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Modeling the impacts of an employer based travel demand management program on commute travel behavior

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Modeling The Impacts Of An Employer Based Travel Demand Management Program On Commute Travel Behavior

by

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MODELING THE IMPACTS OF AN EMPLOYER BASED TRAVEL DEMAND MANAGEMENT PROGRAM ON COMMUTE TRAVEL BEHAVIOR

Liren Zhou

ABSTRACT

Travel demand Management (TDM) focuses on improving the efficiency of the transportation system through changing traveler's travel behavior rather than expanding the infrastructure. An employer based integrated TDM program generally includes strategies designed to change the commuter's travel behavior in terms of mode choice, time choice and travel frequency. Research on TDM has focused on the evaluation of the effectiveness of TDM program to report progress and find effective strategies. Another research area, identified as high-priority research need by TRB TDM innovation and research symposium 1994 [Transportation Research Circular, 1994], is to develop tools to predict the impact of TDM strategies in the future. These tools are necessary for integrating TDM into the transportation planning process and developing realistic expectations. Most previous research on TDM impact evaluation was worksite-based, retrospective, and focused on only one or more aspects of TDM strategies. That research is generally based on survey data with small sample size due to lack of detailed information on TDM programs and promotions and commuter travel behavior patterns, which cast doubts on its findings because of potential small sample bias and self-selection bias. Additionally, the worksite-based approach has several limitations that affect the accuracy and application of analysis results.

Based on the Washington State Commute Trip Reduction (CTR) dataset, this dissertation focuses on analyzing the participation rates of compressed work week schedules and telecommuting for the CTR affected employees, modeling the determinants of commuter's compressed work week schedules and telecommuting choices, and analyzing the quantitative impacts of an integrated TDM program on individual commuter's mode choice. The major findings of this dissertation may have important policy implications and help TDM practitioners better understand the effectiveness of the TDM strategies in terms of person trip and vehicle trip reduction. The models developed in this dissertation may be used to evaluate the impacts of an existing TDM program. More importantly, they may be incorporated into the regional transportation model to reflect the TDM impacts in the transportation planning process.

CHAPTER 1 INTRODUCTION

1.1 TDM Development

After the Second World War until the mid-1970's, American public policy focused on the construction of new highway facilities to meet the transportation needs from continued urban expansion and accelerating automobile travel. During that time period, a contention held by most transportation policy makers was that land use patterns and economic growth were two major sources of traffic. As a consequence, they believed that more roads should be built to reach adequate capacity to accommodate growing transportation needs and handle future demand [Wachs, 1990]. Empirical evidence, however, suggests that because of so-called induced travel, building more roads leads to more automobile travel. A study conducted by Fulton et al. [2000] finds that, on average, every ten percent increase in lane-miles results in two to six percent increase of vehicle miles traveled (VMT). Lomax and Schrank [2005] conclude in *The 2005 Urban Mobility Report* of Texas Transportation Institute (TTI) that "This analysis shows that it would be almost impossible to attempt to maintain a constant congestion level with road construction alone."

On the other hand, compared with the rapid growth of population, licensed drivers, and even faster growth of vehicle miles traveled, the highway supply has experienced a much lower growth for the last thirty years. For example, from 1976 to 1996, while the population increased by about 22 percent, the number of the licensed drivers increased by 34 percent, the vehicle miles traveled increased by 77 percent. In contrast, while the highway capital outlay adjusted by inflation increased by 56 percent from 1976 to 1996, the road mileage only increased by 2 percent. In fact, highway expenditures by all levels of government in 1996, after inflation adjusted, were about 56 percent of what they were for each vehicle mile of travel in 1976 [Winters, 2000]

Facing ever increasing congestion despite the expansion in road capacity, coupled with growing limits of transportation budgets and environmental concerns from air pollution to global warming, transportation policy makers gradually changed their view that building more roads is the only effective way to reduce congestion. Starting in 1980's, transportation professionals and public policy makers started to look at the demand side for solutions. The travel demand management (TDM) strategies were first implemented in early 1980's. A variety of incentives and subsidy programs aimed at increasing ride sharing and transit use by commuters were introduced.

Since then, more and more communities are recognizing TDM as an essential part of the overall effort to effectively address transportation congestion [Bhattacharjee et al., 1997; Nozick et al., 1998]. They look for ways such as carpooling, vanpooling, parking charges and financial incentives to lower congestion by reducing the number of vehicle trips on the road and increasing the number of passengers in each vehicle [Wilson, 1992; Parkhurst, 1995, 2000; Rose, 2002]. They also use new technologies such as smart card and advanced traveler information systems to change the amount of time that vehicles use the road, thus lowering the load of the road network during the peak-hour periods [Winters, 2000]. Road pricing lowers traffic volume during peak hours [Thorpe et al., 2000; Viegas, 2001; Nakamura and Kockelman, 2002]. Alternative work schedules, including compressed work weeks, telecommuting, and flexible work hours, shift traffic out of the peak hour period and reduce commuting personal trips [Giuliano and Golob, 1990; Tanaboriboon, 1994; Bhattacharjee et al., 1997; Nozick et al., 1998; Ory and Mokhtarian, 2005].

