some cases the event of interest has not occurred at the time of the analysis, and third, there are predictors or explanatory variables whose effects on the waiting time are wished to be assessed.

Let T be a non-negative random variable representing the waiting time between the start of the day (i.e., 6:00 AM) until the departure time for daily commute. We will assume for now that T is a continuous random variable with probability density function (p.d.f.) $f(t)$ and cumulative distribution function (c.d.f.) $F(t) = Pr\{T < t\}$, giving the probability that the event has occurred by duration t.

It will often be convenient to work with the complement of the c.d.f, the survival function

$$S(t) = Pr\{T \geq t\} = 1 - F(t) = \int_t^\infty f(t)dt \quad (3\text{-}17)$$

which gives the probability of being alive just before duration t, or more generally, the probability that the event of interest has not occurred by duration t.

The hazard at time t on the continuous time scale is defined as the instantaneous probability that the duration preceding shopping trip departure will end in an infinitesimally small time period h after time t, given that the duration has not elapsed until time t. A mathematical definition for the hazard in terms of probabilities is as follows:

$$\lambda(t) = \lim_{h \to 0^+} \frac{Pr\{t < T < t + h | T > t\}}{h} = \frac{f(t)}{S(t)} \quad (3\text{-}18)$$

In words, the hazard rate of occurrence of the event at time t equals the density of events at t, divided by the probability of surviving to that duration without experiencing the event. This formula provides a convenient tool to calculate the cumulative distribution function $F(t)$ and the survival function $S(t)$.

$$\lambda(t) = \frac{f(t)}{S(t)} = \frac{\frac{dF(t)}{dt}}{S(t)} = \frac{\frac{-dS(t)}{dt}}{S(t)} = -\frac{d}{dt}\log[S(t)] \tag{3-19}$$

$$S(t) = \exp(-\int_0^t \lambda(u)du\ ) \tag{3-20}$$

To accommodate the effect of exogenous covariates, a Proportional Hazard (PH) function is used as the following (Cox, 1972):

$$\lambda_i(t|X_i) = \lambda_0(t).\exp(X_i'\beta) \tag{3-21}$$

$$S(t) = \mathrm{S}_0(\mathrm{t})^{\exp(X_i'\beta)} \tag{3-22}$$

$$S_0(t) = \exp(-\int_0^{\mathrm{t}} \lambda_0(u).\mathrm{du}) \tag{3-23}$$

where,

$\lambda_0(t)$	=	baseline hazard function that describes the risk (hazard rate) for Individuals with $X_i = 0$, who serve as a reference cell or pivot, and
$\exp(X_i'\beta)$	=	relative risk, a proportionate increase or reduction in the hazard rate, associated with the set of characteristics X_i.

The term “proportional hazard” refers to the fact that the increase or reduction in risk is the same as all durations. As can be seen from the formula, the hazard rate is based on two different terms: the baseline hazard, which is a function of time, and the exponential term which incorporates the effects of exogenous variables (could be time dependent or constant over time). Therefore, the shape of the baseline hazard has a substantial impact on

the model estimation. Several attempts have been done in order to adopt a parametric definition for the baseline hazard function. However, Bhat and Steed (2002) argued that the parametric approach will generally lead to an inconsistent estimation of the hazard function when the assumed parametric form is incorrect and that with a non-parametric form, the resulting estimates are consistent and the loss of efficiency (resulting from disregarding information about the hazard's distribution) may not be substantial.

The survival function is expected to supply helpful information about commute departure time among individuals. Not only does the analysis give helpful hints about the impacts of socio-demographic attributes on departure to work, but also it provides a foundation to compare part-day teleworking versus regular work and evaluate the efficiency of part-day telecommuting adoption in reducing peak hour congestions.

3.5. Data

The 2010-2011 Regional Household Travel Survey (RHTS) was sponsored by the New York Metropolitan Transportation Council (NYMTC) and the North Jersey Transportation Planning Authority (NJTPA). The RHTS was a comprehensive study of the demographic and travel behavior characteristics of residents within 28 counties of New York, New Jersey, and Connecticut. The purpose of the RHTS was to obtain household travel data to update NYMTC’s travel demand model, the New York Best Practice Model (NYBPM). The survey data provides new information on travel and mobility patterns, and will enable updates for state and regional travel demand models and ultimately assist transportation professionals and decision makers in better understanding the needs of the traveling public. In total, 143,925 linked trips were derived from 18,965 households and 43,558 participants, including a sub–sample of 1,930 households whose members provided

travel data using wearable global positioning system (GPS) devices. The GPS sample was used to assess the magnitude and pattern of under-reporting of travel in the diary-based portion of the survey, and estimate correction factors that can be applied to more fully account for travel in the full sample.

The survey was conducted from September 2010 through November 2011 by NuStats of Austin, Texas. NuStats was assisted at various stages of the data collection effort by GeoStats and Parsons Brinckerhoff. The 2010/2011 RHTS, like all recent household travel surveys, relied on the willingness of area residents to complete diary records of their daily travel over a 24-hour period. Random recruitment of households was conducted by telephone through a "recruitment interview," in which respondents were informed of the survey, its purpose, and the respondent's obligation to complete travel diaries. Data on households and household members were also collected during the recruitment interview. Participating households were assigned a specific "travel day" (typically 10 days after the recruitment interview) to record their travel. Each household member was asked to record travel information in a travel diary for the specified 24-hour period. Immediately following the assigned date, households were contacted by telephone to retrieve the diary information. In total, 31,156 households were recruited to participate in the survey. Of these, 18,965 households completed travel diaries. Travel information was retrieved from all household members, regardless of age.

The survey used a scientifically formulated sample design; industry-appropriate instruments for data collection; a package of written materials to communicate with survey respondents; a toll-free survey hotline; and data collection, processing, and reporting

procedures consistent with standards of the Council of American Survey Research Organizations (CASRO).

All households within the 28-counties constituting the New York/New Jersey/Connecticut metropolitan area were eligible for inclusion in the survey through a random sampling process. The study area comprises the following counties (Figure 3-6):

1. New York: Bronx, Duchess, Kings, Nassau, New York, Orange, Putnam, Queens, Richmond, Rockland, Suffolk, Westchester
2. New Jersey: Bergen, Essex, Hudson, Hunterdon, Mercer, Middlesex, Monmouth, Morris, Ocean, Passaic, Somerset, Sussex, Union, Warren
3. Connecticut: Fairfield, New Haven

The data set includes the following types of data:

1. Household File: Demographic information about the household, including household size, household vehicles, housing type, dominant language, telephone ownership, and income. In addition, the data set includes summaries of the travel day (number of places visited, number of children in the household, and number of household workers), as well as the county of residence. Number of records: 18,965 households.
2. Person File: Demographic information about the household members, including age, gender, relationship, employment status, student status, disability status, and licensed driver status. Student level information includes level of school; mode to school; travel time to school if primary mode to school is bicycle; and school address information including school name, address, city, and coordinates.

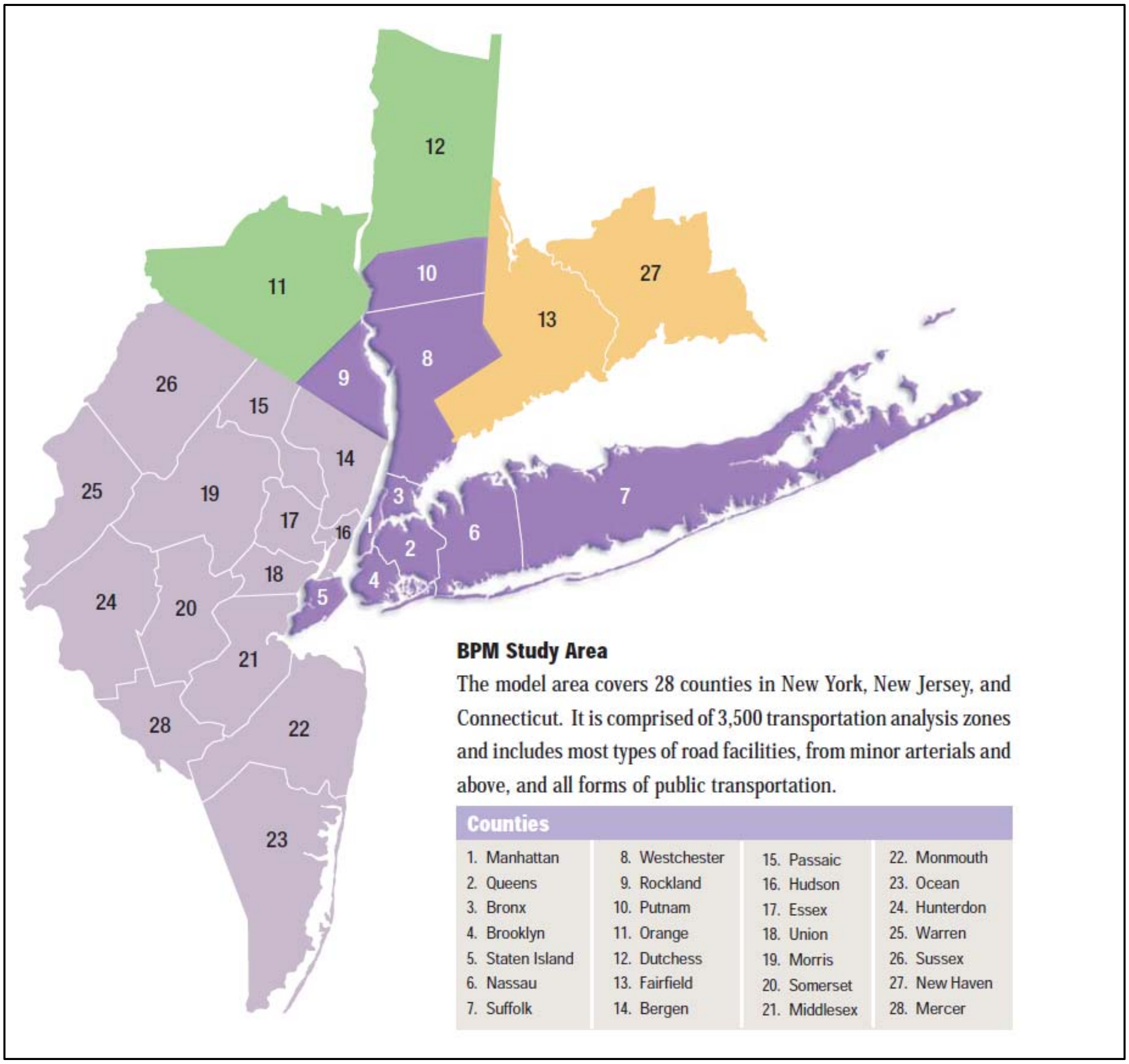

Figure 3-6 RHTS Study Area for NYBPM Model

Employment data are provided for up to two jobs and includes industry and occupation codes; mode to work; typical travel time to work; number of days worked and where; work start and end times; employer-provided transportation benefits; compressed work week information and work address information, including work name, address, city, and coordinates. Proxy reporting information is also included in this file. Number of records: 43,558 persons.

3. Vehicle File: Information about the household vehicles, including year, make, model, body type, fuel type, and subscription status of an E-ZPass tag. Number of records: 29,043 vehicles.
4. Place File: Information about all places visited during the specified 24-hour diary period by all members of completed households, including location type, activities, mode usage, and travel of other household members. Detailed location information is also contained in this file, including place name, address, city, and geocoding information for each location reported. Number of records: 231,715 places.
5. UnLinkedTrips: Each record is an unlinked trip or trip segment, where either the "From" or "To" place may include a Change in Mode of travel (e.g. bus stop, train station, Park N' Ride facility, etc.). Number of records: 188,199 trip segments.
6. LinkedTrips: Each record is a linked trip, where the "From" place represents a trip Origin and the "To" place a trip Destination. For trips involving multiple modes, an "aggregate" Trip Mode is defined, based on a prescribed hierarchy of modes (the decreasing order of hierarchy of modes is as follows: 1) School Bus, 2)Taxi, 3) Commuter Rail, 4) Express Bus, 5) Subway, LRT, Tram, PATH, Ferry, 6) Other Bus, 7) HOV, 8) Local Bus, 9) SOV, 10) Bike, 11) Walk, 12) Air Train or Other, including the Trip Mode definitions for the travel measures enhancement (over-sampling) objectives established for the Sampling Plan. Number of records: 143,925 linked trips.

The RHTS is similar to and complements several other surveys or databases available to transportation analysts and planners in the region regarding detailed travel by the resident population. It was designed to both overcome the limitations of these other travel databases,

while at the same time provide as much comparability as practical for cross-analysis and validation.

1. Census Transportation Planning Package (CTPP): This is the “journey-to-work” data obtained in the decennial census of population. Every ten years, it provides transportation planners with data about the characteristics of workers, their workplaces, and their “usual” travel between home and work. Its strength is that it is based on a very large sample of households, with minimal non-response problems. The most significant shortcoming of the 1990 CTPP addressed by the RHTS is that Census travel data is for work travel only, and then for only the “primary” job that respondents worked at in the week prior to the census. Also, since the Census 2000 data will not be available for a number of years yet, the RHTS provides a more current profile of travel in the region than available from the 1990 Census data.
2. Nationwide Personal Transportation Survey (NPTS): Unlike the CTPP data, but like the RHTS, the NTPS includes data for all travel by households, not just work travel. The most recent NPTS was conducted in 1995, with NYTMC participating in the “over sample” program, yielding a larger sample of households from New York counties in the metro region than would have been found in the national sample. Connecticut and New Jersey counties in the region, however, were not augmented. Consequently, the sample size does not support reliable statistics for most counties in the region. More importantly for model development needs, the regional NPTS data does not provide precise locational data (“geocoding”) for

travel origins and destinations, and lacks many of the detailed mode and other specific trip characteristics needed to develop the BPM. The NPTS data includes weekend and weekday travel. Due to this lack and the focus on weekday travel for the BPM, it was decided that only weekend travel data would be collected from New Jersey from a relatively small sample of households in the RHTS to supplement the information on weekend travel that is available from the NPTS.

3. NJDOT: North Jersey Household Travel Survey. Similar in many respects to the RHTS, this was a travel diary survey collected in 1986 in 12 counties in northern New Jersey. It has been used by NJTPA and NJDOT to develop the current set of NJTRM travel forecasting models.
4. MTA: Comprehensive Total Travel Survey (CTTS): This was a household travel survey conducted by the MTA in 1989 for use in transit ridership analysis and forecasting in the MTA service area. The RHTS was planned and implemented to provide a similar profile of household travel measures and patterns, only to be more current and geographically comprehensive, and with a sampling approach designed to support regional analysis.

Providing a rich source of socio-economic and demographic information both at individual and household level along with activity/travel diary of individuals, The RHTS dataset is expected to be a reliable and appropriate source of data for the purpose of this research.

3.6. Summary

This chapter expounded on the details of research methodology. First, a comprehensive flowchart was presented that indicated how different telecommuting engagement forms are defined. In the next step, each stage of the flowchart was compiled

into meaningful telecommuting dimensions. In particular, two new dimensions were introduced and applied, including "telecommuting daily engagement" and "additional daily commute". For each of the dimensions, appropriate modeling tools were introduced. A combination of these dimensions will lead to different telecommuting forms based on concepts of regularity (choice), daily engagement, and substitution effect.

In the second phase, previously derived engagement forms will be used as exogenous variables in two different directions: First, Structural Equations Models (SEM) will be applied both for workers and non-workers to explore the impacts of telecommuting on non-mandatory activities in a time-use framework. This is expected to provide valuable insight on how telecommuters might change workers' daily activity plans and if so, to what extent. Second, the impacts of part-day telecommuting on commute displacement need to be quantified. Measuring commute departure time changes is expected to produce more accurate estimates of telecommuting impacts over congestion alleviation mainly during peak hours. The results of each phase are presented in the upcoming chapters.

CHAPTER 4

PHASE I: TELECOMMUTING ESTIMATION RESULTS

The chapter ahead presents the outcomes of modeling steps along with subsequent statistical analyses. In order to maintain the general structure of the research work, this chapter is divided into two major subsections: telecommuting estimation and telecommuting impacts. Before presenting the results and in order to create a more transparent picture of the dataset, relevant descriptive statistics are discussed.

4.1. General Overview of the Data

The very first step includes extracting the workers' subsample. This requires selecting individuals who work for pay and also had at least one occasion of work activity on the survey day, either at home or at their regular workplace. Moreover, home-based workers were identified and removed from the sample using the work location (WLOC) variable. This step assures that the dataset is compatible with the major (but rather hidden) assumption in telecommuting studies:

"*The concept of telecommuting applies if and only if workers have a regular workplace out-of-home. In other words, they have to commute in the absence of telecommuting option.*"

The dataset needs to be cleaned and processed, which includes removing any missing values. This is a time consuming and step-by-step procedure as it depends on identification of significant variables which need to be included in the model. The final subsample of workers includes 15,844 individuals which made a total of 61,255 daily trips, visiting a total of 99,137 places. A summary of useful variables in this study are illustrated in Table 4-1, which provides useful information regarding major attributes of the dataset.

Table 4-1 Descriptive Statistics of the Sample Dataset

	Parameter	Percentage or Mean
	AGE	46.95
	Driving license	93.00%
Ethnicity	White	78.50%
	African American	7.90%
	Asian	6.20%
	American Indian, Alaskan native	0.30%
	Pacific islander	0.10%
	Multiracial	1.80%
	Hispanic Mexican	5.20%
Household structure	HH size	2.73
	No. of HH workers	1.83
	No. of HH drivers	1.97
	No. of HH students	0.73
	No. of HH vehicles	1.93
	No. of HH children	0.50
	No. of HH members 5 years old and younger	0.16
	No. of HH members 6-11 years old	0.19
	No. of HH members 12-15 years old	0.15
	No. of HH members 16-17 years old	0.09
	No. of HH members 18-24 years old	0.20
	No. of HH members 25-34 years old	0.28
	No. of HH members 35-49 years old	0.62
	No. of HH members 50-64 years old	0.86
	No. of HH members 65-79 years old	0.14
	No. of HH members 80 and older	0.03
Income	Low income: below 50 K	18.10%
	Medium income: 50-150 K	56.10%
	High income: above 150K	20.90%
	Other/unknown	4.90%
Work time variability	No start time variability	45.60%
	Start time variability 0-15	9.50%
	Start time variability 15-30	10.10%
	Start time variability 30-60	11.10%
	Start time variability more than 60 min	23.70%
	No end time variability	32.90%
	End time variability 0-15	6.70%
	End time variability 15-30	9.70%
	End time variability 30-60	14.20%
	End time variability more than 60 min	36.50%

Table 4-1 Descriptive Statistics of the Sample Dataset (continued)

	Parameter	Percentage (mean)
Employment type	Private employment	59.70%
	Government employment	22.50%
	Non-profit employment	12.50%
	Self employed	5.30%
Work type	Full-time one job	71.20%
	Full-time more than one job	5.70%
	Part-time one job	20.50%
	Part-time more than one job	2.60%
Occupation	Management	12.70%
	Business and financial operations	8.40%
	Computer and mathematical	5.20%
	Architecture and Engineering	2.70%
	Life, physical and social science	1.60%
	Community & social services	3.80%
	Legal occupations	3.20%
	Education, training & library	15.80%
	Art, design, entertainment, etc	4.40%
	Healthcare practitioner & technical	5.30%
	Healthcare support	6.00%
	Protective service	0.80%
	Food preparation & serving	2.90%
	Building, ground cleaning & maint.	1.30%
	Personal care & service	2.10%
	Sales and related	7.80%
	Office & administrative support	8.00%
	Farming, fishing, etc	0.20%
	Construction & extraction	1.40%
	Installation, maint. & repair	2.60%
	Production occupations	1.10%
	Transportation & material moving	2.70%
	Military specific	0.10%
Compressed work schedule	Type 1: 4/40	4.00%
	Type 2: 9/80	1.20%
	Type 3: No compressed schedule	94.80%
General work attributes	Total weekly work hours	37.97 (hrs)
	Average travel time to work	34.73 (min)
Day of week	Shoulder days: Monday and Friday	17.80%
	Weekend: Saturday and Sunday	37.20%
	Mid-weekday: Rest of the week	45.00%

For instance, one can easily observe that the average age of workers in this study is slightly below 47 years, or the dataset is mostly comprised by white people (78.5%). More than 70% of the sample holds one full-time job, with private employment showing the highest rate with an approximate value of 60%. The majority of the sample (56.1%) could be labeled as medium income category. Education, management, and sales-related jobs are respectively the three most popular jobs.

4.2. Telecommuting Estimation Model Steps

The telecommuting estimation process includes two major modeling procedures: the choice/frequency procedure which focuses on long-term decisions of telecommuters, along with daily engagement/additional commute which emphasizes on daily trends of workers towards telecommuting action. The major idea of Phase I is to estimate shares of different telecommuting forms based on the basic foresaid dimensions.

4.3. Telecommuting Choice/Frequency Model Results

The choice/frequency procedure includes two different modeling scenarios into account. First, it is assumed that there is no dependence (correlation) between the two decision levels. In view of that, two independent models are developed and significant contributors are identified. The significant variables are then incorporated in a joint sample selection structure which maximizes a joint maximum likelihood formulation with respect to the correlation parameter. Results are reflected in the upcoming sections.

4.3.1. Choice Model

The dataset includes 15,844 workers, out of which 2,943 individuals reported positive telecommuting hours. This represents 18.6% of the workers' sample as being "regular"

telecommuters (17.5% after applying weight factors; one may refer to Table 4-2 for further details).

Table 4-2 Regular versus Non-regular Telecommuters

	Without weight factor		With weight factor	
	Frequency	**Percent**	**Frequency**	**Percent**
Non-regular	12901	81.4	5788382	82.5
Regular	2943	18.6	1229710	17.5
Total	15844	100	7018092	100

A binary probit model was developed to estimate the choice of telecommuting. The model results are shown in Table 4-3. A wide range of socioeconomic and demographic (SED) variables at personal and household levels were tested. The Table only shows significant contributors at 90% confidence level.

Results indicate that among SED variables, age, having drivers' license and household size play significant roles in an individual's decision-making about telecommuting. The positive sign for age reflects a higher tendency for regular telecommuting as workers grow older. This may rise from higher capabilities of older experienced workers to get adapted to new work arrangements (Popuri and Bhat, 2003), in addition to companies' desire to use telework as a tool to retain senior employees. Meanwhile, workers who hold a driving license also demonstrate a positive tendency to regular telecommuting. The positive impact of drivers' license on telecommuting is concordant with literature (Vana et al., 2008; Popuri and Bhat, 2003; Walls et al. 2006). This may be reasonably justified by the fact that drivers are more prone to allocate any daily time budget saving to out of home non-mandatory activities and therefore may welcome any telecommuting opportunity.

It is also interesting that while household size has a negative impact on telecommuting choice, number of children tends to increase the probability to telecommute. Presence of children may refer to a historically well-emphasized advantage of telecommuting choice where parents stay longer at home to establish a balance between their in-home and out-of-home responsibilities. A variety of other SED variables including household structure, number of household members based on their age category, income, gender, vehicle ownership and etc. were also tested, none of which showed any significant contribution to the model.

Work time flexibility is another important parameter in the choice model. Detailed levels of both start time and end time flexibility were considered in the model structure. Non-flexible start time schedule has the highest negative impact on regular telecommuting while end time variability between 30 to 60 minutes reflect the lowest discouraging effect.

Twenty three occupation categories were defined in the data source, most of which contributed significantly to the choice model. It is notable that only one occupation type denoted as education and training, demonstrates a positive impact on telecommuting. This might well be justified by the nature of such jobs which facilitates workers to work from home instead of regular commute to a fixed traditional workplace.

A quick review of work status and employment type variables reveals interesting results. While part-time workers with multiple jobs are considered as the based category, all other work types demonstrate negative effect on the telecommuting choice probability. The trend is noteworthy; as the number of jobs increases or work status turns from full-time to part-time, the model reflects a lower negativity which consequently results in a higher probability towards telecommuting.

Likewise, while self-employed workers are considered as the base group, government employees tend to show the highest negative impact on telecommuting.

Total weekly work hours and average daily commute time also reflect positive influence on telecommuting choice. The positive sign for the latter may indicate the general desire of system users to minimize their total transportation cost. This results in a higher desire to avoid daily commute to work and substitute other work schedule alternatives, including telecommuting. This fairly complies with the results of similar studies. However, recent studies reveal that a more sophisticated structure including instrumental and endogenous variables are required to fully analyze the relationship between telecommuting and commute length (Mokhtarian et al., 2004; Jiang, 2008; Zhu, 2011; and Zhu, 2012).

4.3.2. Frequency Model results

As mentioned earlier, regular telecommuters are identified as those who reported positive number of hours in responding to this question – "How many hours per week does this person work for his/her main job from home on a regular basis (often referred to as telecommuting)?" (Main Job= where person works the most hours per week).

Unless otherwise noted, "telecommuting hours" and "total work hours" in this section are specifically referring to those for the main job.

From the survey response, the telecommuting hours ranged from 0 (almost 81.4%) to 75 hours per week, as shown in Figure 4-1 illustrated by the blue line. Among those who telecommuted regularly, about 70% telecommuted for less or equal to 10 hours a week, about 18% worked from home between 10 to 20 hours, another 10% falls within

20 to 40 hours a week of telecommuting, and the rest telecommuted beyond 40 hours a week.

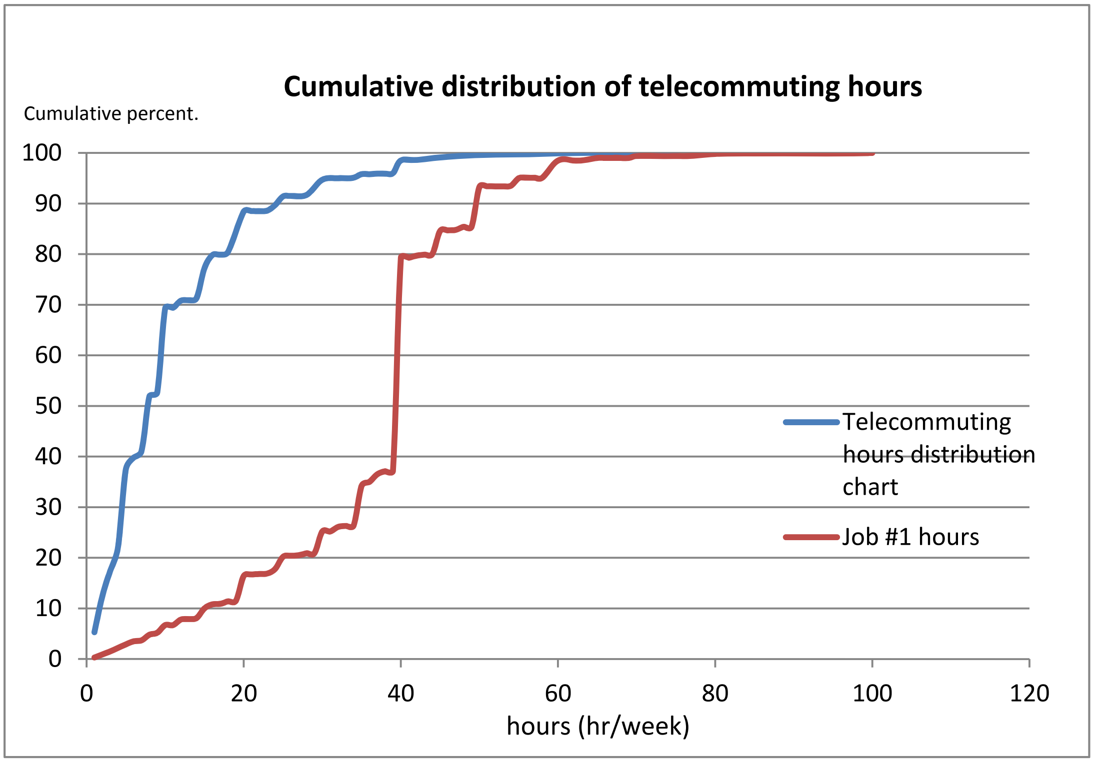

Figure 4-1 Telecommuting Hours per Week for Regular Telecommuters

Although the absolute number of hours itself measures intensity, the same hours of telecommuting does not necessarily lead to the same level of relaxation of space-time constraints for different workers. For example, 20 hours of telecommuting for a worker who works 40 hours a week has far more impact than for a worker who works 80 hours a week. As shown in Figure 4-1, the red line presents cumulative percentage of total work hours for the main job. A significant portion (larger than 20%) of observations showed work hours beyond the conventional 40 hours a week.

To consider the range of total work hours, it is decided to use an indicator derived as the share of telecommuting hours against the total work hours for the main job, referred to as TCSHARE. This indicator is a relatively fair representation of the intensity of telecommuting, which reduces the complexity of defining telecommuting phenomenon among various working scenarios. One should note that this index does not intend to replace the role of work types (such as full-time, part-time, single job, multiple job, etc.), which will also be considered as determinant factors in characterizing telecommuting behavior.

Once the intensity measurement is defined, the next step is to define telecommuting frequency levels. Cluster analysis is chosen for this purpose, as it helps identify relatively homogeneous groups. Cluster analysis or clustering is defined as "the task of grouping a set of objects in such a way that objects in the same group (called cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters)". Theoretically speaking, consider the given set of data $\mathrm{A} = \{\mathrm{a_i} \epsilon \mathrm{R^n} \colon \mathrm{i} = 1, \dots, \mathrm{m}\} \subset \mathrm{R^n}, |\mathrm{A}| = \mathrm{m} \gg \mathrm{n}$ should be partitioned into $1 \leq \mathrm{k} \leq \mathrm{m}$ non-empty disjoint subsets $\pi_1, \dots, \pi_\mathrm{k}$. Also assume that d is a defined distance function which calculates the arbitrary distance between each two separate points. Therefore, the center for each cluster π_j may be computed by the following function:

$$C_j = C(\pi_j) = argmin \sum_{a_i \epsilon \pi_j} d(x, a_j), \quad j = 1, \dots, k \tag{4-1}$$

In this way, clusters may be identified by finding the optimum $\pi^* = \{\pi_1^*, \dots, \pi_\mathrm{k}^*\}$ which minimizes the average (summation of) distance value for all the points in one cluster

and also over the whole clusters. This might well be expressed using the following objective function:

$$F(\pi) = \sum_{j=1}^{k} \sum_{a_i \epsilon \pi_j} d\left(C_j, a_i\right) \tag{4-2}$$

Various clustering methods and grouping criteria were tried, the final set of clusters for regular telecommuters are shown in Figure 4-2:

- Light telecommuter - telecommuting hours equal to or less than 25% of the total work hours (1839 observations, 62.5% of workers);
- Medium telecommuter - less than 65% but larger than 25% of the work hours are spent telecommuting (820 observations, 27.9% of workers);
- Heavy telecommuter - 65% or more of the work hours are telecommuting (284 observations, 9.7% of workers).

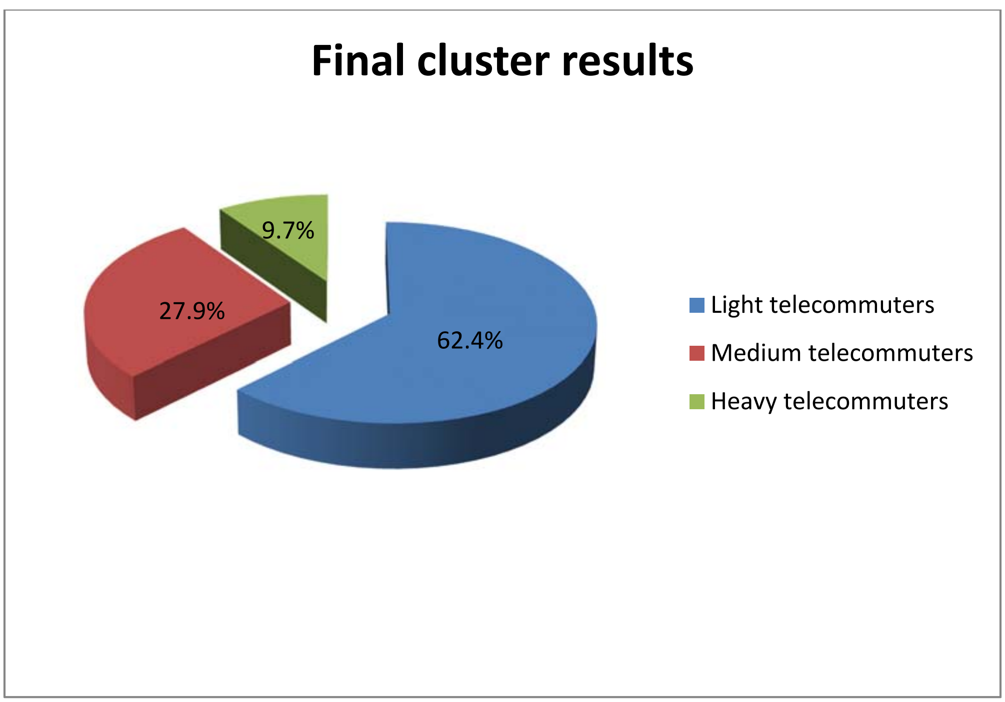

Figure 4-2 Cluster Analysis Outcomes

Ordered probit model was developed to estimate telecommuting frequency. The final model specifications are presented in Table 4-3. Three SED variables turn out to be significant including age, gender and household structure. Based on the results, male workers, and workers from households with 2 or more adults and youngest kid between 5-16 years old tend to telecommute less frequently. Instead, households with only one adult and youngest kid younger than 5 years old reflect a high tendency towards frequent telecommuting. Moreover, as individuals grow older, they are more likely to telecommute more frequently.

Among employment variables, private employees reflect the highest negative impact on telecommuting frequency. As far as occupation is concerned, three categories are found to be significant contributors in frequency model, all with negative impacts. Results also indicate that workers with one part-time job and workers with compressed work week schedule tend to telecommute more frequently. Work start and end time flexibility variables are also influential parameters at frequency level. A "compressed work week" option is usually regarded as a sign of overall work schedule flexibility which may provide employees with more freedom to adopt more frequent telecommuting. This delivers lucid explanation for the negative sign of the "no compressed week" variable. The sign and value of work hour flexibility variables, on the other hand, require further investigation as they do not follow a distinguished pattern.

One may find it interesting to take a general overview of the two models presented by now and make an overall comparison. At the first stage, individuals decide whether to telecommute or not.

Table 4-3 Choice/Frequency Model

		Independent Models		Sample Selection	
	Parameter	**Choice**	**Frequency**	**Choice**	**Frequency**
SED Variables	Age	0.00747 (7.047)	0.00375 (1.875)	0.00747 (6.74)	0.00388 (1.81)
	Male		-0.1219 (-2.599)		-0.12227 (-2.57)
	Driving license	0.2554 (4.489)		0.25516 (4.49)	
	HH type: 2+ adults, youngest kid 5-16		-0.1034 (-1.761)		-0.1024 (-1.65)
	HH type: 1 adult, youngest kid 0-5		1.0655 (2.103)		1.06606 (2.08)
	No. of HH children	0.1774 (8.408)		0.17742 (8.26)	
	HH size	-0.1163 (-7.503)		-0.11631 (-7.35)	
Work Time Variability	No start time variability	-0.4201 (-10.555)	-0.2384 (-3.275)	-0.42005 (-10.34)	-0.24711 (-2.09)
	Start time variability 0-15	-0.2416 (-4.385)	-0.2997 (-3.046)	-0.24149 (-4.35)	-0.30506 (-2.94)
	Start time variability 15-30	-0.2484 (-4.823)	-0.284 (-3.463)	-0.24804 (-4.82)	-0.28964 (-3.39)
	Start time variability 30-60	-0.1383 (-3.373)	-0.2254 (-3.225)	-0.13827 (-3.34)	-0.22819 (-3.28)
	No end time variability	-0.2551 (-6.393)	0.1686 (2.137)	-0.25523 (-6.27)	0.16361 (1.95)
	End time variability 15-30	-0.2699 (-4.152)	0.293 (2.324)	-0.27011 (-4.2)	0.28763 (2.29)
	End time variability 30-60	-0.0989 (-1.951)		-0.09975 (-1.95)	
Employment Type	Private employment	-0.6664 (-13.435)	-0.3209 (-4.584)	-0.66652 (-13.57)	-0.33241 (-4.03)
	Government employment	-0.8707 (-14.909)	-0.3032 (-3.517)	-0.87078 (-14.81)	-0.3156 (-3.19)
	non-profit employment	-0.5007 (-8.515)	-0.2053 (-2.382)	-0.50077 (-8.6)	-0.2134 (-2.31)
Work Type	Full-time one job	-0.7637 (-9.382)		-0.76366 (-9.27)	
	Full-time more than one job	-0.9005 (-8.996)		-0.90089 (-9.02)	
	Part-time one job	-0.3839 (-5.012)	0.4713 (5.797)	-0.38373 (-5.06)	0.47315 (5.72)
Occupation Type	Job: Community & social services	-0.354 (-4.51)		-0.35441 (-4.51)	
	Job: Management		-0.1924 (-2.937)		-0.19094 (-2.9)
	Job: Legal Occupations		-0.3105 (-2.469)		-0.3096 (-2.53)

Table 4-3 Choice/Frequency Model (continued)

		Independent Models		Sample Selection	
	Parameter	**Choice**	**Frequency**	**Choice**	**Frequency**
Occupation Type	Job: Education, training & library	0.2302 (5.755)		0.23035 (5.54)	
	Job: Healthcare practitioner & technical	-0.5423 (-8.581)	-0.4168 (-3.049)	-0.54234 (-8.79)	-0.42655 (-2.78)
	Job: Healthcare support	-0.4396 (-7.207)		-0.43883 (-7.28)	
	Job: Protective service	-0.5702 (-3.266)		-0.56907 (-3.52)	
	Job: Food preparation & serving related	-0.8044 (-6.983)		-0.8041 (-7.26)	
	Job: Building, ground cleaning & maintenance	-0.8561 (-5.148)		-0.85626 (-5.33)	
	Job: personal care & service	-0.4996 (-4.971)		-0.50088 (-5.1)	
	Job: Office & administrative support	-0.3018 (-5.771)		-0.30174 (-5.68)	
	OCCU45	-1.2089 (-2.775)		-1.21468 (-2.17)	
	Job: Construction & extraction	-0.5728 (-4.773)	-0.5554 (-2.097)	-0.57278 (-4.95)	-0.56687 (-2.38)
	Job: installation, maintenance & repair	-0.667 (-6.69)		-0.66697 (-6.95)	
	Job: transportation & material moving	-0.7904 (-7.415)		-0.79072 (-7.88)	
General Work Attributes	Total weekly work hours	0.0233 (15.85)	-0.00837 (-3.967)	0.02327 (16.34)	-0.00805 (-3.32)
	No compressed schedule		-0.2005 (-2.23)		-0.19923 (-2.26)
	Average travel time to work	0.00305 (6.916)		0.00304 (8.96)	
Cut Values	Intercept3		-0.5949 (-3.29)		1.06953 (31.48)
	Intercept2		0.4747 (2.631)		0.4375 (1.82)
	Intercept	-0.5335 (-4.261)		-0.53363 (-4.29)	
	Correlation				0.02485 (0.24)
Model Statistics					
Testing Global Null Hypothesis		**Chi-square**	**Chi-square**		
Likelihood ratio		2112.998 (<.0001)	316.7952 (<.0001)		
Score		2037.963 (<.0001)	323.373 (<.0001)		
Wald		1747.824 (<.0001)	308.245 (<.0001)		
Log Likelihood		-8966.81		-8967.84	

If the answer is yes, they will go through another process to determine the frequency. Perhaps, the most remarkable outcome of this analysis is the difference observed in how similar or dissimilar the variables may influence the two choices.

While there seems to be similarities in variables applied in the two stages, their influence on workers' decision-making seems naturally different. For instance, being a licensed driver turns out to significantly impact telecommuting choice while it does not show any influence over frequency. Or, workers with one part-time job tend to lower the probability of telecommuting choice. However, the same variable, when applied in a frequency model, reflects a significant effect on the opposite direction that is increasing the telecommuting frequency.

Moreover, while several job types affect workers decision towards telecommuting or not, only a few of them remain significant at frequency level. Likewise, the total weekly work hours increase the probability of telecommuting choice while they have a discouraging effect on frequency. Although this may look somewhat paradoxical at first, such inconsistencies might confirm the fact that the underlying logistics of the two decision-making factors, choice and frequency, are principally different.

4.3.3. Joint Choice/Frequency Model Results

The results for the joint model are also presented in Table 4-3. The magnitude of coefficients for the second level (frequency) are smaller in most cases, which confirms the hypothesis that joint modeling will solve the overestimation problem induced by independent models. However, the differences are not statistically significant. In general, it should be noted that although the model reflects a positive correlation parameter, it is not significant at 90% confidence level. Moreover, the independent model shows a slightly

better log likelihood value. This may suggest use of other dependency structures than simple bivariate normal distribution.

4.4. Engagement/Commute Model

As discussed in Chapter 3, it should be noted that telecommuting choice is simply an index of workers' experience towards telecommuting observed in an extended period of time (based on their self-report) and does not necessarily represent their short-time decision-making behavior in a daily framework. In other words, taking one random day into account, being a regular telecommuter does not guarantee that the worker will telecommute. Furthermore, the survey results provide compelling evidence that even a person with no regular telecommuting experience may report telecommuting activity on a random day. This requires a thorough investigation of an individual's daily plan and find out whether they participated in telecommuting activity or not. This is well established through the primary and secondary trip purpose variables (TPURP and TPURP2, respectively) as any "working at home" activity is assigned a value of 1. Though daily reflection of telecommuting activity provides useful information, the exploration is not complete without considering its impact on routine daily commutes. The fact that telecommuting totally removes the daily commute (substitution effect, also referred to as full-day telecommuting) or it simply shifts it temporally to avoid congestion and peak hours (complementary effect, also known as part-day telecommuting) seems to be an important aspect of daily telecommuting pattern. In this regard, a new variable labeled "additional commute" is constructed based on the existence of any work or work-related trip purposes in the diary (respectively coded as 9 or 10). Relevant descriptive statistics are presented in Table 4-4.

Table 4-4 Classification of Telecommuting Behavior

	Non-telecommuter	Full-day	Part-day	Total
Non-regular	12269	198	434	12901
Regular	2183	370	390	2943
Total	14452	568	824	15844

Figure 4-3 illustrates a schematic view of the share among the categories for regular and non-regular telecommuters respectively, taking weight factors into consideration. As expected, regular telecommuters showed a higher engagement rate than non-regular telecommuters (24.3% versus 4.6%). Both subsamples exhibited higher chances of part-day telecommuting than a full-day schedule; however, the observed differences are not significant at the 95% confidence interval based on the z-test.

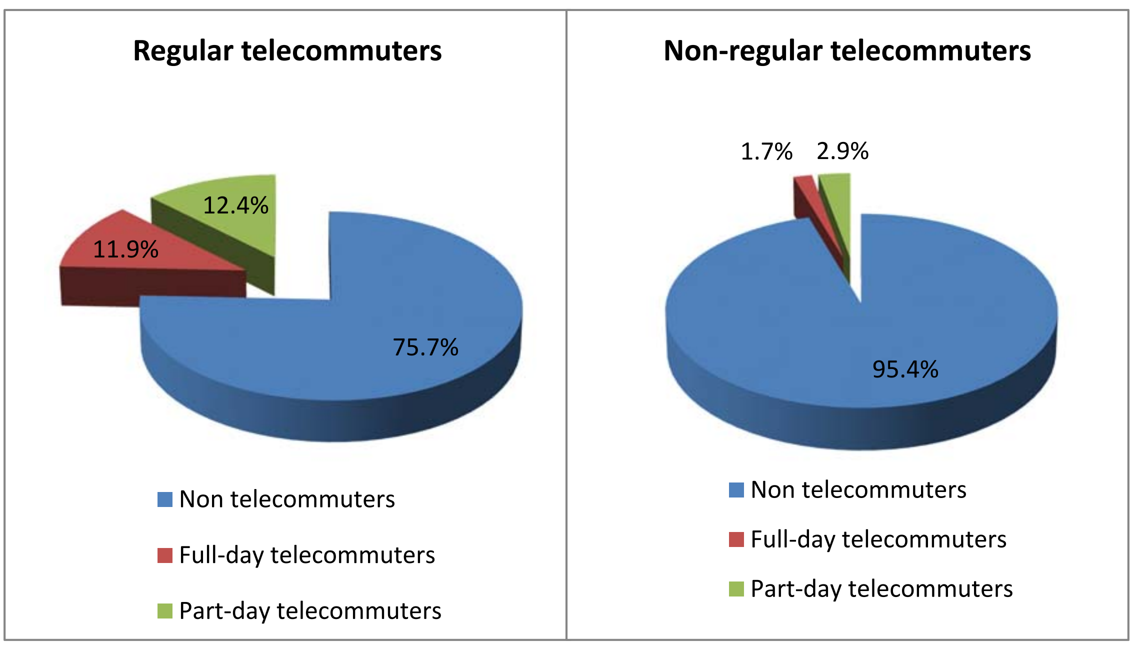

Figure 4-3 Telecommuting Engagement Rates

Relevant statistics are also presented to explore the impacts of demographic and job-related attributes on telecommuting behavior. While this does not provide sufficient information on the causal effects, it helps acquire a general view of the telecommuting activities by personal and household characteristics. Table 4-5 presents telecommuting engagement patterns by a few key variables. A proportion comparison (z-test) is also carried out using the Bonferroni method. Most variables showed statistically significant differences at 5% significance level.