Travel Demand Management focuses on improving the efficiency of the transportation system through changing the traveler's travel behavior rather than expanding the infrastructure. Traditionally, TDM focuses on changing commuter's mode choice by providing incentives or disincentives and support services. Contemporary TDM addresses not only mode choice, but also route choice, time choice, location choice, and travel frequency.

1.2 Employer Based Travel Demand Management Program

Most of the TDM programs are employer based, either mandatory or voluntary. Generally, the basic objective of a typical employer-based TDM program, such as the Washington State Commute Trip Reduction (CTR) program, is to "reduce traffic congestion, reduce air pollution, and petroleum consumption through employer-based programs that decrease the number of commute trips made by people driving alone" [Washington State DOT, 2007]. The employers participating in the TDM program are required to implement programs that encourage alternatives to drive-alone commuting to their worksites.

Specifically, the general strategies that the employers can choose to implement to achieve their CTR goals include:

- Alternative Work Schedules: Compressed work weeks and telecommuting. In terms of TDM, this group of strategies functions to reduce personal trips and change the travel time.
- Employer TDM Support Strategies: Non-monetary inducements to encourage employees to use alternative modes rather than drive-alone. These include preferential parking for high occupied vehicle (HOV) parking, rideshare matching services, employer transportation coordinators, and guaranteed rides home. It also includes the activities focusing on promoting the TDM program, such as the regularly posting or distributing of CTR promotion material, conducting transportation events, and so on. In terms of TDM, this group of strategies functions to reduce the drive-alone trips by encouraging employees taking alternative modes.
- Travel Cost Changes: Measures such as imposition of parking fees, differential rates or discounts for carpools or vanpools parking, transit fare subsidies, or in specific modal incentives or disincentives to any or all modes. In terms of TDM, this group of strategies functions to reduce the driving alone trips by increasing travel cost of driving alone or decreasing the travel cost of alternative modes.

1.3 Effectiveness Evaluation and Forecasting of an Employer-based TDM

Research on TDM has focused on the evaluation of the effectiveness of TDM to report progress and find effective strategies. Another research area, identified as a high-priority research need by TRB TDM innovation and research symposium 1994 [Transportation Research Circular, 1994], is to develop tools to predict the impact of TDM strategies in the future. These tools are necessary for integrating TDM into the transportation planning process and developing realistic expectations [Winters, 2000].

The direct measurement of the effectiveness of the CTR program is the vehicle trips or peak period vehicle trips reduction. Based on the number of reduced vehicle trips, other measurements, such as the reduction of delay, travel time, and fuel consumption and emission, can then be derived. Generally, a comprehensive employer based TDM program achieves the goal of vehicle trip reduction through implementing worksite-based TDM strategies that focus on changing the commuter's mode choice, travel time, and travel frequency. Specifically, through the compressed work week and telecommuting program to change the commute travel frequency and the time the commute trip occur, the employer TDM supports strategies and financial incentives or disincentives to encourage employees to use alternative modes to drive-alone, therefore reducing the vehicle trips. An integrated procedure of the employer-based TDM effectiveness evaluation, therefore, consists of estimating the number of employees working on compressed work week and telecommuting and percentage of employees shifted from driving alone to the alternative modes.

The evaluation of the effectiveness of the employer-based TDM program can be categorized to evaluating an existing program based on the employee travel behavior survey and predicting or estimating the impacts of a program based the employer program implementation data. For an existing employer-based TDM program for which both the employer promotion data and employee travel behavior information are available, such as the Washington State CTR program, the evaluation process generally consists of calculating and comparing the vehicle trip rate or vehicle miles traveled for the program affected employer before and after the implementation of the program based on the employee travel behavior data. For most of other employer-based TDM programs, where the employee travel behavior information is not available, the program assessment normally includes applying the TDM models, such as EPA's COMMUTER model, to estimate or predict the vehicle trip rate change based on employer program implementation data.

1.4 Focus of This Dissertation

Most previous research on TDM impact evaluation was worksite-based, retrospective, and focused on only one aspect of TDM strategies. Such research is generally based on survey data with small sample size due to lack of detailed information on TDM programs and promotions and commuter travel behavior patterns, which cast doubts on its findings because of potential small sample bias and self-selection bias. Additionally, the worksite-based approach, as I will elaborate later, has several limitations that affect the accuracy and application of analysis results.

The Washington State Commute Trip Reduction database provide a detailed information on both TDM strategies implemented by employer, worksite characteristics and employees' travel behavior and their job related characteristics, which makes a employee based systematic analysis of TDM effectiveness possible. This database tracks more than 1,000 worksites and around 300,000 individual employees from 1993 to 2005, which enables this research to avoid the problems of self-selection and small sample biases.

Using this unique dataset, this dissertation intends to analyze the TDM effectiveness and develop tools to predict the impact of TDM strategies by addressing three issues: (1) For the CTR affected employees, what are the overall trends of compressed work week (CWW) schedule participating rate, what are the factors that determine employees' CWW choices; (2) For the CTR affected employees, what are the overall trends of telecommuting participation rate, what are the determinants affecting employees' telecommuting choices; (3) how TDM strategies, including the program promotion activities, parking management, and financial incentives or disincentives can affect commuter's modal choice. The results from this dissertation may be directly used to evaluate the impacts of an existing TDM program and to identify the effective strategies based on the worksites characteristics. More importantly, it may be incorporated into the regional transportation forecasting model to provide realistic prediction of the TDM impacts in the future, and, at the same time, to improve the accuracy and predictability of the travel forecasting model.

1.4.1 Compressed Work Week

The first issue involves compressed work weeks (CWW) schedule, which allows employees to work their "regular" number of hours in shorter-than-normal days per week or per pay period. In terms of TDM, compressed work week functions to reduce the commuter's travel frequency and change the time the work trips occur. For example, if an employee works 4 days a week, she has to work 10 hours per day. This means she needs to leave home earlier and leave the office later. Therefore, people working on compressed work weeks not only reduce the number of work trips, but also shift the work trips from peak period to non-peak period.

1.4.1.1 Determinants of Employee's Work Schedule Choice

Earlier studies on the compressed work week focus on the benefits and problems associated with its implementation [Allen and Hawes, 1979; Nollen, 1981; Ronen and Primps, 1981; Wachs, 1990]. More recent studies focus on the impacts of CWW on vehicle trip reductions [Giuliano and Golob, 1990; Ho and Stewart, 1992; Hung, 1996] and individual activity travel patterns [Sundo and Fujii, 2005]. Restricted by data availability, there are no analysis on the CWW participation trend and no studies on examining the factors that determine commuters' decision to take the CWW. With Washington State CTR dataset, these important questions will be answered for the first time, which helps enrich the literature and provides new insight on TDM strategies to meet the goal to reduce trip rates and traffic congestion.

There is no previous theoretical model or empirical work discussing the drive or constraints for CWW choices. Mokhtarian and Salomon [1994], however, presents a conceptual framework for modeling telecommuting choices, which I believe may also be suitable for modeling the work schedule choice. Following this guideline, the determinants that affect commuter's choice of telecommuting would include (1) the commuter's job characteristics, (2) the commuter's journey-to-work travel characteristics, (3) the commuter's socio-demographic characteristics, (4) the attitudes of the employer towards CWW, and (5) the commuter's personal preference.

1.4.1.2 Compressed Work Week Participation Trend

Chapter 3 analyzes the trend of CWW participating rate from 1993 to 2005 and identifies the factors that influence commuters' CWW choice. The analysis of the longitudinal CTR data indicates that for the employees affected by the CTR program, the participation rates of CWW increase steadily from 14.5 percent in 1993 to 20 percent in 2005. While the major pattern of CWW is still working four days 40 hours per week (4/40) (7.3 percent in 2005), the percentage of employees working on nine days 80 hours per two weeks (9/80) doubled from 1993 (2.9 percent) to 2005 (5.85 percent).

1.4.1.3 Modeling the Compressed Work Week Choice

A multinomial logit (MNL) model is first applied to analyze the determinants of CWW choices using the CTR data in 2005. From the MNL model, I find that employer's promotion level of TDM programs is one of the key determinants of commuter's decision of CWW choices. Commuters are more likely to participate in CWW programs with the increase in the promotion level, a measure of supportiveness of employer on TDM programs aimed at reducing vehicle trip rates. I also find that distance from home to work is another key factor that influences commuter's decision of CWW choices. The longer the distance from home to work, the higher the probability to choose alternative work schedules. People using a single mode of transit and shared ride are more likely to work on compressed work schedules compared with those using a single mode of driving alone. Another important finding is that the number of CWW program years, defined as the number of years the CWW program has been implemented by the employer since 1995, has significant, positive, and non-constant impact on the commuter's CWW choices. The CWW program implementation year has increasing effect on CWW choices until it reaches its peak in year 5. After year 5, its marginal effect falls until year 8, after which, it goes flat. This may suggest that it takes time for the employees to understand the benefits and the feasibility of CWW based on their personal information and job characteristics. Employees' decision to participate in CWW programs are also affected by their job title and their employer's major business type.

There are arguments, however, that the employee's choice of work schedules, including working 6 days (3/36), 7 days (7/80), 8 days (4/40), 9 days (9/80), and 10 days (regular hours) per two weeks, is ordinal discrete choice. For an ordinal dependent variable, the appropriate model is ordered logit or probit regression. There differ from the multinomial logit model, which is based on random utility theory. In the ordered logit or probit model, the ordinal choice variable is assumed as the discrete realizations of an underlying, unobserved (or latent) continuous random variable. The choice set for each of the alternatives for the ordinal logit or probit model, therefore, is fixed. This constitutes the major drawback for its application in modeling employee's work schedule choice since most of the employees do not have the full options of the compressed work week schedules (less than 10 percent of CTR affected employees have the full options of compressed work week schedules).