Among regular telecommuters, Whites and American Indians showed the highest rate of engagement (either full-day or part-day) while African Americans showed the least percentage of daily engagement (11.3%). In terms of non-regular telecommuters, multi-racial, American Indians and Asians reflect the higher telecommuting engagement than others. Among non-regular telecommuters, it is also interesting to see that American Indians and pacific islanders only took part in full-day telecommuting.

Considering household structure, households with youngest child between 5 and 16 years old, showed the highest engagement rates among regular telecommuters (26.4% and 27.7%). Non-regular telecommuting, on the other hand, shows the highest popularity among households with one adult with no kids, and households of 2+ adults with youngest child between 0 and 5 years old. Furthermore, it is interesting to see that households of one adult with youngest kid between 0 and 5 showed no non-regular telecommuting activity.

Among the four employment categories, self-employed workers show the highest engagement rate in both regular (24.3%) and non-regular fashion (7.60%). Government employees showed the lowest engagement rate in both regular and non-regular means (16.7% and 3.9%).

Table 4-5 Engagement Rate by Personal/Household Attribute

SED Variables		Regular Telecommuter			Non-regular Telecommuter		
		No-telecommute	Full-day telecommute	Part-day telecommute	No-telecommute	Full-day telecommute	Part-day telecommute
Race	White	73.50%	12.60%	13.80%	95.20%	1.80%	3.00%
	African American	88.70%	7.90%	3.40%	97.00%	1.10%	1.90%
	Asian	78.90%	8.30%	12.80%	94.90%	1.80%	3.20%
	American Indian/ Alaskan native	72.80%	22.20%	5.00%	94.90%	0.00%	5.10%
	Pacific islander				95.80%	0.00%	4.20%
	Multiracial	88.40%	6.90%	4.70%	92.80%	3.00%	4.30%
	Hispanic/Mexican	84.60%	11.40%	3.90%	95.40%	1.90%	2.70%
Employer Type	Private	77.50%	10.30%	12.20%	95.80%	1.50%	2.70%
	Government	83.20%	7.00%	9.70%	96.00%	1.20%	2.70%
	Non profit	75.60%	12.30%	12.10%	93.40%	2.90%	3.70%
	Self employed	59.40%	23.50%	17.20%	92.40%	4.00%	3.60%
Start Time Variability	Fixed	80.40%	8.60%	11.10%	96.00%	1.20%	2.80%
	< 15 minutes	87.60%	3.10%	9.20%	95.20%	2.40%	2.40%
	15-30 minutes	80.00%	9.90%	10.00%	95.90%	1.60%	2.50%
	30-60 minutes	76.60%	10.20%	13.30%	94.10%	2.00%	3.90%
	more than an hour	67.50%	17.80%	14.60%	94.50%	2.60%	2.90%
End Time Variability	Fixed	79.80%	8.00%	12.10%	96.40%	1.10%	2.50%
	< 15 minutes	83.90%	8.10%	8.00%	97.90%	1.10%	1.00%
	15-30 minutes	84.70%	8.80%	6.60%	93.00%	2.80%	4.30%
	30-60 minutes	77.30%	12.40%	10.30%	95.60%	1.30%	3.10%
	more than an hour	71.50%	13.80%	14.70%	94.40%	2.40%	3.20%
Work Type	Full-time one job	76.30%	10.60%	13.10%	95.80%	1.10%	3.10%
	Full-time 2+ job	70.50%	11.80%	17.70%	92.90%	2.00%	5.10%
	Part-time one job	77.00%	14.90%	8.20%	95.20%	3.00%	1.70%
	Part-time 2+ job	63.40%	26.20%	10.30%	90.70%	6.20%	3.10%
Compressed Schedule	40 hours per 4 days	66.80%	14.50%	18.70%	94.60%	1.60%	3.70%
	80 hours per 9 days	86.10%	4.20%	9.80%	98.00%	1.60%	0.40%
	no compressed	76.00%	11.80%	12.10%	95.40%	1.70%	2.90%
Household Type	1 Adult, No Kids	78.60%	10.70%	10.80%	95.00%	1.40%	3.60%
	2+ Adult, No Kids	73.50%	13.70%	12.70%	95.70%	1.90%	2.40%
	1 Adult, Kids 5-16	72.30%	12.00%	15.70%	98.10%	0.20%	1.70%
	2+ Adult, Kids 5-16	73.40%	12.60%	14.00%	95.40%	1.60%	3.00%
	1 Adult, Kids 0-5	79.90%	0.00%	20.10%	100.00%	0.00%	0.00%
	2+ Adult, Kids 0-5	81.80%	7.60%	10.60%	94.40%	1.80%	3.90%

Among different work types, similar behaviors are observed in the two subsamples. Part-time workers with multiple jobs showed the highest engagement rate (36.5% and 9.3%). Regarding alternative work schedules, compressed schedule (4/40) showed the highest engagement percentage in both regular and non-regular telecommuting (33.2% and 5.3% respectively).

The model results for regular telecommuters are illustrated in Table 4-6. Only variables and categories that are significant at 90% confidence level are presented in the Table. A quick comparison between the independent model and joint model structures shows that, for engagement choice both models show very similar coefficients values, while the joint structure estimates significantly lower coefficient values for the additional commute choice. The joint model reveals a positive correlation between the two choices, which is statistically significant at 10% confidence interval. This is consistent with previous observations that a majority of telecommuters engaged in part-day telecommuting, having at least one work-related trip besides working at home. While the significant correlation parameter justifies the application of the joint bivariate structure, the independent model shows slightly better performance with higher log likelihood value.

4.4.1. Results for Regular Telecommuters

Looking at engagement choice first, it is interesting to see that socio-economic variables do not show much contribution to the model. Only ethnicity along with one specific household structure type plays significant roles in daily engagement choice. Compared with other people, Whites and households with two or more adults with the youngest kid between 5 and 16 years old are more likely to engage in telecommuting.

Table 4-6 Engagement/Commute Model for Regular Telecommuters

Regular Telecommuters		Independent models		Joint Sample selection model	
		Engagement	Add. Commute	Engagement	Add. Commute
	Intercept	-1.161 (-7.78)	-0.268 (-1.55)	-1.156 (-7.83)	0.2067 (1.56)
SED Variables	Race: White	0.261 (3.36)		0.269 (3.5)	
	HH Type 6: 2+ Adults, Youngest Kids 5-16	0.109 (1.68)		0.115 (1.79)	
Work Time Flexibility	No End Time Variability		0.258 (1.76)		0.065 (1.21)
	End Time Variability Between 30-60 Minutes	0.154 (1.89)		0.159 (1.97)	
	Start Time Variability Between 30-60 Minutes	0.2670 (3.13)		0.256 (3.00)	
	Start Time Variability More Than An Hour	0.382 (6.48)		0.379 (6.46)	
Employment Type	Private	-0.382 (-4.86)		-0.394 (-5.1)	
	Government	-0.675 (-6.08)	0.448 (2.96)	-0.670 (-6.07)	0.137 (2.58)
	Non-Profit	-0.497 (-4.93)		-0.503 (-5.05)	
Occupation Type	Management		-0.325 (-2.34)		-0.130 (-2.68)
	Computer & Mathematical	0.178 (1.97)		0.187 (2.09)	
	Life, Physical And Social Science	0.372 (1.91)		0.404 (2.11)	
	Education, Training & Library	0.312 (3.85)		0.286 (3.48)	
	Personal Care & Service	-0.693 (-2.35)		-0.648 (-2.25)	
	Construction & Extraction	0.450 (1.72)	-0.798 (-1.99)	0.450 (1.73)	-0.236 (-1.63)
General Work Attributes	No. Of Jobs	0.259 (4.37)		0.262 (4.53)	
	Total Travel Time To Work		-0.006 (-3.22)		-0.002 (-3.36)
	Total Work Hours/Week	0.008 (4.32)	0.021 (6.14)	0.008 (4.28)	0.008 (6.58)
Telecommuting Frequency	High	0.261 (2.85)	-0.982 (-6.7)	0.260 (2.82)	-0.278 (-4.25)
	Medium		-0.669 (-6.32)		-0.188 (-3.83)
	Low	-0.532 (-9.04)		-0.531 (-9.02)	
Correlation	Rho			0.287 (1.86)	
Sigma	Sigma				0.472 (24.19)

Table 4-6 Engagement/Commute Model for Regular Telecommuters (continued)

Model Statistics			
Testing Global Null Hypothesis	**Chi-Square**	**Chi-Square**	
Likelihood Ratio	307.42	129.457	
Score	304.77	120.723	
Wald	283.471	115.158	
Model Prediction	**Chi-Square**	**Chi-Square**	
Hosmer & Lemeshow test	4.426 (0.82)	4.165 (0.84)	
Log Likelihood	-1989.16		-2012

The complexity of responsibilities in a big family and the attention demanded by children in this age range provide compelling reason for the positive impact. Relatively, the presence of smaller children (0-5 years old) may not contribute to telecommuting engagement as there are higher chances that these children will be staying at home which do not present suitable working environment at home.

Work time flexibility also exhibited positive impacts on telecommuting engagement, for both start-time and end-time flexibility. Start-time flexibility provides higher opportunities for telecommuting than end-time flexibility, and higher level of flexibility also leads to higher chances of engaging in telecommuting activities. In terms of employment type, government employment reflects the highest discouraging effect over telecommuting engagement, while self-employed workers (the base category) show highest probability of telecommuting as they have the highest degree of flexibility than other employment types.

Four occupation types are identified as positive contributors to telecommuting engagement, including “Mathematical and computer occupations”, “Life, physical and social science”, “Education, training and library”, and “construction and extraction”. Considering the nature of the tasks involved, scientific, education, computer and design

related occupations are highly suitable for telecommuting given the advent of online courses, powerful search engines and high-speed internet which offers quick and easy transmission of data. As expected, “personal care and services” shows negative impact on telecommuting engagement, as these types of work also require in person activities and interactions.

As the number of jobs increases, workers tend to prioritize different activities and try alternative work schedules in order to optimize their use of time, balance their responsibilities and also avoid additional costs such as unnecessary commutes and time wastes in traffic. This may well explain the positive coefficient for number of jobs in the telecommuting engagement model. Although travel time to work does not seem to have a significant impact on engagement choice, the total work hours shows positive effects.

The telecommuting frequency variable illustrates significant effects on the engagement choice. As mentioned previously, this variable reflects the intensity of telecommuting from a long-term lifestyle choice perspective. Naturally, those who telecommute more frequently would show higher chances of telecommuting engagement on a given day.

For those who engage in telecommuting, the additional commute model provides some insights on the factors that influence whether it is substitution or supplementary. Only few job-related attributes tend to be influential. In particular, government employees are more likely to make additional daily commutes, potentially because that their work is less likely to be fully replaceable by telecommuting. On the other hand, two occupation categories show significant negative effects - Management, and Construction and

Extraction. This seems reasonable and consistent with the literature as managerial tasks do not require frequent physical presence.

The positive coefficient for total work hours points out the popularity of part-day telecommuting among workers with long hours of work. Apart from the concept of over-working at home, which may have caused a bias, the change of work environment has been traditionally proven to be a refreshing strategy for workers to resist fatigue and maintain quality. As expected, the total travel time to work, also known as commute length, would discourage any desire towards additional commuting. While the phenomenon is easily explained through individuals' desire to minimize any costs in terms of time or monetary values, one should also be careful in interpreting the causal effect as the endogeneity issue rises. In other words, not only do long commute lengths lead to higher desires of full-day telecommuting, but also there is a probability of workers' choosing long distance jobs or living further from work if an option for full-day telecommuting is offered.

As to telecommuting frequency variable, there is a negative association between telecommuting frequency and additional commutes. In other words, more frequent telecommuters are more likely to telecommute on a full-day basis.

From a joint decision perspective, four variables affect both decision-making factors. They include high telecommuting frequency, construction and extraction occupations, government employment, and total work hours. All other variables reflect an independent impact, i.e., they affect only one of the two decision-making factors. Among the four mentioned variables, the first three variables illustrate "differential" impacts. For example, construction occupations and highly frequent telecommuters both encourage full-day telecommuting, i.e., they show positive impacts on the engagement model, but have

negative effect on the additional commute model. The role of government employment is interesting as well. In general, it discourages telecommuting engagement, and even when telecommuting takes place, it is more likely to be supplementary. Total weekly work hours show a commonality effect on the model, as it is positively associated with both telecommuting engagement and additional commute. This partially reflects the over-working at home phenomenon, where people engage in additional work activities at home, without full or partial replacement or temporal shifts of commute at all.

4.4.2. Results for Non-regular Telecommuters

Compared with regular telecommuters, more variables tend to show significant contributions in the models for non-regular telecommuters (mainly in terms of SED attributes), as shown in Table 4-7. There are five attributes that influence both decisions. In particular, holding a driver's license improves the chances of telecommuting, especially part-day telecommuting. Workers with no children seem to be less likely to engage in telecommuting, and even if they do, it is more likely to be on a part-day basis (or perhaps over-working). This is not surprising, given that without other family responsibilities, these workers may prefer more social interactions and actual presence at workplaces. On the other hand, working in farming, fishing and forestry seems to encourage full-day telecommuting, although the result may not be reliable due to the small sample in this occupation.

Among those variables that only influence the engagement choice, households with one adult with youngest child between the age of 5-16, and employees with private firms and government agencies are less likely to telecommute.

Table 4-7 Engagement/Commute Model for Non-regular Telecommuters

Non Regular Telecommuters	Parameter	Separate Models		Joint Sample Selection Model	
		Engagement	Add. Commute	Engagement	Add. Commute
	Intercept	-1.661 (-11.05)	-1.947 (-4.63)	-1.662 (-11.05)	-0.254 (-1.19)
SED Variables	Licensed Driver	0.254 (3.09)	0.575 (2.32)	0.254 (3.09)	0.212 (2.55)
	HH Size	-0.098 (-3.6)	0.172 (2.23)	-0.098 (-3.58)	0.049 (2.05)
	HH Type 1: 1 Adult, No Kids	-0.296 (-3.03)	0.724 (2.6)	-0.296 (-3.02)	0.218 (2.49)
	HH Type 2: 2+ Adults, No Kids	-0.213 (-3.66)	0.495 (2.97)	-0.213 (-3.65)	0.143 (2.68)
	HH Type 5: 1 Adult, Youngest Kids 5-16	-0.424 (-1.84)		-0.424 (-1.84)	
	No. Of HH Members Age 16-17	0.176 (2.67)		0.175 (2.67)	
Work Time Flexibility	No End Time Variability	-0.124 (-2.84)		-0.124 (-2.84)	
	End Time Variability Within 15 Minutes Or Less	-0.177 (-2.17)		-0.179 (-2.19)	
	End Time Variability Between 15-30 Minutes	0.159 (2.26)		0.160 (2.26)	
	No Start Time Variability		0.327 (2.82)		0.108 (2.95)
	Start Time Variability Between 15-30 Minutes	-0.172 (-2.28)		-0.175 (-2.31)	
	Start Time Variability Between 30-60 Minutes		0.342 (1.72)		0.110 (1.8)
Employment Type	Private	-0.140 (-2.75)		-0.140 (-2.76)	
	Government	-0.199 (-3.3)		-0.202 (-3.33)	
Work Type	Full-time One Job		0.268 (1.92)		0.086 (1.85)
Occupation Type	Life, Physical & Social Science	0.311 (2.35)		0.311 (2.36)	
	Education, Training & Library	0.318 (6.02)		0.316 (5.93)	
	Art, Design, Entertainment, Sports & Media	0.272 (3.13)		0.275 (3.16)	
	Healthcare Support		-0.449 (-2.03)		-0.153 (-2.11)
	Farming, Fishing & Forestry	0.514 (1.68)	-1.679 (-2.15)	0.512 (1.65)	-0.486 (-2.15)
General Work Attributes	No. Of Jobs	0.256 (5.74)		0.258 (5.77)	
	Total Work Hours Per Week		0.020 (4.36)		0.007 (4.98)

Table 4-7 Engagement/Commute Model for Non-regular Telecommuters (continued)

Non Regular Telecommuters	Parameter	Separate Models		Joint Sample Selection Model	
		Engagement	Add. Commute	Engagement	Add. Commute
Weekday Category	Shoulder Days (Mondays & Fridays)		0.346 (2.16)		0.100 (2.09)
Correlation	Rho			0.146 (0.75)	
Sigma	Sigma				0.435 (26.83)
Model Statistics					
Testing Global Null Hypothesis		**Chi-Square**	**Chi-Square**		
Likelihood Ratio		153.207	86.4887		
Score		172.651	85.817		
Wald		152.986	77.6432		
Model Prediction		**Chi-Square**	**Chi-Square**		
Hosmer & Lemeshow test		5.128 (0.7438)	6.425 (0.5997)		
Log Likelihood		-2810.31		-2811	

Three specific occupation types tend to be more exposed to non-regular telecommuting occasions: “Life, physical and social science”, “education, training and library occupations”, “entertainment and media occupations”. As expected, the probability of non-regular telecommuting increases in parallel with the number of jobs involved. Flexibility of work schedule is still a significant contributor to the model. Considering end-time flexibility, the results seem rational as rigid work hour schedules (i.e., schedules with no end-time flexibility or less than 30 minutes) are likely to discourage telecommuting engagement. However, when it comes to start-time variability, jobs with 30-60 minutes of flexibility display a negative coefficient which might seem surprising.

For those engaged in telecommuting on a non-regular basis, the additional commute model aims at further categorizing whether it is full-day or part-day telecommuting. Most variables show positive impacts, indicating higher possibilities for part-day telecommuting instead of complete replacement of working at the workplace. Similar with regular telecommuters, total work hours is positively associated with part-day telecommuting.

Taking daily variations into account, the model indicates a higher probability of part-day telecommuting on shoulder days (Mondays and Fridays). This might reflect the workers' propensity towards simulating a three-day weekend schedule by reducing the number of office hours and taking some tasks home on shoulder days. Obviously, licensed drivers are more likely to make any work-related trips.

Disregarding "farming and forestry occupations" which is subject to statistical bias as explained before, "healthcare occupations" also decrease the probability of any additional commute according to their negative coefficient. In other words, they are more prone towards full-day telecommuting. Analysis of work type variable provides noteworthy results. The variable covers two different dimensions simultaneously, number of jobs and full-time versus part-time status. Based on the results, workers holding one full-time job are more likely to make additional commutes. Comparing the joint versus independent structure could provide valuable outcomes. In terms of correlation parameter, still a positive correlation is observed. However, considering the insignificance of the correlation value at a 0.1 level rejects the hypothesis of dependency between the two decision makings. This may rise from the non-regular nature of their behavior where a more random attitude is observed towards working schedule compared to regular-telecommuters.

4.5. Summary

This chapter provided details of a modeling framework that recognizes various forms of telecommuting arrangements, and provides a connection between telecommuting choice/frequency as a lifestyle arrangement, and telecommuting engagement/commute as

a short-term daily choice. Four levels of decision-making in telecommuting behaviors were considered, specifically choice, frequency, engagement and commute.

In the first step, binary probit and ordered probit models were developed to estimate workers' propensity toward regular telecommuting and the corresponding weekly intensity. Model results reveal interesting findings on the determinant factors that contribute to both decisions. The findings are consistent with existing literatures, and also confirm that the underlying logic of the two decision-making behaviors are principally different.

It is recognized that telecommuters may not be regarded as a homogeneous group, and that people exercise many different forms of telecommuting engagements, which would play distinctive roles in affecting their travel-activity behavior. Therefore, this study extends the modeling to a daily framework that investigates the interactions of telecommuting engagement with other daily choices. Specifically, two levels of decisions are modeled: whether an individual telecommutes on a given day, and whether the individual performs additional work at the workplace on the same day. In other words, it investigates whether telecommuting plays a partial or total substitution role.

Longer-term lifestyle arrangements, which are derived from the previous step, are also taken into account to recognize the connection between lifestyle arrangement and daily activities. In terms of choice, regular and non-regular telework arrangements are identified, and distinctive telecommuting behaviors are observed for these two subsamples based on the model results. Frequency, which represents the intensity of telecommuting on a long-term basis, also provides significant contribution to the models.

Two different approaches are explored in this study: independent and joint sample selection structures, given the assumption that the decisions on telecommuting engagement and additional commute may take place simultaneously and may be correlated. The model results reveal a positive correlation between the two decisions, which reflects similar impacts of unobserved factors on both levels. This might be interpreted as a sign of general tendency (or reality) toward part-day telecommuting. The correlation is not statistically significant for non-regular telecommuters, which may stem from the randomness of their actual engagement. Comparing the coefficients across the two modeling structures, variables for the engagement choice show comparable values, while those for the additional commute choice show much smaller values in the joint model, for both regular and non-regular telecommuters. This is consistent with the expectation that the independent modeling approach ignores the presence of the potential correlation between the unknown factors that govern both decisions and therefore may overestimate the effects of exogenous variables on the second level.

A wide range of demographic, socio-economic and work-related variables were investigated in the models. Most of the variables exhibit expected signs and reasonable values. In terms of regular-telecommuting, the model suggests that job-related variables play more significant roles than demographic attributes. Non-regular engagement, however, is more sensitive to individual and household demographic attributes, although the results may seem too complicated to explain.

From a general perspective, the proposed framework paves the path toward a better understanding of how and to what extent telecommuting potential is converted into different forms of actual engagement. It builds a foundation to further distinguish the

various daily telecommuting arrangement forms, such as primary telecommuting, ancillary telecommuting and passive telecommuting, as indicated in the framework. In particular, the decision to telecommute is complex and influenced by a host of factors, including lifestyle/household arrangements, personal preference, work attributes, etc. To better categorize whether telecommuting plays a substitution role or supplementary role on one's daily travel-activity pattern, future work will be carried out focusing on the following perspectives. First, the characterization of over-working at home needs to be defined, as it may not present any effects on one's regular commute travel or other activities. It is not easy to define over-working, as everyone has different work arrangements. This needs to be done by cross-examining all aspects associated with working activities, such as the timing, sequencing, duration, location, etc. Another direction should focus on the entire daily activity pattern to investigate how various telecommuting forms affect the temporal and spatial dynamics differently. In addition, household-level decision-making could be taken into account, which may capture the work-related and household responsibility-related arrangements among household members. Such steps, titled "telecommuting impacts" form the major foundation of the next chapter.