To further examine the technical feasibility of the model, an ordered logit model is estimated based on the sub-sample of the employees with full options of work schedules and the results are compared with that of the MNL model. Overall, the results from the ordered logit model are consistent with the major findings from the MNL model.

1.4.2 Telecommuting

The second issue addresses telecommuting choices. Telecommuting is designed to allow commuters to use telecommunication technology to work at home or at a location close to home during regular work hours, rather than commuting to a conventional worksite at regular work hours, thus saving their driving time to work and, more importantly, eliminate vehicle trips, which helps reduce congestion.

1.4.2.1 Previous Empirical Studies on Telecommuting

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. Most earlier research focused on the impacts of telecommuting on household travel behavior. Many hypotheses have been formulated and tested [Mokhtarian, 1991; Pendyala et al., 1991]. Although the impact of telecommuting remains an unresolved issue because of conflicting findings, it seems that most researchers agree that, on net, telecommuting reduces total trips, especially peak-period trips, and generates a positive effect on the environment [Hamer, 1991; Sampath et al., 1991; Quaid and Lagerberg, 1992, Choo et al., 2005].

Most of the empirical analyses of telecommuting adoption and frequency have been based on either stated preference (SP) [Bernardino et al., 1993; Mahmassani et al., 1993; Mokhtarian and Salomon, 1995] or revealed preference (RP) data [Mannering and Mokhtarian, 1995; Mokhtarian and Salomon, 1997; Drucker and Khattak, 2000; Popuri and Bhat, 2003]. The findings, from both SP based and RP based analyses, however, seem to be inconsistent. Those inconsistencies may derive from the wide gap between preferring to telecommute and actually telecommuting. As discussed in Mokhtarian and Salomon [1995], while 88 percent of the total of 628 respondents preferred to telecommute, only 13 percent actually did.

One of the common drawbacks shared by most earlier empirical studies on telecommuting is data limitation. Most previous empirical studies are based on small samples and have not clear definition either the telecommuters or their telecommuting frequency. For example, in most studies that apply the discrete choice model, the choice set is defined as frequently, infrequently, and rarely telecommuting, rather than number of telecommuting days per time period. The commuters are not distinguished between those self-employed or those who do not have or need a conventional office rather than home and those who have a fixed office but telecommute regularly.

1.4.2.2 Contributions of This Study

To further strengthen the findings on telecommuting choices, this dissertation develops an ordered logit model to estimate telecommuting choices based on a unique dataset with more than 200,000 observations. The employees' choices of telecommuting are made from a set of mutually exclusive and collectively exhaustive alternatives, including not telecommuting, telecommuting one day, telecommuting two days, and telecommuting three or more days per two weeks. To model the telecommuting choice and its frequency through a discrete choice model, the dependent variable, therefore, is an ordinal discrete choice. Although multinomial logit and probit models have been widely used in discrete choice modeling and in several earlier studies on telecommuting choices, they may not appropriate because they fail to account for the ordinal nature of outcomes [Greene, 2000]. For an ordinal dependent variable, ordered logit or probit regression is more appropriate.

The data, collected from the Washington State Commute Trip Reduction (CTR) program, in program year 2005, has more than 200,000 observations that have detailed information on employers' characteristics and employees' telecommuting patterns. The dataset includes only those employees who work in a worksite with at least 100 full-time employees with regular working schedules starting between 6:00 a.m. and 9:00 a.m. (inclusive) on two or more weekdays for at least twelve continuous months [Washington State Legislature, 2007]. This indicates that the sample excludes the self-employed and other types of employees who do not have or need an office other than home.

Furthermore, in this sample, the telecommuters are defined as those who regularly telecommute one or more days per two weeks. In other words, the employees who randomly or casually telecommute are not counted as telecommuters. This probably can explain why the telecommuting rate reported by the WA CTR data is dramatically lower than that reported by other studies. For example, Drucker and Khattak [2000] reported a total telecommuting rate of 14.3 percent from the 1995 National Personal Transportation Survey, while based on the WA CTR database, the telecommuting rate was only 1.51 percent in 1995. In another study conducted by Popuria and Bhat [2003] based on 1997 - 1998 Regional Transportation Household Interview Survey in New York, the total telecommuting rate was 15.4 percent, compared with the results from WA CTR data in 1997 of 2.21 percent. I believe this strict definition may help generate more reliable results.

Finally, this study focuses on examining the effectiveness of telecommuting as a component of an integrated TDM program and predicting the telecommuting rate in the future. The empirical evidence may be applied to evaluate or predict the effectiveness of a TDM program. It may also be incorporated into local or regional travel demand forecasting models to better measure the overall performance of transportation system. The findings from this dissertation may also help policy makers when they consider alternative combinations of TDM strategies to be implemented.