CHAPTER 5

PHASE II: ANALYSIS OF TELECOMMUTING IMPACTS

5.1. Directions of Impact Analysis

The results of Phase I provide a rich source of information on how different individual, household, and job-related attributes affect a worker's propensity toward telecommuting adoption. If the worker telecommutes, the next question involves finding out what type of telecommuting he/she will engage in. When correspondent shares of telecommuting forms are defined, it is inevitable to explore and analyze how they will impact individuals' activity/travel behavior, which will be further summed up into aggregate transportation system impacts. Considering the nature of this study and as it was previously discussed in the methodology section, two major disaggregate impacts of telecommuting adoption are analyzed in this section:

1. Exploring time-use data: Focuses on how telecommuters differ from regular workers in terms of allocating their limited time budget to different types of activities. Like any other time-use analysis, non-mandatory activities are under emphasis. Structural Equations Models (SEM) are developed for both workers and non-workers which reflect how telecommuting affect individuals' activity durations on a random they. In view of the importance of household context in the activity/travel decision-making behavior of individuals, the non-workers' model enables the researcher to also observe and analyze the impact of telecommuting on other non-working household members.
2. Commute displacement**:** This is expected to provide a reliable measurement on how telecommuting alleviates traffic congestion during AM peak hours. One major

argument in aggregate terms is that literature only focuses on full-day telecommuting (where commute is totally removed from the daily plan) and does not consider part-day telework arrangements. Therefore, not only is there a possibility of overestimation of telecommuting effects, but also the fact that some commutes are diverted to other time-of-day segments is totally neglected.

Before presenting the results, a brief summary of data preparation and relevant descriptive statistics are discussed. In parallel, some of the shortcomings of the research including data limitations are well explained.

5.2. Data Preparation and Descriptive Statistics

The 2010/11 RHTS trip (place) file encompasses 29 major trip purposes, based on which activities are derived. Therefore, for more convenience and to comply with the literature, four major non-mandatory out-of-home activities are recognized and classified. They include: 1) Out-of-home shopping, 2) Out-of-home maintenance, 3) Out-of-home discretionary, 4) Escort.

Furthermore, in-home activities are also classified as the following: 5) Online shopping, and 6) Other in-home activities.

Out-of-home work (regular work) and telecommute durations are also considered as two major mandatory activities which are expected to restrict non-mandatory participation. Though regular work durations are easy to derive, there seems to be problems in calculating telework durations. The major shortcoming is that in most cases, the reported duration of telecommuting does not seem to be valid. This may stem from some of these main underlying factors: First, in presence of telecommuting activity, there seems to be a bias among respondents to give a higher priority to report telecommuting compared to other in-

home activities. For example, if there is a self-reported telecommuting activity from 10 AM to 4 PM, this does not truly guarantee that the respondent had net teleworking duration of 6 hours. He/she has probably spent some time for lunch, rest, or child care. In other words, there is a self-reported bias which leads to an overestimation of teleworking duration. One major adjustment was applied when telecommuting was done during the morning period. According to the data dictionary rules, the start point of the day was fixed at 3:00 AM. So any telecommuting activity duration in the morning was automatically computed from 3:00 AM. In order to resolve this issue, the earliest telecommuting start time was shifted to 6:00 AM which corrected any unreasonably long duration by subtracting 3 hours. Second, when telecommuting is reported as a secondary purpose, there is no tool to clearly quantify its duration. In this regard, all secondary telecommuting purposes were removed from time-use analysis. This included 392 observations, almost 13% of the telecommuters' sample. The final daily durations of non-mandatory activities are presented in Figure 5-1.

Accordingly, primary telecommuters show higher durations of out-of-home non-mandatory activities, complying with the hypothesis that complete removal of daily commute will robustly relax the existing restrictions on workers' daily activity planning. One interesting observation is that part-day telecommuters (either ancillary or passive) show lower durations of shopping, maintenance, and discretionary activities compared to regular workers (non-telecommuters). As we will further discuss, this might stem from the fact that part-day telecommuting is somewhat involved with over-working, which in turn decreases the remaining time budget for part-day telecommuters for non-mandatory activity participation.

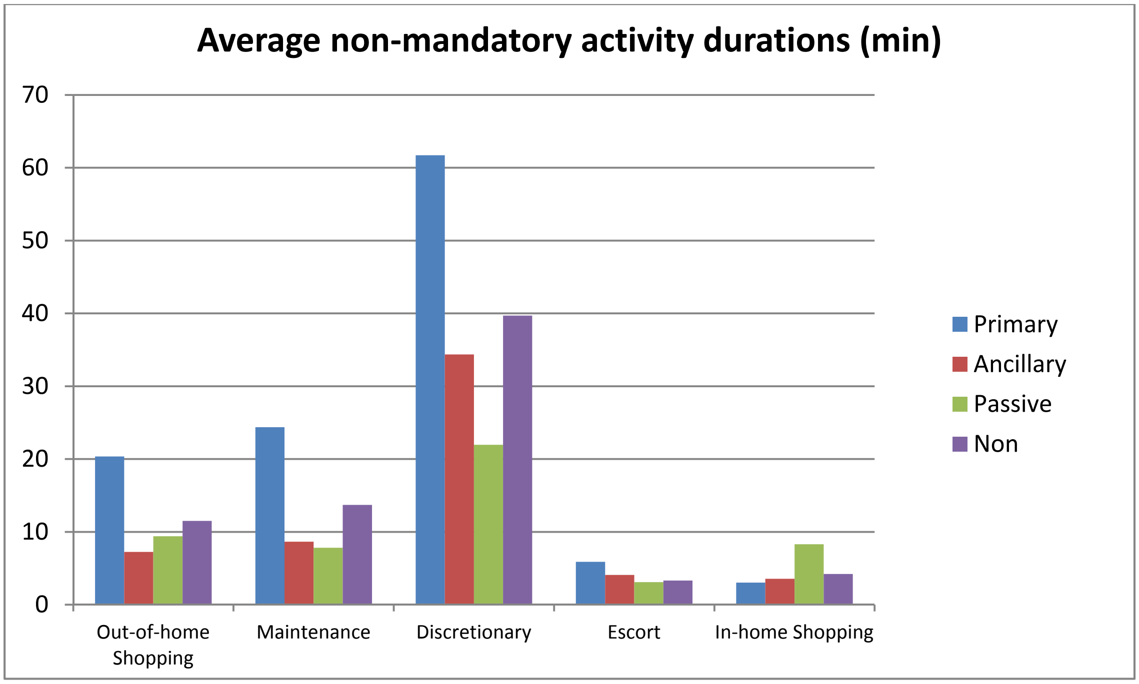

Figure 5-1 Average Daily Durations for Non-mandatory Activities

In order to validate the observations in terms of statistical significance, results are also accompanied by an Analysis of Variance (ANOVA) test. Consequently, the computed F values confirm significant differences among non-mandatory out-of-home activities' durations among different telecommuting patterns (Table 5-1). The only exception is for escort activities where the values (and therefore the differences) are too small.

Table 5-1 ANOVA Test for Non-mandatory Activity Durations

		Sum of Squares	df	Mean Square	F	Sig.
Shopping	Between Groups	42060.587	3	14020.196	8.257	.000
	Within Groups	26231597.456	15448	1698.058		
	Total	26273658.043	15451			
Maintenance	Between Groups	69623.875	3	23207.958	6.368	.000
	Within Groups	56295622.654	15448	3644.201		
	Total	56365246.529	15451			
Discretionary	Between Groups	329062.967	3	109687.656	10.651	.000
	Within Groups	159083216.502	15448	10297.981		
	Total	159412279.469	15451			
Escort	Between Groups	3158.213	3	1052.738	1.393	.243
	Within Groups	11675817.660	15448	755.814		
	Total	11678975.873	15451			
In-home shopping	Between Groups	5757.058	3	1919.019	.786	.502
	Within Groups	37728683.161	15448	2442.302		
	Total	37734440.219	15451			

Figure 5-2 illustrates total work durations for different telecommuting forms, which are decomposed into regular work and telework durations for ease of understanding. Results indicate that non-telecommuters show the lowest total work duration, with an average of 485 minutes per day which is well within the range of the expected eight hour schedule. Primary telecommuters reported an approximate daily duration of 10 hours which seems reasonable, taking into account that in-home work is perhaps accompanied by some other activities in parallel, including cooking or child care. Part-day telecommuting, however, reflects significantly higher values compared to primary or non-

telecommuters. The fact that part-day telecommuting, either in form of ancillary or passive, does not decrease regular work hours is of the essence. This can provide compelling evidence that part-day telecommuting stems from prolonged work hours for one job or holding multiple jobs. Whether such type of over-working at home will impact transportation system or not will be exhaustively addressed in the upcoming sections (Time-of-day analysis).

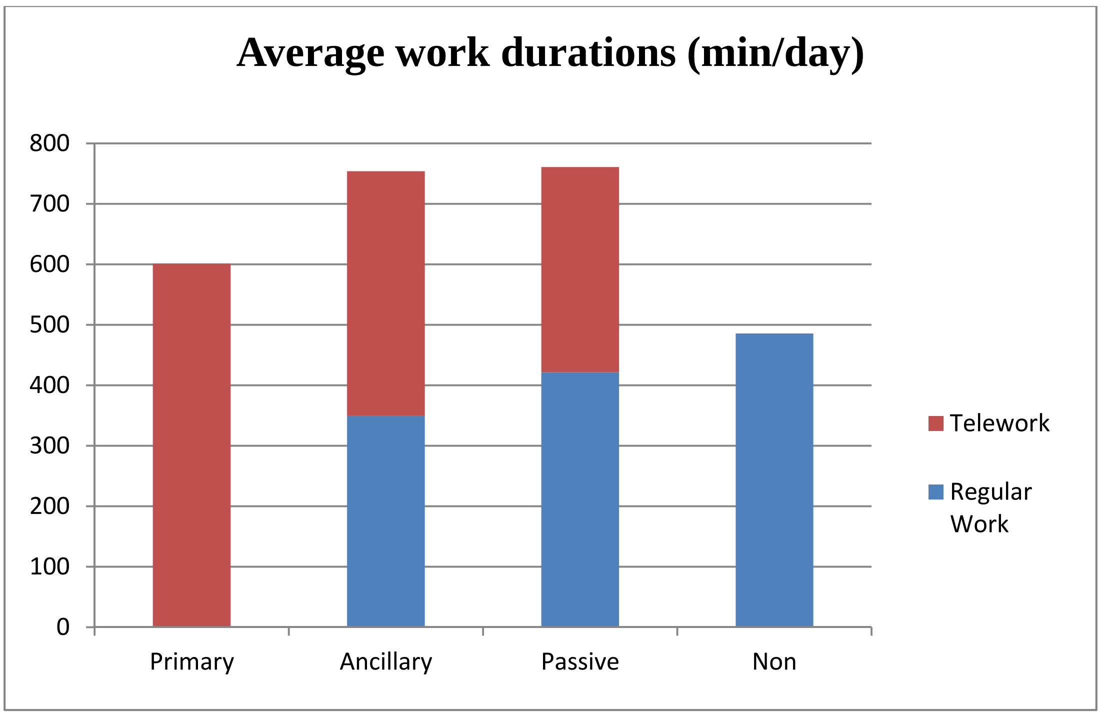

Figure 5-2 Average Daily Work Durations

Besides activity duration and time-use analysis, transportation planners are also interested in how various telecommuting forms will result in different trip generation outcomes. Average daily trip rates are depicted in Figure 5-3. It is interesting to notice that telecommuters (regardless of their telecommuting form) tend to show higher daily trip rates

than non-telecommuters. This may confirm the hypothesis that any change in daily work schedule (including complete removal or temporal shift) will provide the individuals with sufficient freedom to participate in other out-of-home activities (mainly non-mandatory) and therefore leads to higher magnitudes of daily trip rates. From a statistical standpoint, however, it is necessary to verify the significance of the observed contrasts. This is accomplished using Analysis of variance (ANOVA) test. Results indicate that there are statistically significant differences among the four telecommuting categories (Table 5-2).

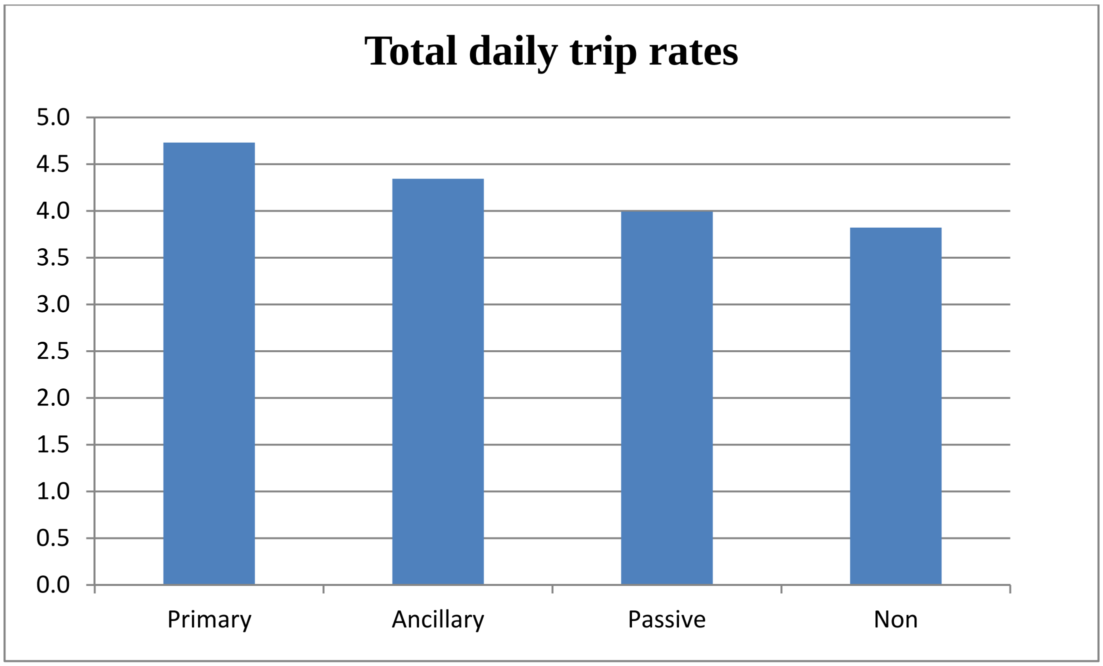

Figure 5-3 Total Daily Trip Rates for Different Telecommuting Patterns

Table 5-2 ANOVA Test for Daily Trips

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	437.601	3	145.867	27.192	.000
Within Groups	82868.854	15448	5.364		
Total	83306.455	15451			

5.3. Time Use and Trip Generation

Two SEM models are developed in this section, focusing on workers and non-workers samples respectively. In each of the two models, endogenous variables consist of five aforementioned non-mandatory activities along with total number of daily trips. Exogenous variables include regular work duration, telework durations based on adoption form, presence of other telecommuters in the household, and socioeconomic and demographic attributes. Results include path coefficients including total, direct and indirect effects. Furthermore, appropriate goodness of fit indices are presented and discussed.

5.3.1. Workers' Sample

This section focuses on the results of the Structural Equations Model for workers sample. The model outcomes can be observed in Tables 5-3 and 5-4. For a better understanding, results are analyzed in the following segments: Non-mandatory activity interactions include the existing causal relationships among different out of home and in-home activity durations. This is expected to provide a rich source of information on how different daily activities compete with each other in terms of consuming individuals' limited time budget. Telecommuting impacts emphasizes on different work arrangement scenarios two major aspects of telecommuting throughout a 24-hour period, namely telecommuting form (which is actually derived from phase I results), and telecommuting duration. This is in fact the major objective of phase II of this study, which targets how telecommuting may impact individuals' time-use and daily activity patterns. Moreover, In order to improve the overall goodness-of-fit of the model, it is important to take into account socioeconomic and demographic variables.

Table 5-3 SEM for Workers' Sample, Non-standardized Coefficients

			Out-of-home Activities				In-home Activities		Telecommuting Duration			Socio-economic & Demographic	
			Shopping	Maint.	Disc.	Escort	Shopping	Regular work duration	Primary	Ancillary	Passive	Age	Number of HH vehicles
Out of home Activities	Shopping	Tot.		-0.0182	0.0005	-0.0001		-0.0355	-0.0115	-0.0138	0.0002	0.1539	0.0273
		Dir.	-	-0.0182	0	0	-	-0.0364	-0.0118	-0.0138	0	0.1583	0
		Ind.		0	0.0005	-0.0001		0.001	0.0004	0	0.0002	-0.0045	0.0273
	Maintenance	Tot.	0.0022		-0.0288	0.0032	0.0016	-0.0524	-0.0194	0.0011	-0.0116	0.2452	-1.5007
		Dir.	0	-	-0.0288	0	0	-0.0552	-0.0194	0	-0.0129	0.2388	-1.4993
		Ind.	0.0022		0	0.0032	0.0016	0.0028	0	0.0011	0.0013	0.0064	-0.0014
	Discretionary	Tot.	-0.0759	0.0014		-0.1096	-0.055	-0.0976	0.0009	-0.0371	-0.046	-0.2214	0.0485
		Dir.	-0.0759	0	-	-0.1096	-0.055	-0.1014	0	-0.0382	-0.046	-0.2133	0
		Ind.	0	0.0014		0	0	0.0039	0.0009	0.001	0	-0.0081	0.0485
	Escort	Tot.						-0.0091				-0.0325	
		Dir.	-	-	-	-	-	-0.0091	-	-	-	-0.0325	-
		Ind.						0				0	
In home Activities	In-home Shopping	Tot.						-0.0031					-0.919
		Dir.	-	-	-	-	-	-0.0031	-	-	-	-	-0.919
		Ind.						0					0
	Total daily trips	Tot.	0.0091	0.0021	0.0045	0.0086	-0.0014	-0.0027	-0.0007	-0.0003	-0.0002	0.0059	0.0551
		Dir.	0.0095	0.0022	0.0045	0.0091	-0.0011	-0.0017	-0.0006	0	0	0.0052	0.0569
		Ind.	-0.0003	-0.0002	-0.0001	-0.0005	-0.0002	-0.001	-0.0001	-0.0003	-0.0002	0.0007	-0.0018

Table 5-3 SEM for Workers' Sample, Non-standardized Coefficients (continued)

	Absolute fit indices		Relative fit indices		Parsimony fit indices	
Model's Goodness-of-fit	**CMIN**	113.3273	**NFI**	0.9811	**PNFI**	0.4757
	df	33	**RFI**	0.961	**PCFI**	0.4782
	CMIN/df	3.5415	**IFI**	0.9864		
	GFI	0.9988	**TLI**	0.9717		
	AGFI	0.997	**CFI**	0.9863		
	RMSEA	0.0128				

Table 5-4 SEM for Non-workers' sample, Standard Coefficients

			Out-of-home Activities				In-home Activities		Telecommuting Duration			Socio-economic & Demographic	
			Shopping	Maint.	Disc.	Escort	Shopping	Regular work duration	Primary	Ancillary	Passive	Age	Number of HH vehicles
Out of home Activities	Shopping	Tot.		-0.0266	0.0013			-0.205	-0.0332	-0.0192	0.0003	0.0492	0.0008
		Dir.	-	-0.0266	0	-	-	-0.2105	-0.0342	-0.0192	0	0.0506	0
		Ind.		0	0.0013			0.0055	0.001	0	0.0003	-0.0014	0.0008
	Maintenance	Tot.	0.0015		-0.0484	0.0014	0.0013	-0.2067	-0.0384	0.001	-0.0114	0.0535	-0.0298
		Dir.	0	-	-0.0484	0	0	-0.2177	-0.0383	0	-0.0128	0.0521	-0.0298
		Ind.	0.0015		0	0.0014	0.0013	0.0111	0	0.001	0.0013	0.0014	0
	Discretionary	Tot.	-0.0308	0.0008		-0.0297	-0.0268	-0.2288	0.001	-0.021	-0.0269	-0.0287	0.0006
		Dir.	-0.0308	0	-	-0.0297	-0.0268	-0.2379	0	-0.0215	-0.0269	-0.0277	0
		Ind.	0	0.0008		0	0	0.009	0.001	0.0006	0	-0.0011	0.0006
	Escort	Tot.						-0.0787				-0.0156	
		Dir.	-	-	-	-	-	-0.0787	-	-	-	-0.0156	-
		Ind.						0				0	
In home Activities	In-home Shopping	Tot.						-0.0147					-0.0223
		Dir.	-	-	-	-	-	-0.0147	-	-	-	-	-0.0223
		Ind.						0					0
	Total daily trips	Tot.	0.1618	0.0537	0.1964	0.1019	-0.0296	-0.2741	-0.0378	-0.0073	-0.006	0.0334	0.0285
		Dir.	0.1679	0.058	0.199	0.1077	-0.0243	-0.174	-0.0302	0	0	0.0294	0.0294
		Ind.	-0.006	-0.0043	-0.0026	-0.0058	-0.0053	-0.1001	-0.0076	-0.0073	-0.006	0.004	-0.0009

Therefore, based on the knowledge obtained from research background, specific demographic variables are tested and the results are respectively analyzed under Socio-economic and demographic variables segment. In addition to activity durations, each segment also focuses on daily trip rates which indicate how existing variables will contribute to trip generation on a random day.

As mentioned before, five major categories of non-mandatory activities are introduced and categorized as endogenous variables. They include out-of-home shopping, out-of-home maintenance, out-of-home discretionary, escort, and In-home-shopping. This section focuses on the tradeoff among these endogenous variables.

Several inferences could be made based on the direct effects on non-mandatory activities. It is interesting to notice that all existing direct effects are accompanied by negative coefficients. A negative coefficient is a sign of substitution or replacement effect, indicating that any increase in the duration of one activity will subsequently result in the reduction of others. As an example, maintenance activities tend to replace out-of-home shopping, or out-of-home shopping errands show a negative impact on discretionary activities. Such general expectation that non-mandatory activities tend to compete in utilizing individuals' time budget and therefore indicate a replacement effect is well documented in the literature. All remaining positive (supplementary) impacts are actually indirect and stem from a more complicated set of interactions. For instance, the positive impact of maintenance over discretionary activities is easily explained through the indirect path going from maintenance to discretionary via out-of-home shopping. The highest replacement coefficients are assigned to the impacts of escort over discretionary and shopping activities. Accordingly, one hour of escort will lead to a reduction of 6.6 minutes

in discretionary activities ($60\times0.1096=6.57$ min) or 4.6 minutes in out-of-home shopping. In return, one may also notice that escort activities are not affected by any other non-mandatory activities. To explain this, one might claim that escort activities show some type of priority compared to other non-mandatory activities. In other words, other out-of-home activities have no direct or indirect impact on escort durations. This may rise from the fact that escort activities usually involve some type of underlying mandatory factors. For instance, escorting children to school may not seem mandatory at first glance, but it usually involves a fixed time schedule and a fixed duration. So it is acceptable that escort duration can have a negative impact on other non-mandatory activities with no reverse impact on itself, just as illustrated in Table 5-3.