1.4.2.3 Determinants of Telecommuting Choice

Mokhtarian and Salomon [1994] develop a behavioral model of the individual choice to telecommute, in which they identify the possible constraints and drives of telecommuting choices. They define constraint as a factor that prevents the choice to telecommute while drive is a factor that motivates commuters to begin telecommuting. Key constraints on telecommuting choices relate to "awareness of telecommuting options, the organization, job, and psychological factors."

The authors identify the key drives as work related, family related, leisure related, ideology related, and travel related. Work related drives include the desire to be more productive, independent, and flexible. Family and leisure related drives include the desire to spend more time with family and have more leisure time for other non-work activities. Ideology related drive include certain people's belief that telecommuting can help protect the environment by reducing auto travel. If a commuter lives a long distance from work, or if the work related commute is burdensome, then these two factors both work as drives.

Given data availability, the variables included in my empirical analysis include most of constraints and drives identified by Mokhtarian and Salomon. I use TDM promotion activities, the allowance of flexible start/end work time, and the time the employer transportation coordinator spends on TDM promotion to measure supportiveness from employers, which may capture organization related constraints. The number of years telecommuting has been allowed at the worksite may capture the awareness constraint. I include employees' job titles and work schedules to capture job related constraints. The commute mode choice will be used to capture the travel related drive. The variables of commute distance, whether the worksite is located downtown, and the average property value by ZIP code in which the commuter resides can measure the family and leisure related drives. I believe the variables employers' major business type and the existence of multiple shifts at the worksite can measure the work related drives.

1.4.2.4 Telecommuting Participation Trend Analysis and Telecommuting Choice Modeling

The data analysis from the Washington State CTR database indicates that, overall, the absolute number and percentage of telecommuters are small. In 2005, 5.83 percent of employees affected by the CTR law actually chose to regularly telecommute at least one day per two weeks. Compared with 1993, two years after the CTR law was passed, however, the number and percentage of telecommuters increased by at least five times by all job titles and employers' business types. This suggests that telecommuting is a TDM program strategy with growing support and acceptance from both employers and commuters.

I estimate the relationship between telecommuting choices and a group of explanatory variables using a generalized ordered logit model. Telecommuting is categorized into not telecommuting, telecommuting one day, two days, and three or more days per two weeks. To evaluate the model, I estimate the model again on a randomly-selected 80 percent sample and use the remaining 20 percent to test the model's predictability. The model is further evaluated using 2003 data.

1.4.3 TDM Impacts on Commuting Mode Choice

One of the major objectives of the employer-based Commuter Trip Reduction (CTR) program is to reduce vehicle trips by implementing programs that encourage alternatives to drive-alone commuting to worksites [Washington State DOT, 2007]. Therefore, the impacts of the implemented TDM programs on commuter's modal choices could be an important measure of TDM effectiveness. The third goal of this dissertation is to address the impact of an integrated TDM program on journey to work modal choices.

1.4.3.1 Limitations of Employer Based Method

Most previous research on TDM impacts have been worksite based, focused on one or more aspects of TDM strategies, and based on small samples [Mehranian et al., 1987; Brownstone and Golob, 1991; Peng et al., 1996; Cervero, 1996; Kuppam et al., 1999; Washbrook et al., 2006]

The worksite-based approach estimates changes in mode split at an aggregate, worksite level by treating the worksite as the analysis unit. Although most commute trip reduction programs are employer-based, using worksite as the analysis unit has limitations.

Firstly, calculation of the aggregate mode split is highly affected by some factors that are hard to control or measure, for example the survey response rate. The non-respondents are generally treated as having the same distribution of mode shares as that of valid respondents. It can be argued, however, that people driving alone are less likely to answer the questionnaire. Based on this assumption, some studies treat the non-respondents as driving alone, or treat the non-respondents as driving alone when the response rate is less than a certain amount, e.g. 70 percent. Since the impact of TDM on the worksite's mode split is relatively low, the bias induced by the calculation could be significant.

Secondly, some of the important determinants of mode choice, such as travel time and travel cost, can only take average values at the worksite level, while those variables are meaningful only from the perspective of individuals. The worksite-based approach also fails to catch varieties of individual trips, which is critical when the study focuses on quantifying the impact of reduced individual trips. In addition, the worksite-based approach reduces the number of observations available from which to make the estimates. This is especially important when the study area is a sub-area, such as downtown or corridor.

1.4.3.2 Modeling the Impacts of an Integrated TDM Program on Employee's Journey to Work Mode Choice

An employer-based TDM program generally includes different strategies. For most of those strategies, their impacts are more interactive than independent. For example, an internal or external ride match program will be more effective if combined with reserved high occupancy vehicle (HOV) parking space or an HOV parking charge discount program. Focusing on only one aspect of TDM strategies without controlling for the availability of other TDM programs may result in omitted variable bias.