In-home shopping activities follow the same pattern as escort assignments, in the way that they are not restricted by other non-mandatory errands. However, this may not signify any type of priority or latent obligation. Instead, this rather confirms the initiative that individuals, regardless of their hectic out of home activity plans, tend to maintain certain minimum hours staying at home and that, out-of-home non-mandatory missions have no significant impacts on in-home activities.

The total effects of activities on daily trip generations comply with both the literature and general anticipations. In view of that, out-of-home activities tend to generate more trips while in-home shopping discourages trip generation. The highest positive impacts belong to out-of-home shopping and escort activities, reflecting the prevalence of these two purposes among workers on a random day.

As discussed in the previous chapters, the RHTS 2010/11 dataset provides a profuse source of individual and household attributes. However, using too many variables in the

model will complicate the interactions which in turn contradict the parsimony of the proposed model structure. In order to obtain acceptable parsimony indices and avoid model complexity, only five major SED variables are taken into account. Such variables were selected based on a comprehensive review of the literature and include: age, gender, driving license, number of HH children and vehicle ownership.

The foresaid variables were gradually added and tested on the model. Although many strong causal effects were observed, only age and vehicle ownership produced acceptable goodness-of-fit measures. All other variables were consequently removed from the model structure. The final results indicate that as individuals grow older, they are more likely to spend longer durations in out-of-home shopping, and out-of-home maintenance. On the other hand, negative impacts of age are observed on out-of-home discretionary, and escort. The reduction in out-of-home discretionary duration can be easily explained through their lifestyles as older individuals are usually more involved in work and other household responsibilities and may not have that much free time to spend on discretionary activities. When it comes to escort errands, a quick review of dataset reveals two major underlying factors. First, older individuals are more likely to have higher household responsibilities and therefore are more likely to have more complicated trip chaining behaviors which in turn can reduce the escort activity durations. The second reason is that in some cases, it is observed that the escort duty is totally shifted to a younger adult in the household (a member other than parents) which partially elucidates the negative impact of age on escort assignments. In view of trip generation, the positive coefficient of age bodes for the positive association between age and trip making behavior. Only two activity types are directly affected by number of household vehicles, namely: out-of-home maintenance

and in-home shopping. It looks as if the ownership of more than one vehicle in the household provides more freedom for non-working household members and therefore shifts the responsibility of maintenance duties from workers to non-workers. Such direct reduction in maintenance activities is then compensated for by indirect increases in shopping and discretionary durations. It is also reasonable that in general, vehicle ownership has a discouraging impact on in-home activities including in-home shopping.

The impacts of telecommuting can be tracked in terms of telework and regular work durations. Although the correspondent coefficients for different telecommuting patterns are illustrated, the impacts cannot be investigated unless different telecommuting scenarios are defined. This is based on the fact that coefficients correspond to unit of time (minutes) and therefore different combinations of work and telework durations can lead to different results. For convenience, four major work arrangements are defined and compared. They include: 8-hour regular work, 8-hour primary telework, 4-hour ancillary telework+ 4-hour regular work, and 4-hour passive telework + 4-hour regular work. Results can be observed in Tables 5-5 and 5-6.

In general, compared to an 8-hour regular workday, any form of telecommuting will increase the duration of out-of-home non-mandatory activities, indicating how relaxing regular work restrictions will positively impact non-mandatory activity participation. As expected, primary telecommuting, which encompasses completed removal of work-related trips, reflects the highest impacts. As an example, primary telecommuting increases out-of-home shopping, maintenance, and discretionary activities by approximately 11, 16, and 49 minutes respectively. When it comes to part-day

telecommuting, Ancillary and passive patterns show similar impacts on escort and in-home shopping.

Table 5-5 Work Arrangements' Impacts on Non-mandatory Activities

		8-hour regular work	8-hour primary telework	4-hour regular work + 4-hour ancillary telework	4-hour regular work + 4-hour passive telework
Shopping	Total	-17.04	-5.52	-11.832	-8.472
	Dir.	-17.472	-5.664	-12.048	-8.736
	Indir.	0.48	0.192	0.24	0.288
Maintenance	Total	-25.152	-9.312	-12.312	-15.36
	Dir.	-26.496	-9.312	-13.248	-16.344
	Indir.	1.344	0	0.936	0.984
Discretionary	Total	-46.848	0.432	-32.328	-34.464
	Dir.	-48.672	0	-33.504	-35.376
	Indir.	1.872	0.432	1.176	0.936
Escort	Total	-4.368	0	-2.184	-2.184
	Dir.	-4.368	0	-2.184	-2.184
	Indir.	0	0	0	0
In-home Shopping	Total	-1.488	0	-0.744	-0.744
	Dir.	-1.488	0	-0.744	-0.744
	Indir.	0	0	0	0
Total daily trips	Total	-1.296	-0.336	-0.72	-0.696
	Dir.	-0.816	-0.288	-0.408	-0.408
	Indir.	-0.48	-0.048	-0.312	-0.288

Table 5-6 Telecommuting Impacts on Non-mandatory Activities

		8-hour primary telework	4-hour regular work + 4-hour ancillary telework	4-hour regular work + 4-hour passive telework
Shopping	Total	11.52	5.208	8.568
	Dir.	11.808	5.424	8.736
	Indir.	-0.288	-0.24	-0.192
Maintenance	Total	15.84	12.84	9.792
	Dir.	17.184	13.248	10.152
	Indir.	-1.344	-0.408	-0.36
Discretionary	Total	47.28	14.52	12.384
	Dir.	48.672	15.168	13.296
	Indir.	-1.44	-0.696	-0.936
Escort	Total	4.368	2.184	2.184
	Dir.	4.368	2.184	2.184
	Indir.	0	0	0
In-home Shopping	Total	1.488	0.744	0.744
	Dir.	1.488	0.744	0.744
	Indir.	0	0	0
Total daily trips	Total	0.96	0.576	0.6
	Dir.	0.528	0.408	0.408
	Indir.	0.432	0.168	0.192

Ancillary telecommuters show higher durations of maintenance and discretionary while passive telecommuters spend longer durations in out-of-home shopping. The positive impact of all telecommuting forms on in-home shopping duration soundly clarifies the idea that telecommuters are more familiar and experienced with online services.

In terms of trip generation, all telecommuting forms increase number of daily trips, which means there might be evidence that not only non-mandatory trip generation compensates for commute removal (or displacement) but also it can produce more trips compared to non-telecommuters. Results indicate that primary telecommuters show the highest positive impact on trip rate (0.96), followed by passive telecommuters (0.6) and ancillary telecommuters (0.576) respectively. Higher trip rates for passive telecommuters (compared to ancillary telecommuters) may stem from their irregular decision-making patterns, which encourages them to make the most of their infrequent telecommuting opportunity and accomplish more out-of-home activities, leading to higher daily trip rates.

5.3.2. Non-workers' sample

One important concept in behavioral studies is that decisions are not made merely on an individual basis but rather in household context. In other words, there exist certain interactions among household members which can (and will) affect any decisions made by any of the household members. Such concept well conforms to activity/travel behavior studies and has been well explored in literature. For instance, the probability that a licensed driver member of family chooses “drive alone” mode is well affected by availability of private vehicle at a specific time which is in turn affected by other household members' decisions. Similarly, organizing joint/solo activities and the duration spent on non-mandatory activities is expected to be influenced by other household members. In agreement with the aforementioned hypothesis, this section focuses on non-workers subsample and puts an effort to identify the impacts of telecommuting on non-working members of the household (Tables 5-7 and 5-8).

Table 5-7 SEM for Non-workers' sample, Non-standard Coefficients

			Out-of-home Activities				In-home Activities	Presence of Telecommuters in HH			Socio-economic & Demographic
			Shopping	Maint.	Disc.	Escort	Shopping	Primary	Ancillary	Passive	Male
Out of home Activities	Shopping	Tot.	-0.7649	-0.009	-0.1533		-0.0061	-0.1269	-0.0564	0.1366	-6.0252
		Dir.	0	-0.0383	-0.6521	-	-0.0266	0	0	0	-5.7029
		Ind.	-0.7649	0.0293	0.4988		0.0205	-0.1269	-0.0564	0.1366	-0.3223
	Maintenance	Tot.					-0.0168	14.0732	-0.1546	-15.1525	-3.464
		Dir.	-	-	-	-	-0.0168	14.0732	0	-15.1525	-3.4967
		Ind.					0	0	-0.1546	0	0.0327
	Discretionary	Tot.	1.173	-0.045	-0.7649		-0.0305	-0.633	-0.2813	0.6815	0.7777
		Dir.	4.9888	0	0	-	0	0	0	0	30.8363
		Ind.	-3.8158	-0.045	-0.7649		-0.0305	-0.633	-0.2813	0.6815	-30.0586
	Escort	Tot.	-0.0021	0.0001	-0.0004		0.0001	0.0011	0.0005	-0.0012	-0.6847
		Dir.	0	0	-0.0018	-	0	0	0	0	-0.6834
		Ind.	-0.0021	0.0001	0.0013		0.0001	0.0011	0.0005	-0.0012	-0.0014
In home Activities	In-home Shopping	Tot.							9.2209		-1.9495
		Dir.	-	-	-	-	-	-	9.2209	-	-1.9495
		Ind.							0		0
	Total daily trips	Tot.	0.006	0.0009	-0.0011	0.014	-0.0011	0.4087	0.5108	-0.0136	-0.0802
		Dir.	0.0117	0.0011	0.0028	0.014	-0.0009	0.3961	0.5208	0	0
		Ind.	-0.0057	-0.0002	-0.004	0	-0.0002	0.0126	-0.0099	-0.0136	-0.0802

Table 5-7 SEM for Non-workers' sample, Non-standard Coefficients (continued)

	Absolute fit indices		Relative fit indices		Parsimony indices	
Model's Goodness-of-fit	**CMIN**	39.3573	**NFI**	0.9829	**PNFI**	0.5242
	df	24	**RFI**	0.9678	**PCFI**	0.5297
	CMIN/df	1.6399	**IFI**	0.9932		
	GFI	0.9996	**TLI**	0.9872		
	AGFI	0.9991	**CFI**	0.9932		
	RMSEA	0.0057				

Table 5-8 SEM for Non-workers' Sample, Standard Coefficients

			Out-of-home Activities				**In-home Activities**	**Presence of Telecommuters in HH**			**Socio-economic & Demographic**
			Shopping	Maint.	Disc.	Escort	Shopping	Primary	Ancillary	Passive	Male
Out of home Activities	Shopping	Tot.	-0.7649	-0.0196	-0.4189		-0.009	-0.0003	-0.0001	0.0003	-0.0569
		Dir.	0	-0.0832	-1.7817	-	-0.0391	0	0	0	-0.0539
		Ind.	-0.7649	0.0637	1.3628		0.0302	-0.0003	-0.0001	0.0003	-0.003
	Maintenance	Tot.					-0.0113	0.013	-0.0001	-0.0136	-0.0151
		Dir.	-	-	-	-	-0.0113	0.013	0	-0.0136	-0.0152
		Ind.					0	0	-0.0001	0	0.0001
	Discretionary	Tot.	0.4293	-0.0357	-0.7649		-0.0164	-0.0005	-0.0002	0.0005	0.0027
		Dir.	1.8259	0	0	-	0	0	0	0	0.1066
		Ind.	-1.3966	-0.0357	-0.7649		-0.0164	-0.0005	-0.0002	0.0005	-0.1039
	Escort	Tot.	-0.004	0.0003	-0.0022		0.0002				-0.0125
		Dir.	0	0	-0.0093	-	0	-	-	-	-0.0125
		Ind.	-0.004	0.0003	0.0071		0.0002				0
In home Activities	In-home Shopping	Tot.							0.0103		-0.0125
		Dir.	-	-	-	-	-	-	0.0103	-	-0.0125
		Ind.							0		0
	Total daily trips	Tot.	0.1219	0.0393	-0.0631	0.1464	-0.0319	0.0166	0.017	-0.0005	-0.0153
		Dir.	0.237	0.0495	0.1554	0.1464	-0.0267	0.0161	0.0173	0	0
		Ind.	-0.1152	-0.0101	-0.2185	0	-0.0052	0.0005	-0.0003	-0.0005	-0.0153

The variables are generally similar to the previous model. Work and telework durations do not apply and are therefore removed. The telecommuting variables used in this segment were also modified and include presence of telecommuters (decomposed by their forms) in the household. In terms of demographics, number of household workers was also tried however it turned out to be insignificant and was consequently eliminated. A detailed analysis of results is presented in the upcoming sections.

A quick review of the activity interrelations reveals some noticeable points. First, most of the existing statistically significant (direct) coefficients bode for replacement effects on one another. In other words, the negative coefficients imply that activities tend to compete with each other in terms of time use. The only exception refers to the impact of out-of-home shopping on discretionary activities. As an example, one hour of discretionary activity will totally reduce out-of-home shopping by almost 9 minutes ($60\times0.1533=9.2$ minutes). The fact that out-of-home shopping has a supplementary impact on discretionary activities might sound interesting. In-home shopping has a direct replacement effect on out-of-home shopping and maintenance, which seems reasonable. In terms of trip generation, it is expected that out-of-home errands reflect a positive contribution to daily trips with in-home duties showing the opposite impact. Results generally conform to such hypothesis, except for discretionary activities. Reviewing the dataset shows that when discretionary activities are selected as part of the individuals' daily plan, the number of daily trips tend to decrease. This might show that in presence of discretionary activities, respondents are more probable to cancel or shift other errands and focus merely on discretionary participation.

The impacts of socio-economic and demographic attributes were tested on the model. Variables include: age, gender, driving license, number of HH children, number of HH workers, and vehicle ownership. Only gender turned out to be appropriate in terms of both t-tests and goodness-of-fit indices. Results for the gender variable show that in most cases, females dominate non-mandatory activity durations. For instance, females increase the durations of out-of-home shopping and maintenance activities by 6 and 3.5 minutes, respectively. The only exceptions are discretionary activities where males reflect a positive contribution to the model. Furthermore, males are prone to generating slightly fewer daily trips compared to females.

Results indicate that primary telecommuting has a remarkable positive impact on non-workers' out-of-home maintenance and discretionary durations. One reason may stem from household (compared to personal) maintenance activities which can be accomplished by any of the household members. As the primary telecommuting totally removes work trip (and perhaps any other secondary stops), it is probable that such responsibilities will be shifted to other household members, including non-workers. Accordingly, primary telecommuting will increase the maintenance duration by 14 minutes for other household members. Passive telecommuters, however, show exactly the opposite effect. Accordingly, passive telecommuting decreases maintenance participation for non-working household members by 15 minutes. It might originate from the situations where passive telecommuting is representing "overworking", thus inhibiting other family members' freedom to pursue any joint non-mandatory activities, or it may simply be a sign of a sudden unplanned change in worker's daily arrangement which shifts the maintenance

activities from non-working members to the telecommuting individual due to his partially relaxed schedule. Model results also show that ancillary telecommuting increases in-home shopping by 9 minutes.

Overall, presence of primary or ancillary telecommuters has a positive impact on total daily trip rates. This could point out the role of telecommuting in expanding joint out-of-home activities where any relaxation in the worker's schedule will also provide more freedom for other non-working members. Another hypothesis may rise from the fact that as telecommuters spend more hours at home, thus providing opportunities for other non-working members to replace some in-home activities with out-of-home errands. Passive telecommuters, on the other hand, show a trivial negative indirect impact on trip generation of non-working members. This might signify their irregular work pattern which does not permit Joint activity/trip planning in longer horizons and therefore may have a negative impact on non-working members' daily trip generation.

5.4. Analysis of Telecommuting Impacts on Commute Displacement

Excluding primary (full-day) telecommuters who totally remove their work trips (adding up to 568 observations), the remainder of the dataset (daily commuters) could be divided into three major groups: 1) Regular workers (non-telecommuters), 2) Ancillary telecommuters (part-day engagement on a regular basis), and 3) Passive telecommuters (part-day engagement on a random basis). It is assumed that each of the categories reflect different commute behavior including departure times. Hence, separate hazard functions are developed for each of these categories and the results are compared.

Based on the trip file from RHTS data, daily commuters' sample generates 15021 daily commutes. Some of the relevant statistics including commute departure time-of-day,

and modal split are presented in Figures 5-4, 5-5, and 5-6. Accordingly, around 93% of daily commutes belong to regular workers (non-telecommuters) while ancillary and passive telecommuters share almost equal portions of daily work trips (3% and 4% respectively).

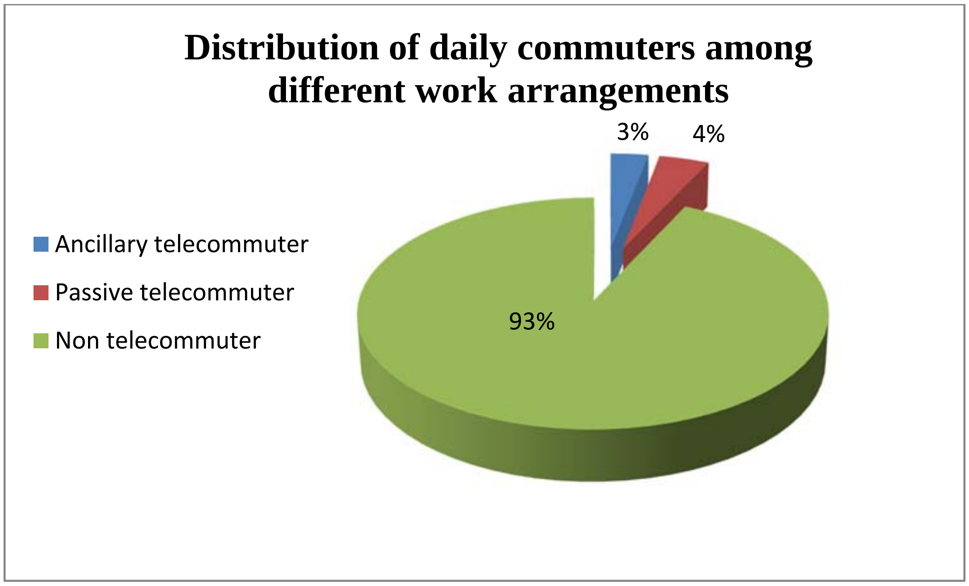

Figure 5-4 Distribution of Daily Commuters

Figure 5-5 illustrates the 24-hour distribution of daily commute departure times for the three commuter categories. Accordingly, regardless of work arrangement, the majority of daily commute departures occur either in AM peak or Midday. However, the Midday share is relatively higher for part-day telecommuters, which indicates telecommuters' propensity to postpone their daily work trip departure times from early morning to midday interval.

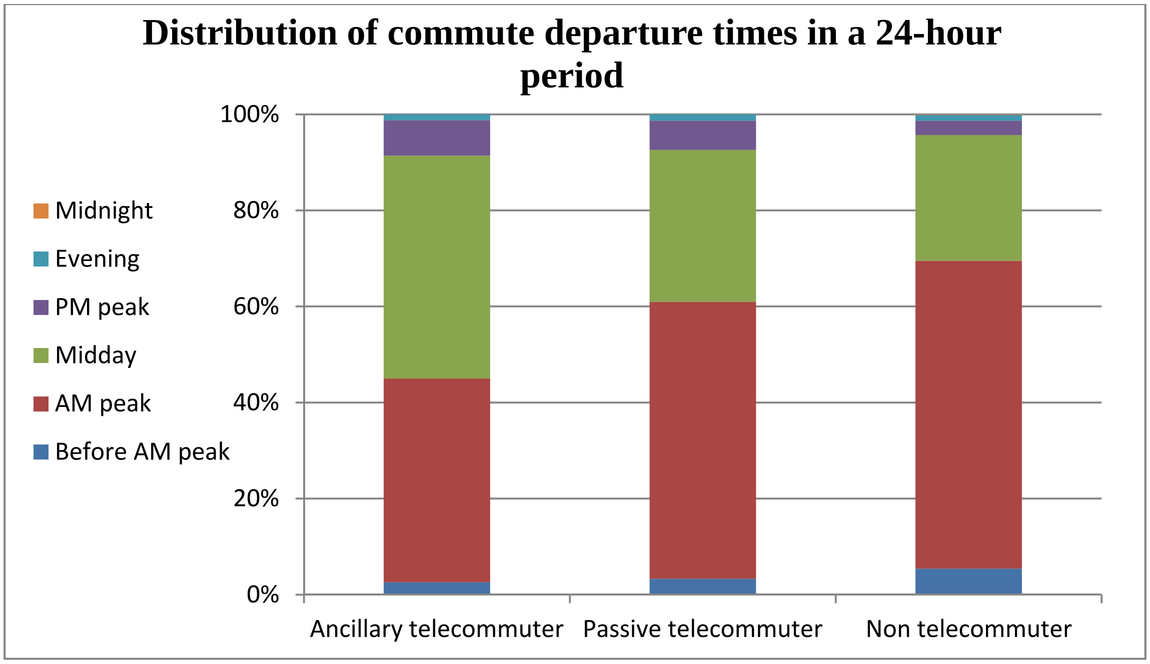

Figure 5-5 Distribution of Commute Departure Times in a 24-hour Period

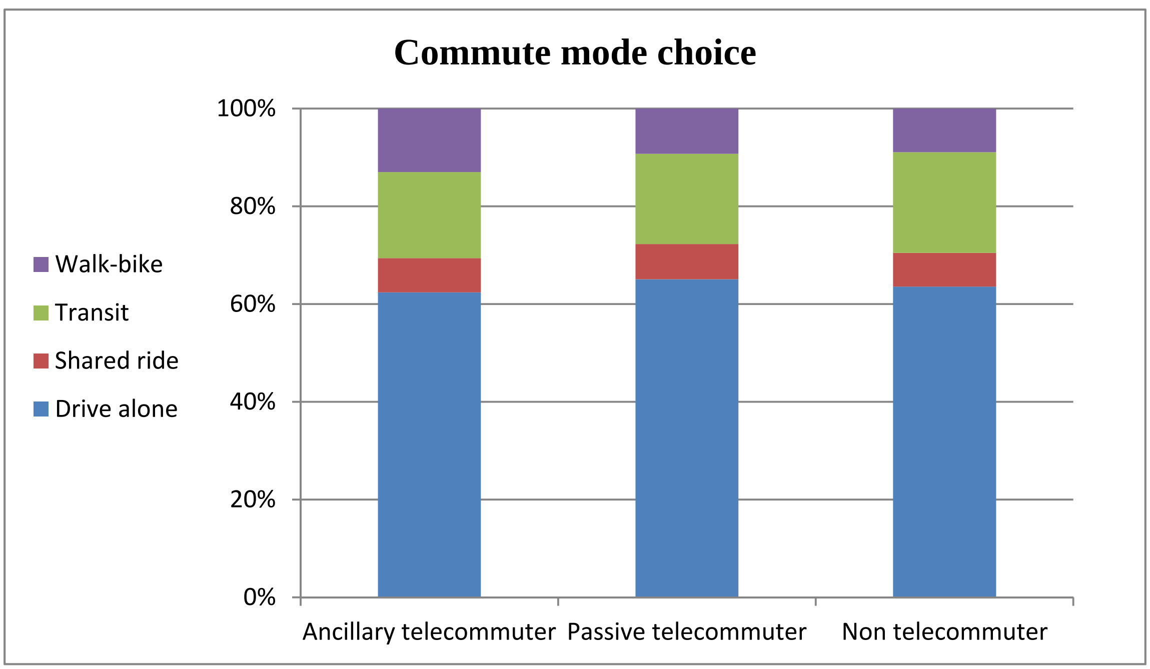

Figure 5-6 Commuters' Mode Choice

It is interesting to see that work arrangements do not reflect significant impacts on commute mode choice. Accordingly, commute mode distribution is almost equal among all three types of commuters, with drive alone and transit reflecting the highest shares. A proportional Bonferroni z-test is also conducted on the dataset which cannot reject the equality of mode shares among regular workers and part-day telecommuters.

A continuous-time hazard function is developed in this section. The dataset includes 15,021 daily commutes. The set of explanatory factors included in the model specification could be classified as follows: (1) Individual demographics, (2) Household characteristics and structure (3) Employment Characteristics, (4) Occupation, and (5) Mode choice, and (6) Trip distance. Each of these sets of variables is discussed in detail below. Consistent with the notation specified in the formulation, a positive coefficient on a covariate increases the hazard and hence increases the likelihood of departure at any time. Therefore, a positive coefficient can be interpreted, in general, as favoring earlier departures.

5.4.1. Hazard Model Results

The empirical results of the hazard model for departure time are presented in Table 5-9. Results indicate that age and gender are the only individual attributes affecting regular workers' departure time, with no impact on telecommuters. Accordingly, older workers are more likely to depart earlier. This agrees with the results from previous studies (reference) and might be a sign of traditional lifestyle. Older individuals are usually accustomed to a certain work schedule starting early in the morning and may not find it desirable to quit their long-term habits. Furthermore, results bode for a higher propensity for female workers to start their commutes earlier.

Table 5-9 Hazard Model for Commute Departure Times

	Analysis of Maximum Likelihood Estimates	Regular worker		Ancillary telecommuter		Passive telecommuter	
	Parameter	Estimate	t-test	Estimate	t-test	Estimate	t-test
	Age	0.005	6.966				
	Male	-0.036	-2.025				
Household Structure	HH type 1: One adult, no kids			-0.379	-3.151	-0.324	-2.722
	HH type 8: 2+ adults, youngest children 16-19	0.099	3.389	0.463	2.535		
Income	Income 50K-150K					-0.191	-2.087
	Income > 150K	0.046	2.202				
Ethnicity	African American	-0.094	-2.925				
	Pacific islander	0.644	2.568				
Employment type	Private	0.105	3.637				
	Government	0.243	7.631	-0.220	-1.661	0.209	2.064
	Self-employed	-0.223	-4.622	-0.356	-2.890	-0.623	-3.303
	Compressed schedule type 1: 4/40	-0.092	-1.973				
Occupation Category	Business and financial operations	0.093	2.948				
	Computer and mathematical	0.114	2.904				
	Architecture and engineering					0.603	2.503
	Life, physical and social science			0.667	1.847		
	Community and social services	-0.125	-2.585				
	Legal occupations	-0.151	-3.211			0.486	1.760
	Education, training and library	0.051	1.829				
	Art, design, sports, entertainment and media	-0.209	-4.589	-0.514	-2.793		
	Healthcare support					-0.425	-1.963
	Protective support	-0.541	-5.514				
	Food preparation and serving related	-0.461	-7.728	-1.935	-3.477		
	Building and grounds cleaning and maintenance					2.361	4.002
	Personal care and service	-0.150	-2.368				
	Sales and related	-0.160	-4.560				
	Farming, fishing and forestry					2.022	1.994

Table 5-9 Hazard Model for Commute Departure Times (continued)

	Analysis of Maximum Likelihood Estimates	Regular worker		Ancillary telecommuter		Passive telecommuter	
	Parameter	**Estimate**	**t-test**	**Estimate**	**t-test**	**Estimate**	**t-test**
	Construction and extraction	0.259	3.545				
	Installation, maintenance and repair			-1.174	-2.718		
	Production			2.208	3.064		
	Transportation and material moving	-0.316	-6.483				
Mode Choice	Drive Alone (SOV)	0.119	3.488				
	Shared ride (HOV)			-0.682	-3.588		
	WALK_BIKE	-0.263	-6.059				
	TRANSIT	0.443	11.749	0.340	2.745		
	Trip distance	0.014	28.312	0.019	5.219	0.005	2.318
Model Fit Statistics							
	Criterion	Without covariates	With covariates	Without covariates	With covariates	Without covariates	With covariates
	-2Log L	239221.4	237496.36	5746.231	5699.8	5230.046	5117.075
	AIC	239221.4	237548.36	5746.231	5719.8	5230.046	5141.075
	SBC	239221.4	237744.54	5746.231	5762.7	5230.046	5188.315
	Test	Chi-square	Pr > chi-square	Chi-square	Pr > chi-square	Chi-square	Pr > chi-square
	Likelihood ratio	1725.045	< 0.0001	46.4267	< 0.0001	112.9705	< 0.0001
	Score	2033.176	< 0.0001	64.0216	< 0.0001	119.5528	< 0.0001
	Wald	2000.644	< 0.0001	53.8344	< 0.0001	108.7175	< 0.0001

One reason could be that female workers are more likely to accomplish more complex commute tours, usually accompanied by secondary activities such as escorting kids to school. The model also reveals that African Americans are more likely to depart earlier. Whether or not this is a lifestyle choice or a cultural issue requires further social studies. The positive impact of pacific islanders on the model also needs to be taken with care as this category form a very tiny portion of the dataset. There is no significant impact of individual demographics on telecommuter categories.

Two types of households are significant contributors to the model. They include single-person households (household type 1), and households with more than two adults and children above 15 years old (household type 8). Results indicate that telecommuters who live by themselves are more prone to delaying their commute departure times, which seems reasonable if we take into account that they probably hold fewer familial responsibilities and more freedom compared to larger households. On the contrary, being part of a more complex household structure such as type 8 increases the hazard ratio for daily commute departure time, which may signify the impact of higher responsibilities and a more hectic daily schedule leading to earlier commute departures.

The positive sign of high-income for regular workers bodes for their propensity to depart earlier in the morning. It is interesting to see that income has no effect on ancillary telecommuting. Moreover, mid-income category is likely to delay commute departures for passive telecommuters.

As expected, self-employed workers tend to delay departure times. This is sensible considering that they are imposed to less managerial constraints and that they certainly have more flexible daily schedules. For regular workers and passive telecommuters,

government employment shows the highest positive impact on the hazard ratio, implying earlier departure times for these workers. This may show that passive telecommuting in government jobs mostly involves regular work schedules followed by overworking at home. The situation for ancillary telecommuters is a bit different as government employed individuals show a tendency towards later commute departures. One may conclude that when it comes to government employment, there is a significant difference between ancillary and passive telecommuting in terms of commute displacement, which originates from the regularity or non-regularity of their behavior. In other words, ancillary telecommuting may be regarded as REAL part-day telecommuting while passive telecommuting may occur as overworking due to sudden or unpredicted overload of responsibilities.

It is interesting to see that a 4-day compressed work schedule (10 hours per day instead of 8 hours) decreases the hazard ratio, therefore leading to delayed departure times. From one perspective, this could sound irrational as individuals with higher work durations may be expected to start their work earlier. However, from another point of view, this could be a sign of more flexible schedules for compressed workers, which may depend on the type of tasks they perform along with the management attitudes.

The RHTS data provides a rich source of data including detailed classification of occupations. In terms of regular workers, results indicate that some jobs including business and financial, computer-related, education, and construction increase the hazard ratio. A positive coefficient could be a sign of strict non-flexible schedules with an early start time. For instance, construction projects usually start early in the morning which justifies the highest positive contribution towards early commute departures suggested by the model.

A negative coefficient, on the contrary, pertains to occupations with more flexible daily schedules such as protective support, sports and entertainment, food catering, personal care, transportation, etc.

Exploring the impacts of occupation type on telecommuters' sample sheds light on interesting outcomes. Accordingly, ancillary telecommuters involved in social sciences along with production occupations are more likely towards earlier departure times while food catering, maintenance, and arts and sports tend to delay the commute start time. In terms of passive telecommuters, being a healthcare professional tends to reduce the hazard ratio. It should be noted that for ancillary telecommuters occupation types are either insignificant or show a negative effect. In other words, majority of occupations take regular part-day telecommuting as a long-term opportunity to temporally shift the daily commute and avoid congestion. However, for non-regular part-day (passive) the story is different. Accordingly, most jobs tend to preserve the daily commute schedule which could be a sign of random overworking.

Public transit has the highest positive impact on the hazard model. Buses and subways usually follow a fixed daily schedule and that they usually include longer durations of waiting or accessibility times compared to other modes of transportation. Thus, it is reasonable that individuals plan their commute departure times earlier in order to increase the reliability of on-time destination arrival. Regular workers choosing to walk or ride a bike are more prone to delayed departure times. It should be noted that first, such modes are usually correspondent to short trip distances and second, pedestrians and bikers are not highly affected by congestion issues and level of service.

The longer the commute distance, the earlier workers tend to start their daily commutes. This happens for all types of commuters including regular workers, ancillary telecommuters, and passive teleworkers.

5.4.2. Overall Comparisons

Although exploring exogenous variables will provide a helpful foundation for examining commute departure times within each of the three categories, pair-wise comparisons cannot be made only based on the model coefficients. It should be kept in mind that the hazard (and consequently the survival) function also relies on the non-parametric baseline hazard (survival) function which will be different among the three categories of commuters. Therefore, in order to make pair-wise comparisons, it is inevitable to calculate the final survival and cumulative probability functions (based on a combination of the baseline function and the exponential term of exogenous variables) versus time scale. This has been done in Figures 5-7, 5-8, and 5-9.

Analysis of the resulting survival and c.d.f graphs provide important outcomes. First, it is observed in most cases that $S_{ancillary}(t) > S_{passive}(t) > S_{regular\ worker}(t)$. In other words, telecommuters have higher survival probabilities compared to regular workers, i.e., regular workers are more likely to depart earlier. Furthermore, passive telecommuting acts as a transition state between regular work and ancillary telework. Due to the irregular nature of passive telecommuting, they are less likely to displace daily commute compared to ancillary telecommuters. By defining the survival probabilities at each of the end points of any time-of-day intervals and subtracting the two values, the probability of commute departure happening in that specific TOD can easily be computed.

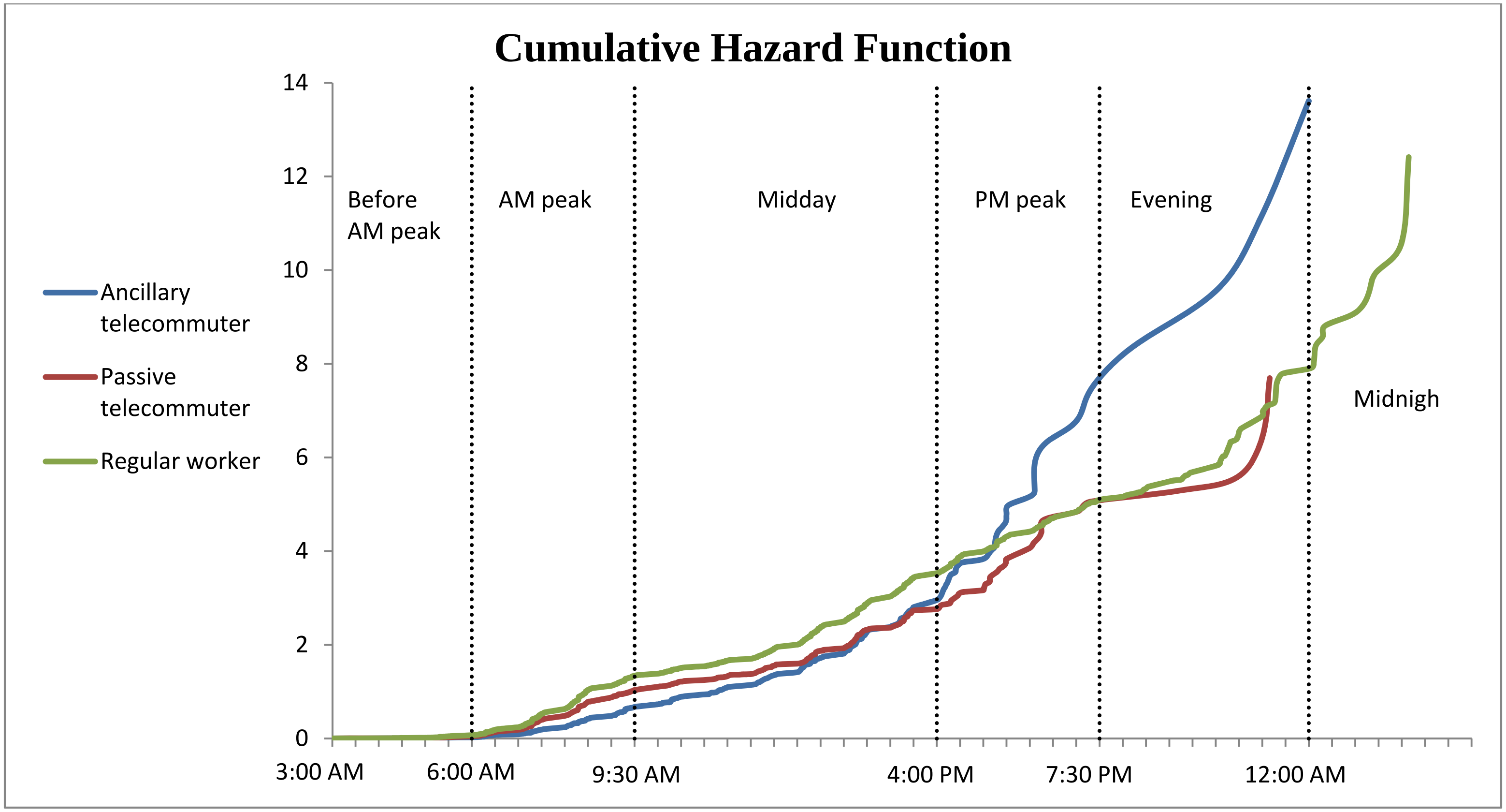

Figure 5-7 Estimated Cumulative Hazard Diagram

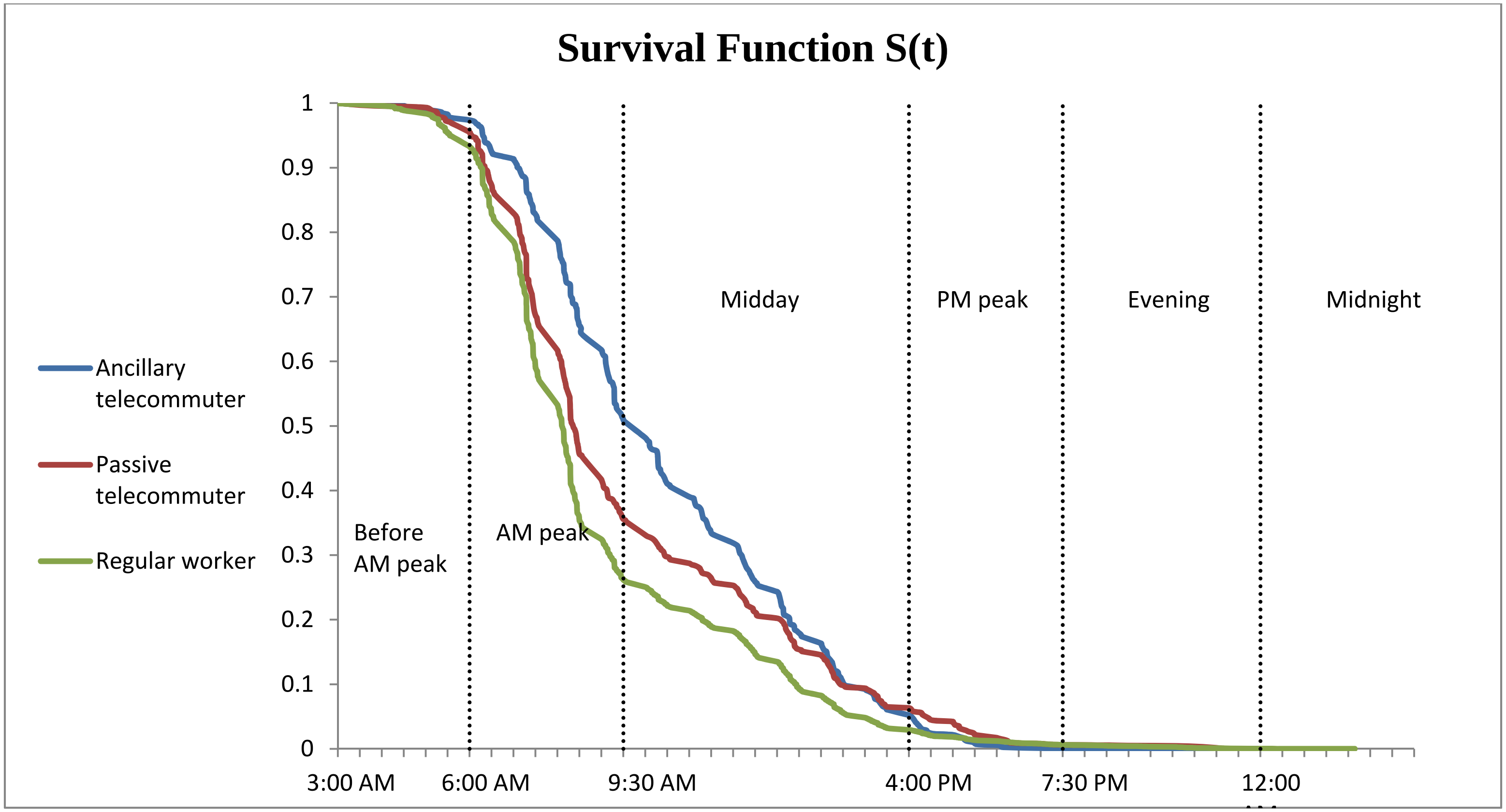

Figure 5-8 Estimated Survival Diagram

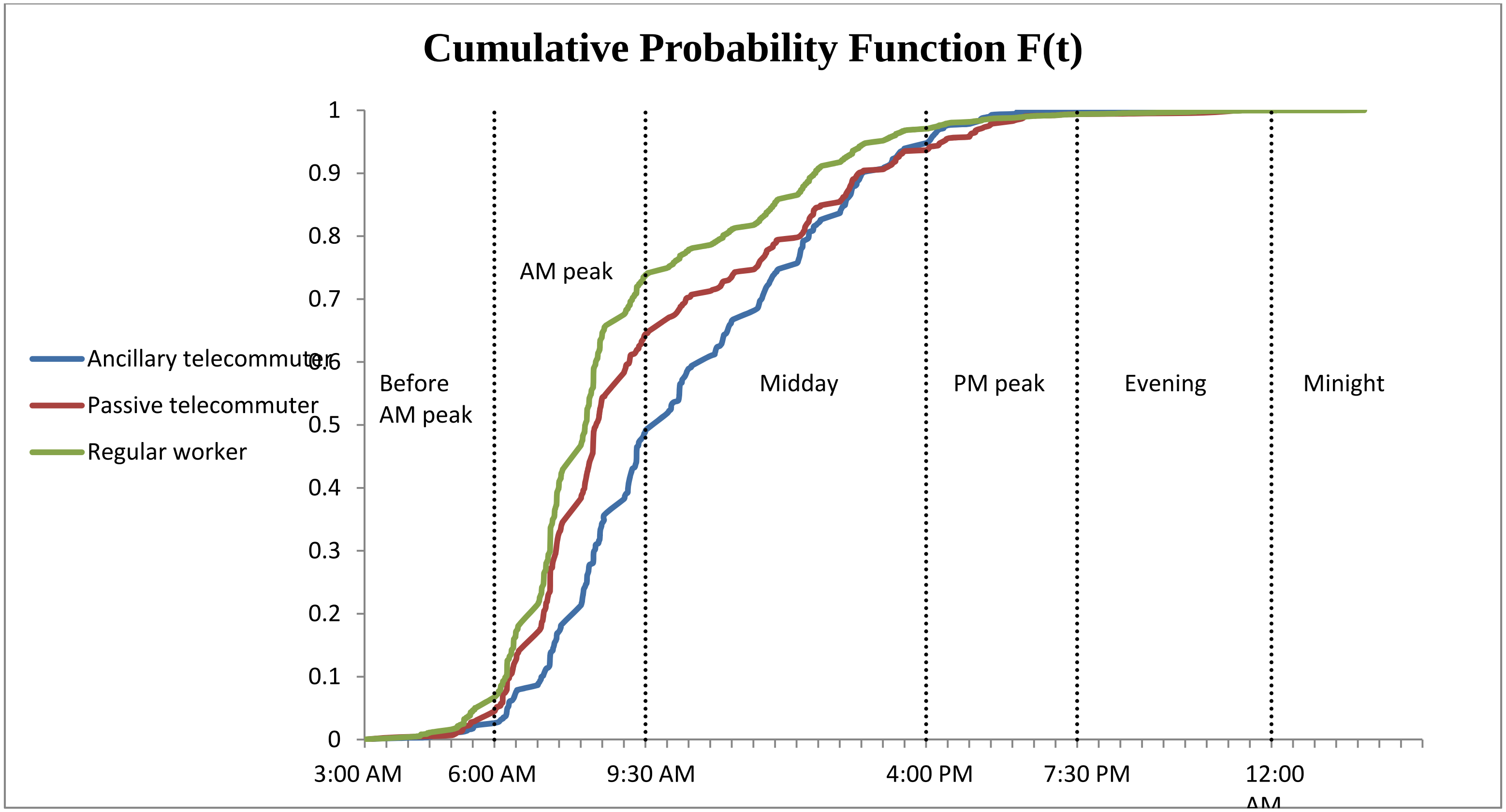

Figure 5-9 Estimated Cumulative Probability Diagram

At an aggregate level, such TOD probabilities turn into market shares of commute departure in a 24-hour daily span (refer to Table 5-10).