Although the commuter's travel behavior in terms of travel mode choice has been studied extensively, there is no empirical work that estimates the combined effects of a TDM program on an individual's modal choices.

Among the various methodologies applied in human behavior study, the discrete choice model has been widely used in the transportation community to study travel-related human behavior, specifically the traveler's mode choice and departure time choice.

In chapter 5, a nested logit model is applied to estimate the determinants of employees' modal choices based on a sample of more than 60,000 observations. I use a two-level nested logit model. The first nest includes motor, transit, and non-motor travel.

In the second nest, motor is divided into driving alone and shared riding. The mode shares of each of the alternative are: motor, 76.71 percent (driving alone, 63.22 percent; Shared ride, 13.47 percent); transit, 15.25 percent; non-motor, 3.61 percent.

Based on the nested logit model, the elasticity and marginal effects of financial incentives and TDM support and promotion programs are further calculated to evaluate the quantitative impacts of various TDM strategies on the modal choices.

The variables in the utility function of the nested logit model include (1) characteristics of the commuter, including job title and work schedule; (2) characteristics of the connections between the commuter's home zip code and the commuter's worksite, including the commuting distance by mode, transit in-vehicle time, transit out-vehicle time, and transit number of transfers; (3) land-use characteristics of the commuter's home ZIP code, including the average property value; (4) characteristics of the employer, including business type, total number of employees, and the existence of multiple shifts at the worksite; (5) parking management at the worksite, including parking charge for SOV and HOV, ratio of onsite parking spaces and total number of employees, and existence of reserved parking spaces for HOV; (6) financial subsidies for alternative modes, including the subsidy for transit, carpool, vanpool, bike, and walk; (7) employer TDM support/promotion strategies/activities, including the availability of a guaranteed ride home program and the promotion activities of distributing program summary material, sending program information through email, conducting transportation events, and publishing TDM articles in employee newsletters; (8) land-use characteristics at the worksite, including area type (downtown, rural, or other), existence of sidewalk, bike-lane, and onsite restaurant, and existence of onsite covered bike racks, clothing lockers, and showers.

The results of this part of the study will not only provide a comprehensive, reliable quantitative and qualitative assessment of the impacts of TMD programs on the affected commuters' mode choice, but it will also explore the framework of a mode choice model that includes the TDM components. This mode choice model may further be incorporated into the regional transportation model to reflect the impact of the TDM on the regional transportation planning process.

The rest of this dissertation is organized as follows: Chapter 2 provides a brief literature review on travel demand management and its overall impact and effectiveness, Chapter 3 analyzes the CWW choices, Chapter 4 addresses telecommuting choices, Chapter 5 analyzes the impact of TDM programs on journey to work modal choices, and Chapter 6 provides the conclusion.

CHAPTER 2 TDM LITERATURE REVIEW

Transportation Demand Management (TDM) programs were first introduced in the urban and transportation planning fields in the 1970's, aimed at providing alternatives for single occupancy commuter travel to save energy, improve air quality, and reduce the increasing congestion in most urban areas during the peak hours [Berman, 2002]. In the years since TDM was introduced, popular concern with travel demand management has grown. By the year 2000, at least 11 states had adopted substantive regulations to implement TDM. The purpose of this chapter is to define TDM and to discuss the policy implications of its research.

2.1 What is TDM?

2.1.1 TDM Definition

The Federal Highway Administration (FHWA) describes transportation demand management [FHWA, 2004] as follows: "to some, the realm of demand management applications is limited primarily to encouraging alternatives to single occupant vehicle travel for the commute to work. In practice, however, this narrow view is no longer consistent with the broad applications of demand-side strategies currently underway across the country. Today's applications are not only limited to facilitating shifts in travel mode—they also address shifts in travel routes and travel departure-times (for all travelers, including single-occupant vehicle drivers). Today's applications also extend beyond a focus on commute trips. At national parks, sports stadiums, university campuses, and other diverse destinations, transportation and facility managers are implementing demand-side strategies as part of coordinated efforts to reduce congestion. On bridges, and along corridors undergoing roadway reconstruction programs, demand-side strategies are helping travelers avoid congestion by utilizing alternative travel routes, travel times and/or travel modes—or by reducing the need for some trips altogether by facilitating work from home options a few days a month. A full understanding of demand-side strategies must recognize the reasonable limits of these applications. Demand-side strategies should not be considered total solutions to regional traffic congestion problems. Rather they should more often be implemented as part of an integrated set of solutions that balance supply-side infrastructure investments and demand-side strategies."

Nationwide, there is no single definition of TDM. Here, I list a few definitions from the leaders in the field. The Victoria Transport Policy Institute [Victoria Transport Policy Institute, 2007] refers to TDM as a general term for strategies that result in more efficient use of transportation resources. TDM is a combination of various strategies that change travel behavior (how, when, and where people travel) to serve two purposes: increase transport system efficiency and achieve specific objectives ranging from reduced traffic congestion, road and parking cost savings, increased safety, improved mobility for non-drivers, energy conservation, to pollution emission reductions. Winters [2000] defines TDM as the all-inclusive term given to measures to improve the efficiency of transportation systems. Washington State Department of Transportation [WSDOT, 2002] has a "working" TDM definition. WSDOT defines TDM as a broad range of strategies that reduce or shift use of the roadway, thereby increasing the efficiency and life of the overall transportation system. TDM programs influence travel behavior by using strategies that accommodate more person-trips in fewer vehicles, shift the location or time of day at which trips are made, or reduce the need for vehicle trips.

From the above discussion, we can see how TDM developed from its traditional perspective to its contemporary one. The traditional TDM focuses on commute trips because they are the causes of peak-hour congestion. The primary mission of traditional TDM, thus, is to get commuters away from drive-alone into carpool, vanpool, transit, or other alternative modes [Berman, 2002]. This may be achieved through the provision of incentives, disincentives, and support services to change commuters' travel behavior. Generally used tools include flexible work hours, compressed work weeks, preferential parking, transit subsidies, carpools and vanpool match services, and telecommuting. The contemporary TDM model broadens its traditional mission and incorporates policies and programs to address not only mode choice, but time choice, location choice, and route choice through technology, improved information flow, and financial mechanisms [Winters, 2000; Berman, 2002].

2.1.2 TDM Components Studied

This research focuses on the employer based commuter trip reduction program. Specifically, the TDM components that will be studied include:

- Alternative Work Schedules: Compressed work weeks and telecommuting works. In terms of TDM, this group of strategies functions to reduce person trips.
- Employer TDM Support Strategies: Non-monetary inducements to encourage employees to use modes other than drive-alone. These include preferential parking for high occupied vehicle (HOV) parking, rideshare matching services, employer

transportation coordinators, and guaranteed rides home. It also includes the activities focusing on promoting the TDM program, such as the regular posting or distributing of CTR promotion material, conducting transportation events, and so on. In terms of TDM, this group of strategies functions to reduce the drive-alone trips by encouraging employees taking alternative modes.

- Travel Cost Changes: Measures such as the imposition of parking fees, differential rates or discounts for carpool or vanpool parking, transit fare subsidies, or in specific modal incentives or disincentives. In terms of TDM, this group of strategies functions to reduce the number of driving alone trips by increasing travel cost of driving alone or decreasing the travel cost of alternative modes.

2.2 Why is TDM Important?

The past thirty years have witnessed a significant attitude change toward transportation planning. After the Second World War until the mid-1970's, American public policy focused on expanding new highway facilities and transit capacity to meet the transportation needs from continued urban expansion and accelerating automobile travel. During that time period, transportation policy makers believe that land use patterns and economic growth were two major sources of traffic. As a consequence, they concluded that more roads should be built to reach adequate capacity to accommodate growing transportation needs and handle future demand [Wachs, 1990]. Empirical evidence, however, suggests that, because of so-called induced travel, more road building leads to more automobile travel. A study conducted by Fulton et al. [2000] finds that, on average, every ten percent increase in lane-miles results in a two to six percent increase in vehicle miles traveled (VMT). Lomax and Schrank [2005] conclude in *The 2005 Urban*

Mobility Report of the Texas Transportation Institute (TTI), "This analysis shows that it would be almost impossible to attempt to maintain a constant congestion level with road construction alone."

On the other hand, the highway supply has experienced a much lower growth during the last thirty years than that of population, licensed drivers, and even faster growth of vehicle miles traveled. For example, from 1976 to 1996, the population increased by about 22 percent, the number of licensed drivers increased by 34 percent and vehicle miles traveled increased by 77 percent. In contrast, over the same period highway capital outlays adjusted for inflation increased by 56 percent, and road mileage only increased by 2 percent. In fact, highway expenditures by all levels of government in1996, adjusting for inflation, were about 56 percent of what they were for each vehicle mile of travel in 1976 [Winters, 2000].

There is no doubt that more severe urban congestion is the direct result of these traffic and highway growth trends. The Urban Mobility Report documents that urban congestion has increased substantially from 1982 to 2003. In 2003, travel time during the rush-hour period in twenty-eight urbanized areas was at least 30 percent longer than that during the non-peak period, compared to only one such urban area having this severe congestion in 1982. Congestion caused 3.7 billion hours of travel delay and 2.3 billion gallons of wasted fuel with an estimated cost of more than $ 63 billion [Shrank and Lomax, 2005].

Facing ever increasing congestion despite expansion in road capacity, coupled with slowing growth of transportation budgets and environmental concerns ranging from air pollution to global warming, transportation policy makers gradually changed their view that building more roads was the only effective way to reduce congestion. More and more communities are recognizing TDM as an essential part of the overall effort to effectively address transportation congestion [Bhattacharjee et al., 1997; Nozick et al., 1998]. These communities look for ways to lower congestion by reducing the number of vehicle trips on the road and by increasing the number of passengers in each vehicle. They also use new technologies such as smart cards and advanced traveler information systems to change the amount of time that vehicles use the road, thus lowering the load of the road network during the peak-hour periods [Winters, 2000].