Table 5-10 Probability of Commute Departure Based on Time-of-Day

	Predicted			Observed		
	Regular	Ancillary	Passive	Regular	Ancillary	Passive
Before AM peak	0.067	0.026	0.045	0.054	0.026	0.033
AM peak	0.671	0.464	0.599	0.641	0.424	0.577
Midday	0.232	0.457	0.292	0.262	0.464	0.316
PM peak	0.023	0.052	0.057	0.030	0.074	0.061
Evening	0.006	0.000	0.006	0.012	0.012	0.013
Midnight	0.000	0.000	0.000	0.001	0.000	0.000

Table 5-10 illustrates both observed and predicted market shares of commute departure time based on different time of day categories. The categories are based on the traffic conditions in the state of New York and include: Before AM peak (3:00 AM-6:00 AM), AM peak (6:00 AM-9:30 AM), Midday (9:30 AM- 4:00 PM), PM peak (4:00 PM-7:30 PM), Evening (7:30 PM- 12:00 AM), and Midnight (12:00 AM- 3:00 AM). Accordingly, 67% of non-telecommuters' work trips are performed during the AM peak, while this value reduces to 60% and 46% for passive and ancillary telecommuters, respectively. In presence of telecommuting, the major temporal transition is between AM peak and midday, i.e., commutes are more prone to being shifted from AM peak to Midday period. In view of that, the share of Midday commutes increase from 23% for regular workers to 29% for passive telecommuters, and 46% for ancillary teleworkers.

5.5. Summary

This section provides an overall summary of the SEM modeling in view of telecommuting impacts on individuals' time use.

1. In general, both out-of-home and in-home work durations restrict non-mandatory activities. This is well documented based on Table 5-3. However, it is noted that negative impacts of an 8-hour regular workday reflect much higher negative magnitudes compared to any of the telecommuting forms (Table 5-5). This implies that when regular work arrangement is substituted by full-day or part-day telecommuting, the total result will lead to a net positive effect on non-mandatory durations (Table 5-6). In other words, telecommuting, regardless of its adoption form, encourages non-mandatory activity participation. For instance, an eight-hour schedule of primary telework leads to an average increase of 16 minutes in out-of-home maintenance or 47 minutes in out-of-home discretionary activities. Hence, the hypothesis that telecommuting provides more freedom for workers and that teleworkers tend to allocate such opportunity to accomplish non-mandatory assignments is documented based on the outcomes of the model. Furthermore, primary telecommuters demonstrate higher durations of non-mandatory duties compared to part-day forms, providing more emphasis on how relaxation of spatiotemporal constraints due to removal of daily commute contributes to non-mandatory activity participation.
2. Among different types of non-mandatory errands, discretionary activities receive the highest positive impacts by all forms of telecommuting.
3. It is difficult to explain the observed differences between ancillary and passive telecommuters' time-use patterns. Results indicate that passive telecommuters are more into out-of-home shopping, while ancillary teleworkers show higher durations of maintenance and discretionary. The fact that passive telecommuting usually

originates from a spontaneous short-term plan complicates their behavioral process and therefore may question the reliability of the results.

4. Interestingly, all forms of telecommuting adoption increase total daily trip rates. Along with the non-mandatory activity encouragement, this may provide compelling evidence that in terms of total trips, not only does the generation of non-mandatory demand compensate for commute removal, but also it adds more trips compared to regular work arrangements. Once again, it is observed that primary telecommuting reflects the highest impact by increasing the total daily trips by 0.96 units.
5. This section also explored the impacts of telecommuting on other household members. This includes both workers and non-workers. In terms of other workers in the household, no significant impact of telecommuters' presence was observed. In view of non-workers, on the other hand, the presence of telecommuters shows statistically significant impacts on almost all non-mandatory activities. However, the effects are too negligible in most cases. Three major exceptions are observed, including the positive impact of primary telecommuters on maintenance, negative impact of passive telecommuters on maintenance durations, and the positive impact of ancillary telecommuters on in-home shopping. Furthermore, the presence of primary and ancillary telecommuters tends to increase the daily trip rates by almost 0.50 for non-working household members. This might originate from joint trips where removing work-related constraints will also benefit other household members. The fact that passive telecommuting demonstrates a negative impact on total daily trips might be a sign of their irregular decision-making patterns, as well

as their “overworking” arrangements, which may discourage other household members.

Furthermore, this chapter made an effort to investigate how part-day telecommuting arrangements lead to temporal shifts in daily commute departure times. Using the hazard function concept, commute departure time was modeled as a continuous variable based on individual/household attributes such as socio-economical, demographic, and job-related characteristics, along with trip-related features such as mode choice and commute distance. Based on researchers' previous works, two major forms of part-day telecommuters were recognized, labeled ancillary and passive telecommuters. These two patterns, along with regular workers, form three basic categories of commuters.

A separate hazard function is developed for each of the categories, and the results are compared. Accordingly, older individuals and females are more likely to depart earlier. Simple household structures are more prone to delaying commute departure times compared to more complicated structures. When it comes to employment type, government employees tend to delay departure times only for ancillary telecommuters. This may confirm the assumption that passive telecommuters are in fact overtime workers that follow the same pattern as non-telecommuters. In terms of mode choice, public transit users are more likely to depart earlier, while walk/bike modes usually correspond to later departure values. Conforming to general belief, commute departures tend to happen earlier as the commute distance increases.

In addition to identifying the major contributors to the commute departure model, one can compare the probabilities of commute departure occurrence for any specific time-interval in a 24-hour daily period among the three commuter types. This will provide

valuable insights on how part-day telecommuters shift their departure times compared to non-telecommuters. In this regard, 67% of non-telecommuters' work trips are performed during the AM peak hours, while this value reduces to 60% and 46% for passive and ancillary telecommuters, respectively. For part-day telecommuters, the major temporal transition is between AM peak period and midday intervals, i.e., commutes are more prone to being shifted from the AM peak period to midday period. Accordingly, the share of midday commutes increase from 23% for regular workers to 29% for passive telecommuters, and 46% for ancillary teleworkers.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1. Summary and Conclusions

Telecommuting has gained special attention from transportation planners and policymakers for the past 20 to 30 years. The popularity of the concept as a transportation demand management (TDM) policy mainly stems from the impacts of commute replacement (or displacement) on individuals, and on a broader perspective, the transportation network. Hence, work, which is considered the major mandatory activity among most individuals, imposes the highest degrees of temporal and spatial constraints on individuals' travel behavior. Consequently, any long- or short-term alteration of work arrangements is expected to influence individuals' decisions about activity/travel behavior.

A quick review of the research background reveals a variety of telecommuting benefits for employees, employers, and the public. Despite such well-documented advantages of telecommuting, there seems to be no trace of the concept in practical statewide or regional models. Lack of a standard framework for telecommuting estimation could be a result of the following shortcomings:

First, there is no unique definition for the terms telecommuter or telecommuting. Though several surveys and analyses are carried out by focusing on the concept, the interpretation of telecommuting tends to differ depending on specific study objectives and targets.

Second, it is essential to recognize different patterns of telecommuting engagement, as different types of engagement are expected to produce dissimilar impacts on the model.

However, when a worker telecommutes, he/she is usually regarded as a full-day teleworker, which may lead to an over- or under-estimation of the study's outcomes.

Third, in the absence of daily observation, it is impossible to recognize different forms of telecommuting engagements (i.e., full-day or part-day). Existing studies usually emphasize telecommuting intensity during extended periods of time (i.e., weekly or monthly) and seldom enter a daily level.

Considering a daily schedule for telecommuting is therefore expected to provide a solid foundation to assist with classifying different engagement forms, as well as reflecting a higher consensus with current daily activity/travel scheduling frameworks.

Taking the abovementioned information into account, the specific objective of this dissertation research is to provide a standard telecommuting analysis module that can be incorporated into the current planning frameworks. The proposed telecommuting module is based on two major consecutive phases, labeled as telecommuting estimation and telecommuting impacts, respectively. Consequently, the research methodology encompassed the following steps:

1. Classify major forms of telecommuting engagement through analyzing various telecommuting dimensions. This step also provides simple and straightforward algorithms in order to categorize the workers' samples based on different types of telecommuting behavior.
2. Develop appropriate statistical models in order to predict the market shares of each telecommuting form.

3. Present a thorough comparison of how different SED, job-related or land-use variables play significant roles in telecommuting behavior.
4. Incorporate the outcomes of the first phase (i.e., telecommuting engagement forms) into an impact analysis framework. The impact analysis includes both activity/trip generation models, along with time-of-day studies. Exploring the model outcomes sheds light on how telecommuting, as an alternative work arrangement, will impact daily activity or tour generation patterns.

This research effort used the Regional Household Travel Survey (RHTS) 2010/2011, which was carried out in 28 counties in three states: New York, New Jersey, and Connecticut. The survey included the household and personal information of 43,558 individuals, along with their daily travel/activity diaries.

An initial framework was developed that produced an overall picture describing how to identify different types of telecommuting. The flowchart steps were then converted into meaningful telecommuting dimensions. Both long-term and short-term aspects of telecommuting were taken into account. Long-term dimensions included choice and frequency, which were founded on respondents' behaviors in a weekly period prior to the survey date. Daily dimensions included telecommuting engagement and additional commute, which were computed based on respondents' behavior on the day they were interviewed. It was assumed that different combinations of long- and short-term telecommuting dimensions would lead to different engagement types. As a result, three major engagement types were recognized: 1) primary (full-day), 2) ancillary (regular part-day), and 3) passive (non-regular part-day).

Taking into account the nature of dependent variables, discrete choice models were applied for each of the predefined dimensions. The long-term analysis included two independent models, a binary probit for choice, and ordered probit for frequency. In order to consider the true intensity of telecommuting, the frequency variable was developed based on a cluster analysis over the ratio of weekly telecommuting hours and encompassed three major categories: Low, medium, and high. Model results revealed interesting findings on the determinant factors that contribute to telecommuting choice and frequency, respectively. The findings are consistent with existing literatures, and also confirm that the underlying logic of the two decision-making factors, choice and frequency respectively, are principally different.

Short-term dimensions included daily engagement and additional commute. The combination of the two would distinguish full-day versus part-day telecommuting activity. Likewise, independent models were developed with the assumption that there was no dependency between the two types of decision-making. Later, the correlation parameter was taken into account using the joint bivariate normal distribution in a sample selection model. Most of the variables exhibited expected signs and reasonable values. In terms of regular telecommuting, the model suggests that job-related variables play more significant roles than demographic attributes. Non-regular engagement, however, is more sensitive to individual and household demographic attributes, although the results are harder to explain compared to regular telecommuters. The model results reveal a positive correlation between the two decisions, which indicates the general tendency (or reality) toward part-day telecommuting. The correlation is not statistically significant for non-regular telecommuters, which may stem from the randomness of their actual engagement.

In the comparison of the coefficients' values across the two modeling structures, the variables for the engagement choice show comparable values, while those for the additional commute choice show much smaller values in the joint model, for both regular and non-regular telecommuters. This is consistent with the expectation that the independent modeling approach ignores the presence of the potential correlation between the unknown factors that govern both decisions and therefore may overestimate the magnitude of effects of independent variables on the second choice.

The impact analysis was divided into two major sections. The first section focused on the direct and indirect effects of telecommuting on non-mandatory activities from a time-use perspective. A Structural Equations Model (SEM) was developed for both workers' and non-workers' sample data. Results indicate that telecommuting, regardless of its engagement type, encourages non-mandatory activity participation. However, there are certain dissimilarities among different engagement types. As expected, primary telecommuters demonstrate higher durations of non-mandatory duties compared to part-day arrangements. Moreover, it could be inferred that in terms of total trips, not only does the non-mandatory demand compensate for commute removal, but also it adds more trips compared to regular work arrangements.

The second subsection explored the temporal distribution of commute departure times in order to reveal the effects of part-day telecommuting on commute displacement. Three categories of daily commuters with respect to telecommuting activity were considered, and for each one, departure time probabilities were estimated using a separate hazard function model. Results imply that the major temporal transition in telecommuting occurs between AM peak hours and midday, i.e., commutes are more prone to being shifted

from AM peak hours to the midday period. In this regard, the share of midday commutes increase from 23% for regular workers to 29% for passive telecommuters, and 46% for ancillary teleworkers.

6.2. Research Contributions

The topics explored in this research dissertation are expected to improve the current planning framework from a variety of perspectives, beginning with estimation. In view of telecommuting estimation, this is a pioneering effort that takes into account different types of telecommuting engagement. To the researcher's knowledge, the existing literature in the U.S. tends to assume that telecommuting involves a full-day schedule that leads to the total removal of daily commutes. Not only is this a restrictive assumption, but it also contradicts real-life situations where survey respondents reflect different patterns of telecommuting behavior. In order to address this issue, the study herein treats telecommuters as a non-homogeneous group where each specific pattern imposes certain impacts on individuals' activity/travel decision-making behavior.

The differentiation between engagement types is expected to influence the current public belief about telecommuting. First of all, not all telecommuters telecommute on a full-day basis. In other words, the net trip-reduction factor imposed by telecommuting implementation used in several aggregate studies needs to be adjusted for part-day telecommuters. Furthermore, part-day telecommuters usually shift their commute departure times in order to avoid congestion hours. The most overlooked concerns in the existing literature include figuring out what the underlying factors are and to what extent this temporal shift affects daily commutes.

In terms of time-use analysis, this study allows for a thorough investigation of the interaction between different non-mandatory activities with an emphasis on the impacts of telecommuting arrangements. The SEM structure provides the capability of defining different scenarios of work arrangements, including regular work, telework, or a combination of both. Comparing a standard eight-hour regular work arrangement with different telecommuting scenarios will answer some of the main questions about telecommuters' daily activity plan (DAP). First, how do telecommuters allocate their time budget in the absence of strict time-space constraints imposed by mandatory commute to work? Which activities gain the highest attention by telecommuters? Second, are there significant dissimilarities among different telecommuting patterns when it comes to time budget allocation? As out-of-home activities form the basis of trip generation, they will probably provide compelling answers to whether telecommuting will finally reduce or increase daily trip rates. Finding reasonable answers to such questions is expected to form a preliminary foundation with regard to addressing the secondary impacts of telecommuting such as daily activity rescheduling and excessive non-mandatory demand generation.

6.3. Study Limitations

Like any other research effort, the results of this study are subject to a number of limitations, including the following:

1. Lack of detailed job attributes. It was clearly explained in the body of the research that the main objective of this study is to produce a standard telecommuting module that is applicable to macro-scale data. Accordingly, national or statewide surveys

hardly provide sufficient information about managerial attitudes, major tasks involved, and telecommuting opportunities.

2. Absence of technology-related variables in the model. Undoubtedly, there is a direct association between telecommuting implementation and technology. Such relationship could be explored from two perspectives: First, whether the employer offers sufficient equipment, including required software or hardware, which could be labeled as “technology availability,” and second, whether the employees are knowledgeable, trained enough, and willing to utilize the available technology. The first dimension requires detailed information of the job, mainly at the managerial level, while the second calls for conducting a detailed personal survey regarding employees’ technical capabilities. Unfortunately, the RHTS data lacks such information.
3. Lack of sufficient land-use variables. The RHTS data provided little to almost no information regarding land-use concepts such as accessibility, entropy index, etc. Incorporating any of these variables into the model is expected to have a significant contribution to individuals' decision-making behavior.
4. Incoherent telecommuting durations. There is no efficient way to extract accurate telework durations. The values reported by respondents usually tend to include other in-home activities, particularly if it includes an overnight period. Moreover, in the presence of two or more activities, respondents are more likely to report telework as the primary activity that will result in a bias in recorded data.
5. There are no repeated observations for time-use analysis. Non-mandatory activities usually call for a repetitive observation of an individual daily diary on successive

days. Such longitudinal data is expected to provide more accurate results compared to the cross-sectional data applied in this study.

6. Model transferability issues. Like any other behavioral model, the spatial transferability of the results is under scrutiny. In general, models confirm that there are different types of telecommuting engagement, which could be estimated using national or regional data, and that each type imposes a specific impact on activity/travel behavior. However, the magnitude of the results and the significance of variables are likely to differ from one area to another. Different parameters such as population, land-use, transit accessibility, employment density, and several other regional and social factors are expected to highly impact the models' transferability.

6.4. Recommendations for Future Research

Future studies to extend this dissertation research could include the following:

1. The telecommuting estimation phase may be enhanced by considering an initial dimension, known as "Telecommuting option," which focuses on whether or not telecommuting is offered as an alternative work arrangement by employers. This is expected to improve the estimation process as all other dimensions are defined only if there is a telecommuting opportunity. However, this requires additional information from the respondents, which should somehow be included in macro-scale surveys. Future surveys may include a couple of more questions that specifically delve into a detailed job environment and possible alternative work arrangements.

2. From a mathematical perspective, improvements can be made to any of the model structures applied in this study. For instance, joint sample selection models may be enhanced by incorporating copula tools and trying different dependency structures rather than normal bivariate distribution. Or, more advanced hazard function formulas could be used by taking heterogeneity issues into account.
3. The impact analysis could be extended by analyzing how time-space constraints are relaxed for telecommuters compared to regular workers. Similar analyses have been conducted for full-day telecommuters in the literature. However, considering different forms of telecommuting engagement is expected to provide new insights into individuals' temporal/spatial distribution of activities in a 24-hour span.

REFERENCES

Abkowitz, M. D., 1981. “An Analysis of the Commuter Departure Time Decision”. Transportation 10 (3), pp. 283-297.

Auld, J. and A. Mohammadian, 2009. "Activity Planning in the ADAPTS Activity-Based Modeling Framework". Paper submitted for presentation at the 12th International Conference of the International Association for Travel Behavior Research.

Balaker, T., 2005. “The Quiet Success. Telecommuting's Impact on Transportation and Beyond”. Policy Study by Reason Foundation. www.Reason.org/studies.

Barrett, P., 2007. “Structural Equation Modelling: Adjudging Model Fit”. Personality and Individual Differences, 42 (5), pp. 815-24.

Belanger, F., 1999. “Workers’ Propensity to Telecommute: An Empirical Study”. Journal of Information and Management, 35(3), pp. 139-153.

Bentler, P.M. and D.C. Bonnet, 1980. "Significance Tests and Goodness of Fit in the Analysis of Covariance Structures". Psychological Bulletin, 88 (3), pp. 588-606.

Bernardino, A. and M. Ben Akiva, 1996. “Modeling the Process of Adoption of Telecommuting: Comprehensive framework”, Journal of Transportation Research Board, Volume 1552, pp. 161-170.

Bernardino, A., Ben Akiva, M. and I. Salomon, 1993. “Stated Preference Approach to Modeling the Adoption of Telecommuting”. Transportation Research Record, 1413, pp. 22-30.

Bhat, C. R. and R. Misra, 1999. “Discretionary Activity Time Allocation of Individuals between In-home and Out-of home and between Weekdays and Weekends”. Transportation (26), pp 193-209.

Bhat, C.R., 1998a. “Accommodating Flexible Substitution Patterns in Multi-Dimensional Choice Modeling: Formulation and Application to Travel Mode and Departure Time Choice”. Transportation Research B, 32, 7, pp. 455-466.

Bhat, C.R., 1998b. “A Model of Post-Home Arrival Activity Participation Behavior”. Transportation Research B, 32, 6, pp. 387-400.

Bhat, C.R. and J. L. Steed, 2002. “A Continuous-Time Model of Departure Time Choice for Urban Shopping Trips”. Transportation Research B, 36, pp. 207-224.

Bollen, K.A., 1989. “Structural Equations with Latent Variables”. New York: John Wiley & Sons.

Bowman, J.L., 1995. "Activity-based Travel Demand Model System with Daily Activity Schedule". Master's Degree Thesis, Department of Civil & Environmental Engineering, Massachusetts Institute of Technology.

Bowman, J.L., 1998. "The Daily Activity Schedule Approach to Travel Demand Analysis". PhD Dissertation, Department of Civil & Environmental Engineering, Massachusetts Institute of Technology.

Choo. S, Mokhtarian, P. L. and I. Salomon, 2005. "Does Telecommuting Reduce Vehicle-miles Traveled? An Aggregate Time Series for the US". Transportation. Vol. 32, no. 1, pp. 37-64.

Cox, D. R., 1972. "Regression Models and Life Tables". Journal of the Royal Statistical Society. Series B (Methodological), Volume 34, Issue 2, pp. 187-220.

Crimando, W. and S.H. Godley, 1985. "The Computer's Potential in Enhancing Employment Opportunities of Persons with Disabilities". Rehabilitation Counseling Bulletin, 28, pp. 275-282.

Crowley, S.L. and X. Fan, 1997. "Structural Equation Modeling: Basic Concepts and Applications in Personality Assessment Research". Journal of Personality Assessment, 68 (3), pp. 508-31.

Cynthia, C. and P.L. Mokhtarian, 2006. "Tradeoffs between Time Allocations to Maintenance Activities/Travel and Discretionary Activities/Travel". Transportation 33(3), pp. 223-240.

De Marco, A., 1995. "The Dawning of the Telecommuter Age". Facilities Design and Management, pp. 48-51.

Doherty, S.T., 2000. "An Activity Scheduling Process Approach to Understanding Travel Behavior". Paper presented at the 79th annual meeting of the Transportation Research Board, Washington, DC, No. 00-0944.

Drucker, J. and A.J. Khattak, 2000. "Propensity to Work from Home: Modeling Results from the 1995 Nationwide Personal Transportation Survey". Transportation Research Record, 1706, pp. 108-117.

Erika, S., Pinjari, A.R., Bhat, C.R., Pendyala, R.M. and K.W. Axhausen, 2009. "An Analysis of Weekly Out-of-Home Discretionary Activity Participation and Time-use Behavior". Transportation, 36(5), pp. 483-510,

Ettema, D. and H. Timmermans, 2003. "Modeling Departure Time Choice in the Context of Activity Scheduling Behavior". Transportation Research Record, 1831, pp. 39-46.

Fitzgerald and Halliday Inc., 2001. "VDOT/DRPT Tele-work Study". Technical memorandum prepared for Virginia Department of Transportation.

Gil Gordon Associates, 1995. “Pilot Project Features Activity-tracking Software”. Telecommuting Review, 12(9), pp. 1-4.

Golob, T.F. and M.G. McNally, 1997. “A Model of Activity Participation between Household Heads”. Transportation Research, 31B (3), pp. 177-194.

Golob, T.F. and H. Meurs, 1987. “A Structural Model of Temporal Change in Multi-Modal Travel Demand”. Transportation Research, 21A (6), pp. 391-400.

Golob, T.F., Bradley, M.A. and J.W. Polak, 1996b. “Travel and Activity Participation as Influenced by Car Availability and Use”. Paper presented at the 75th Annual Meeting of the Transportation Research Board, National Research Council, Washington, DC.

Golob, T.F., Bunch, D.S. and D. Brownstone, 1996a. “Forecasting Future Vehicle Usage Using a Jointly Estimated Revealed- and Stated-Preference Model”. Paper presented at the 75th Annual Meeting, Transportation Research Board, National Research Council, Washington, DC.

Grippaldi, Joseph J., 2002. “An Empirical Study of Attitudes towards Telecommuting among Government Finance professionals”. UNLV Theses/Dissertations/Professional Papers/Capstones. Paper 515.

Haddad, H., Lyons, G. and K. Chatterjee, 2009. “An Examination of Determinants Influencing the Desire for and Frequency of Part-day and Whole-day Homeworking”, Journal of Transport Geography, 17, pp. 124-133.

Hamer, R., Kroes, E. and H. Van Ooststroom, 1991. “Teleworking in the Netherlands: An Evaluation of Changes in Travel behavior”. Transportation 18, pp. 365-382.

Handy, S.L. and P.L. Mokhtarian, 1996. “Forecasting Telecommuting; An Exploration of Methodologies and Research Needs”, Transportation, 23, pp. 163-190.

Handy, S.L., and P.L. Mokhtarian, 1995. “Planning for Telecommuting: Planning and Policy Issues”. Journal of the American Planning Association 61(1), pp. 99-111.

Helminen, V. and M. Ristimaki, 2007. “Relationships between Commuting Distance, Frequency and Telework in Finland”. Journal of Transport Geography, 15, pp. 331-342.

Hendrickson, C. and E. Planck, 1984. “The Flexibility of Departure Times for Work Trips”. Transportation Research A 18 (1), pp. 25-36.

Hu, L.T. and P.M. Bentler, 1999. “Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives”. Structural Equation Modeling, 6 (1), pp. 1-55.

International Telework Association and Council – 1 (ITAC-1), 2001. Available: http://www.telecommute.org/newsletter/newsletter1.1.shtml. [2001, 24 November].

International Telework Association and Council – 2 (ITAC-2), 2001. Available: http://www.telecommute.org/twa/twa2001/newsrelease.htm. [2001, 24 November].

Jiang, Y., 2008. "The Impact of Telecommuting on the Journey to Work: A Two-Sample Instrumental Variable Approach". Dissertation chapter, University of Maryland.

Johnston, J. and J. DiNardo, 1997. "Econometric Methods". Fourth Edition, New York: McGraw-Hill.

Jöreskog, K. and D. Sörbom, 1993. "LISREL 8: Structural Equation Modeling with the SIMPLIS Command Languag". Chicago, IL: Scientific Software International Inc.

Jou, R. C., 2001. "Modeling the Impact of Pre-trip Information on Commuter Departure Time and Route Choice". Transportation Research Part B (35), pp. 887-902.

Jou, R.C., Kitamura, R., Weng, M. C. and C. C. Chen, 2008. "Dynamic Commuter Departure Time Choice under Uncertainty". Transportation Research Part A (42), pp. 774-783.

Judge, G.G., Griffiths, W.E., Hill, R.C., Lutkepohl, H. and T.C. Lee, 1985. "The Theory and Practice of Econometrics". Second Edition, New York: John Wiley & Sons.

Koutsoyiannis, A., 1972. "Theory of Econometrics: An Introductory Exposition of Econometric Methods". Second Edition, New York: Barnes & Noble Books.

Kulkarni, A. and M.G. McNally, 2000. "A Microsimulation of Daily Activity Patterns". UCI-ITS-AS-WP-00-7, University of California Irvine.

Kuppam, A.R. and R.M. Pendyala, 2001. "A Structural Equations Analysis of Commuters' Activity and Travel Patterns". Transportation, 28, pp. 33-54.

Lister, K. and T. Harnish, 2010. "Work Shifting Benefits. The Bottom Line". www.TeleworkResearchNetwork.com.

Lu, X. and E.I. Pas, 1999. "Socio-demographics, Activity Participation and Travel Behavior". Transportation Research, 33A (1), pp. 1-18.

Mamdoohi, A.R., Kermanshah, M. and H. Poorzahedy, 2006. "Telecommuting Suitability Modeling: An Approach Based on the Concept of Abstract Job". Transportation, 33, pp. 329-346.

Mannering, J.S. and P.L. Mokhtarian, 1995. "Modeling the Choice of Telecommuting Frequency in California; An Exploratory Analysis". Technological Forecasting and Social Change, 49, pp. 49-73.

McCafferty, D. and F. L. Hall, 1982. "The Use of Multinomial Logit Analysis to Model the Choice of Time to Travel". Economic Geography 36 (3), pp. 236-246.

McDonald, R. P. and M-H.R. HO, 2002. “Principles and Practice in Reporting Structural Equation Analyses”. Psychological Methods, 7, pp. 64-82.

McIntosh, C., 2006. “Rethinking Fit Assessment in Structural Equation Modelling: A Commentary and Elaboration on Barrett (2007)”. Personality and Individual Differences, 42 (5), pp. 859-67.

Mello, J., 2007. “Managing Telework Programs Effectively”. Employee Responsibilities and Right Journal, 19(4), pp. 247-261.

Mohammadian, A. and S. Doherty, 2005. “A Mixed Logit Model of Activity Scheduling Time Horizon Incorporating Spatial-Temporal Flexibility Variables”. Transportation Research Record, 1926, pp. 33-40.

Mokhtarian, P. L. and I. Salomon, 1994. “Modeling the Choice of Telecommuting: Setting the Context”. Environment and Planning A 26(5), pp. 749-766.

Mokhtarian, P. L. and I. Salomon, 1996. “Modeling the Choice of Telecommuting 2: A Case of Preferred Impossible Alternatives”. Environment and Planning A 28, pp. 1859-1876.

Mokhtarian, P. L. and I. Salomon, 1996. “Modeling the Choice of Telecommuting 3: Identifying the Choice Set and Estimating Binary Choice Models for Technology-Based Alternatives”. Environment and Planning A 28, pp. 1877-1894.

Mokhtarian, P. L. and I. Salomon, 1997. “Modeling the Desire to Telecommute: The Importance of Attitudinal Factors in Behavioral Models”, Transportation Research A 31(1), pp. 35-50.

Mokhtarian, P. L., 1991. “Defining Telecommuting”. Transportation Research Record (1305), pp. 273-281.

Mokhtarian, P. L., Salomon, I. and S. Choo, 2004. “Data and Measurement Issues in Transportation, with Telecommuting as a Case Study”. Research report UCD-ITS-RR-04-29, Institute of Transportation Studies, University of California, Davis.

Mokhtarian, P. L., Salomon, I. and S. Choo, 2005. “Measuring the Measurable: Why Can’t We Agree on the Number of Telecommuters in the US?” Quality and Quantity 39, pp. 423-452.

Mokhtarian, P.L. and I. Salomon, 1997. “Emerging Travel Patterns: Do Telecommunications Make a Difference?” Invited resource paper for the 8th Meeting of the International Association for Travel Behaviour Research, Austin, TX. Chapter 7 in: In Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges, Hani S. Mahmassani, ed., Pergamon Press/Elsevier, 2002, pp. 143-182.

Mokhtarian, P.L., 1991. "An Empirical Analysis of the Transportation Impacts of Telecommuting". Proceedings (Vol. 1), 6th International Conference on Travel Behavior, Quebec City, Quebec.

Mokhtarian, P.L., 1991. "The Transportation Impacts of Telecommuting in Two San Diego Pilot Programs". University of California, Davis, Institute of transportation Studies, Research Report UCD-ITS-RR-91-12.

Mokhtarian, P.L., 1998. "A Synthetic Approach to Estimating the Impacts of Telecommuting on Travel". Urban Studies, 35(2), pp. 215-241.

Mokhtarian, P.L., 2003. "Telecommunications and Travel: The Case for Complementarity". Journal of Industrial Ecology 6(2), Special Issue on E-Commerce, the Internet, and the Environment, pp. 43-57.

Mokhtarian, P.L., Bagley, M.N. and I. Salomon, 1998. "The Impact of Gender, Occupation and Presence of Children on telecommuting Motivations and Constraints". Journal of the American Society for Information Science, 49(12), Special Issue on Social Informatics, pp. 1115-1134.

Mokhtarian, P.L., Collantes, G.O. and C. Gertz, 2004. "Telecommuting, Residential Location, and Commute Distance Traveled: Evidence from State of California Employees". Environment and Planning A, 36, pp. 1877-1897.

Mosa, A., 2011. "Modeling the Impacts of Information and Communication Technologies and Virtual Activities on Activity and Travel Behavior, Case Study of Cairo, Egypt", Transportation Research record, 2231, pp. 102-109.

Mosa, A., Harata, N. and N. Ohmori, 2010. "Exploring the Impacts of In-Home Virtual Activities on Daily Activity and Travel Behavior: An Analysis Using Cairo Activity and Telecommunication Diary Data 2006". Presented at World Conference on Transport Research Society WCTR, Lisbon, 2010. Conditionally accepted for Transportation Journal.

Mulaik, S.A., James, L.R., Van Alstine, J., Bennet, N., Lind, S. and C.D. Stilwell, 1989. "Evaluation of Goodness-of-Fit Indices for Structural Equation Models". Psychological Bulletin, 105 (3), pp. 430-45.

New York Metropolitan Transportation (NYMTC), North Jersey Transportation Planning Authority (NJTPA), 2013. "2010-2011 Regional Household Travel Survey Data User's Manual".

Niles, J., 1994. "Beyond telecommuting: A New Paradigm for the Effect of Telecommunications on Travel". Prepared for The US Department of Energy, Offices of Energy Research and Scientific Computing, Washington, D.C. 20585. Report No. DOE/ER-0626.

Nilles, J.M, 1988. “Managing Teleworking: Final Report. Los Angeles: Center for Effective Organizations, University of Southern California.

Nilles, J.M., 1988. “Traffic Reduction by Telecommuting: A Status Review and Selected Bibliography”. Transportation Research, 22 A, pp. 301-317.

Nilles, J.M., 1994. “Making Telecommuting Happen: A Guide for Telemanagers and Telecommuters”. Van Nostrand Reinhold, New York.

Nilles, J.M., Carlson, F.R., Paul, G.Jr. and G.J. Hanneman, 1974. “Development of policy on the Telecommunications-Transportation Tradeoff”. University of Southern California and the National Science Foundation, Report NSF-RA-5-74-020.

Nilles, J.M., Carlson, F.R., Paul, G.Jr. and G.J. Hanneman, 1976. “The Telecommunications-Transportation Tradeoff: Options for Tomorrow”, New York: John Wiley and Sons.

Parsons Brinckerhoff Quade & Douglas, Inc., Cambridge Systematics, Inc. and Nustats International, 2000. “RT-HIS Regional Travel-Household Interview Survey”. Prepared for the New York Metropolitan Transportation (NYMTC), North Jersey Transportation Planning Authority (NJTPA)

Pendyala, R.M, Konstadinos, G.G. and R. Kitamura, 1991. “Impacts of Telecommuting on Spatial and Temporal Patterns of Household travel”. Transportation (18), pp. 383-409.

Peters, P., Tijdens, K.G. and C. Wetzels, 2004. “Employees’ Opportunities, Preferences, and Practices in Telecommuting Adoption”, Journal of Information and Management, 41, pp. 469-482.

Pioneer Valley Planning Commission (PVPC), 2011. “Telecommuting Patterns and Trends in the Pioneer Valley”. Under direction of The Pioneer Valley Metropolitan Planning Organization.

Pirdavani, A., Brijs, T., Bellemans, T., Kochan, B. and G. Wets, 2013. “Assessing the Impacts of a Teleworking Policy on Crash Occurrence: The Case of Flanders, Belgium”. 92nd TRB Annual Meeting Compendium of Papers DVD, pp. 1-18.

Piskurich, G.M., 1996. “Making Telecommuting Work”. Training and Development, pp. 20-27.

Popuri, Y., and C.R. Bhat, 2003. “On Modeling Choice and Frequency of Home-Based Telecommuting”. Transportation Research Record, 1858, pp. 55-60.

Pratt, J. H., 2000. “Asking the Right Questions about Telecommuting: Avoiding Pitfalls in Surveying Home-based Work”. Transportation, 27, pp. 99-116.

Quaid, M., and B. Lagerberg, 1992. “Puget Sound Telecommuting Demonstration: Executive Summary”. WSEO # 92-138. Olympia, WA: Washington State Energy Office.

Sampath S., Saxena S. and P.L. Mokhtarian, 1991. “The Effectiveness of Telecommuting as a Transportation Control Measure”. Working paper, UCTC No. 78, University of California at Davis.

Schintler, L.A., 2001. “Trip Reduction Study: the Impact of Telecommuting Delay in the Washington, D.C. Area”. The School of Public policy, George Mason University.

Sener, I.N. and C.R. Bhat, 2011. “A Copula-Based Sample Selection Model of Telecommuting Choice and Frequency”. Environment and Planning A, 43(1), pp. 126-145.

Shafizadeh, K.R., Mokhtarian, P.L., Neimeier, D.A. and I. Salomon, 2000. “The Costs and Benefits of Telecommuting: A Review and Evaluation of Micro-Scale Studies and Promotional Literature”, Research Report, UCD-ITS-RR-00-24, Institute of Transportation Studies, University of California, Davis.

Singh, P., Paleti, R., Jenkins, S. and C.R. Bhat, 2012. “On Modeling of Telecommuting Behavior: Option, Choice and Frequency”. Transportation, 40(2), pp. 373-396.

Stanek, D.M. and P.L. Mokhtarian, 1998. “Developing Models of Preference for Home-based and Center-based telecommuting: Findings and Forecasts”. Technological Forecasting and Social Change, 57(1/2), pp. 53-74.

Sullivan, M.A., Mahmassani, H.S. and J.R. Yen. 1993. “Choice Model of Employee Participation in Telecommuting under a Cost-Neutral Scenario”. Transportation Research Record, 1413, pp. 42-48.

Tang, W., Mokhtarian, P.L. and S.L. Handy, 2011. “The Impact of the Residential Built Environment on Work at Home Adoption and Frequency: An Example from North California”. Journal of Transport and Land Use, 4(3), pp. 3-22.

Teo, T.S.H., Lim, V.K.G. and S.H. Wai, 1998. “An Empirical Study of Attitudes towards Teleworking among Information Technology Personnel”. International Journal of Information Management, 18(5), pp. 329-343.

Turnbull K. F., Hall K. M., Lewis C. and C. A. Weatherby, 1996. “Telecommuting programs in Texas, Case studies”. Research report 1446-F, Research study number 0-1446, Texas Transportation Institute.

Vana, P., Bhat, C.R. and P.L. Mokhtarian, 2008. “On Modeling the Choices of Work-Hour Arrangement, Location and Frequency of Telecommuting”. Research Report, UCD-ITS-RR-08-48.

Vu, S. T. and U. Vandebona, 2007 "A Model for Analysis of Impacts of Telecommuting on Network Travel Time". Australasian Transport Research Forum (ATRF), 30th, Melbourne, Victoria, Australia, vol 30.

Vu, S. T. and U. Vandebona, 2007. "Telecommuting and Its Impacts on Vehicle-km Travelled". Proceedings of International Congress on Modelling and Simulation, the University of Canterbury, Christchurch, New Zealand, pp. 253-260.

Vu, S. T. and U. Vandebona, 2008. "Evaluation of Impacts of Telecommuting in Traffic Assignment". 30th Conference of Australian Institutes of Transport Research, December 10-12, Perth WA Australia.

Vu, S.T., 2007. "Analysis of Impacts of Telecommuting for Reduction of Environmental Pollution". Conference of Australian Institutes of Transport Research (CAITR), 29th, Adelaide, South Australia, Australia.

Walls, M. and E. Safirova, 2004. "A Review of the Literature on Telecommuting and Its Implications for Vehicle Travel and Emissions". Discussion Papers DP-04-44, Resources for the Future.

Walls, M., Safirova, E. and Y. Jiang, 2006. "What Drives telecommuting? The Relative Impact of Worker Demographics, Employer Characteristics, and Job Types". RFF-DP-06-41, Resources for the Future.

Washington, S.P., Karlaftis, M.G. and F.L., Mannering, 2011. "Statistical and Econometric Methods for Transportation Data Analysis". Second Edition, Taylor & Francis Group, LLC.

Wells, K., Douma, F., Loimer, H., Olson, L. and C. Pansing, 2001. "Telecommuting Implications for Travel Behavior, Case Studies from Minnesota". Transportation Research record, 1752, pp. 148-156.

Wenjing, W. and J. Zhicai, 2009. "Activity-Travel Behavior Analysis Based on Structural Equation Model". International Conference on Electronic Commerce and Business Intelligence (ECBI), pp. 486-490.

Wernick, S., 2004. "Telecommuting: Working from Home in 21st Century". Master's degree Project, Department of City and Regional Planning, University of North Carolina Chapel Hill.

Yen, J. R. and H. S. Mahmassani, 1994. "The telecommuting Adoption Process: Conceptual Framework and Model Development", Research Report SWUTC/94/60055-1, Center for Transportation Research, University of Texas at Austin.

Yen, J.R., 2000. "Interpreting Employee Telecommuting Adoption: An Economic perspective". Transportation, 27, pp. 149-164.

Zhou, L, 2008. “Modeling the Impacts of An Employer Based Travel Demand Management Program on Commute Travel Behavior”, Ph.D. Dissertation, Department of Civil and Environmental Engineering, University of South Florida.

Zhu, P., 2011. “Telecommuting Travel Behavior and Residential Location Choice: Can Telecommuting Be an Effective Policy to Reduce Travel Demand?". Ph.D. Dissertation, University of Southern California.

Zhu, P., 2012. “Are Telecommuting and Personal Travel Complements or Substitutes?” Annals of Regional Science, 48(2), pp. 619-639.

VITA

HAMIDREZA ASGARI

EDUCATION

2002-2007	B.S., Civil Engineering Sharif University of Technology, Tehran, Iran
2007-2010	M.S., Civil Engineering (Transportation) Sharif University of Technology, Tehran, Iran
2013-2015	Doctoral Candidate Department of Civil and Environmental Engineering Florida International University, Miami, Florida

EMPLOYMENT

2011-2015	Graduate Research/Teaching Assistant Department of Civil and Environmental Engineering Florida International University, Miami, Florida

PUBLICATIONS AND PRESENTATIONS

Asgari, H., and X. Jin, 2015. "Towards a Comprehensive Telecommuting Analysis Framework; Setting the Conceptual Outline". Transportation Research Record, Journal of Transportation Research Board, in press.

Asgari, H., Jin, X. and A. Mohseni, 2014. "Choice, Frequency, and Engagement- A Framework for Telecommuting Behavior Analysis and Modeling". Transportation Research Record: Journal of the Transportation Research Board, No. 2413, pp. 101-109.

Jin, X., H. Asgari, and MS. Hossan, 2014. "Understanding Trip Misreporting Behavior Using Global Positioning System-Assisted Household Travel Survey". In "Mobile Technologies for Activity-Travel Data Collection and Analysis", Chapter 6, IGI Global, 2014. DOI: 10. 4018/978-1-4666-6170-7.

Jin, X., Asgari, H., and M.S. Hossan, 2014. "Understanding Trip Misreporting in Household Travel Surveys by Comparing GPS-Assisted and Diary-Based Samples". CICTP 2014: pp. 3401-3412. DOI: 10.1061/9780784413623.326.

Shams, K., Jin, X., Asgari, H., and M.S. Hossan, 2015. “An Investigation of Temporal Transferability Comparing trip-based and Tour-Based Choice Models”. Presented at the 94th Transportation Research Board (TRB) Annual Meeting, Washington, D.C.

Shams, K., Jin, X., Hossan, M.S., and H. Asgari, 2015. “An Investigation of Tour Generation Models Combining Two Waves of Household Travel Surveys through Pooled Models”. Presented at the 94th Transportation Research Board (TRB) Annual Meeting, Washington, D.C.

Asgari, H. and X., Jin, 2014. “On the Impacts of Telecommuting over Daily Activity/Travel Behavior; A Comprehensive Investigation through Different Telecommuting Patterns”. Presented at the 5th Innovations in Travel Demand Forecasting Conference, Baltimore, Maryland.

Asgari, H., Hu, F., X. Jin, 2014. “Daily Variations in Non-Mandatory Activity Participation: Do Shoulder Days Differ from Mid-week Days?” Presented at the University Transportation Center (UTC) Conference for the Southeastern Region, Atlanta, Georgia.

Asgari, H., Jin, X. and A. Mohseni, 2014. “Choice, Frequency, and Engagement- A Framework for Telecommuting Behavior Analysis and Modeling”. Presented at the 93rd TRB Annual Meeting, Washington, D.C. Also presented on the “Graduate Research Day” poster session in Florida International University, February 2014.

Asgari, H., Jin, X., Lugo, M. and S. Srinivasan, 2014. “Daily Variations in Non-Mandatory Activity Participation: Do Shoulder Days Differ from Mid-week Days?” Poster presented at the “STRIDE” poster showcase, 93rd TRB Annual meeting, Washington, D.C.

Asgari, H. and X. Jin, 2013. “A Two-staged Approach towards Telecommuting Estimation: Frequency and Engagement”. Presented at the 26th ICTPA Annual Conference, Tampa, Florida.

Asgari, H. and M. Lugo, 2013. “Towards a Holistic Understanding of Quality of Life: An Analysis of Activity Travel Patterns on Non- Mid-week Days”. Presented at UTC conference for Southeastern Region, Orlando, FL.

Asgari, H. and X. Jin, 2013. “Analysis of Telecommuting Behavior: Weekly Frequency and Actual Daily Engagement”. Presented at the 92nd TRB Annual Meeting, Washington, D.C. Also presented at ‘Graduate Research Day’ poster session at Florida International University.

Jin, X., Wu, J., Argote, J. and H. Asgari, 2013. “Examining Home-based Telecommuting Behavior and the Impacts on Activity Scheduling”. Presented at the 92nd TRB Annual Meeting, Washington, D.C.