2.3 TDM Strategies and Their Effects

As discussed above, TDM programs include various strategies that work together to reduce congestion. The question is whether the TDM strategies are effective or not. In other words, what combination of strategies works better to serve certain objectives? Earlier work on the evaluation of the effectiveness of TDM has relied on both aggregate data at the regional level and disaggregate data at the individual site level. A brief review of existing research is provided below. To better present the various TDM strategies, I divide the strategies into three major categories: strategies to change travel behavior by changing travel cost; strategies to change travel behavior by changing travel time; and other strategies.

2.3.1 Strategies to Change Travel Behavior by Changing Travel Cost

The basic idea behind this group of strategies stems from economic principles. Like most normal goods, the demand for travel by any mode is not fixed. If travel cost increases, people respond by traveling less. If the relative price of a substitute mode changes enough, people may switch to another mode. The key question here is how commuters or travelers estimate their daily trip cost. There are a lot of studies on this question and they have obtained consistent findings: travelers treat the capital cost of owning a car, such as purchase price, interest payments on car loans, maintenance costs, and insurance premiums as so-called “sunk costs”. On the other hand, travelers generally count as trip costs only their out-of-pocket costs, gasoline, parking, tolls, and transit fares [Johnson, 1975; Louviere, et al. 1981; Adiv, 1980].

Based on the above assumption, TDM strategies aimed at changing commuters’ behavior by changing their travel cost generally include changing parking cost, and providing subsidies to transit use and other alternative modes such as carpooling, vanpooling, and road pricing.

2.3.1.1 Impacts of Parking Cost on Travel Behavior

It is well known that as many as 95 percent of American workers receive free parking from their employers [Vaca and Kuzmyak, 2005]. Free parking could be considered as a subsidy that encourages people to drive alone since it lowers travel cost [Shoup and Pickrell, 1997]. There are several studies on the effect on parking cost changes on journey-to-work mode choice. Francis and Groninga [1969] analyze the journey to work mode choice by employees working in the Los Angeles Civic Center and find that when parking is paid by the county and provided to county employees at no cost, 72 percent of the county employees chose to drive to work alone. At the same site, only 40 percent of federal employees drove to work alone when they had to pay for their parking. In another study, Shoup and Pickrell [1980] find that 20 percent fewer employees drive alone to work when they pay to park than when the employer provides free parking. Comparing components of travel cost, Shoup & Pickrell conclude that free parking is a greater incentive to drive alone than an offer of free gasoline.

Based on a survey of over one hundred TDM programs at suburban mixed land use centers, Higgins [1989] concludes that the key difference between the most successful programs and those with little effect on commuting behavior rests on the increase in the cost of employee parking. In the state of California, state law requires all employers with more than 50 employees to offer commuters the option to choose cash in lieu of any parking subsidies offered. In a case analysis based on eight firms, Shoup [1997] reports that for the affected 1,694 employees in the eight firms he studied, drive-alone dropped by 17 percent after cashing out, while carpools, transit use, and other alternatives such as walking and bicycling increased by 64 percent, 50 percent, and 39 percent respectively. Additionally, vehicle miles traveled by affected employees fell by 12 percent. More importantly, he concludes that providing subsidies to people rather than free parking benefits employees, employers, the community, and the environment.

The impact of parking fees can also be reflected in the price elasticity of demand, which is the percentage change in the number of autos parking per 1-percent change in parking price. This price elasticity of demand obtained either through empirical analysis or from simulation models ranges from - 0.1 to - 0.6, with - 0.3 being the most frequently cited value [Vaca and Kuzmyak, 2005].

2.3.1.2 Impacts of Out-of-the-pocket Cost on Travel Behavior

There is another way to change commuters' travel cost: provide subsidies to transit users. It reduces the out-of-the-pocket cost for transit users and increases the relative attractiveness of transit, which may change commuters' travel behavior. There are many economic studies on the price elasticity of transit fare. It is estimated to range from –0.3 to –0.4, which indicates that 10 percent decrease in transit fare leads to an increase in ridership of 4 percent [Sullivan, 2003]. Based on extensive research, Transport Research Library [TRL, 2004] calculates that bus fare elasticities average around –0.4 in the short-run, -0.56 in the medium run, and -1.0 over the long run, while metro rail fare elasticities are –0.3 in the short run and –0.6 in the long run. Bus fare elasticities are lower (-0.24) during peak than off-peak (-0.51).

The ways to change the travel cost for other alternative mode, such as carpooling, vanpooling, bicycling, and walking, can be direct financial subsidies or indirect incentives. Examples include the discount parking charge for vanpooling or carpooling and free bikes provided to commuters who ride bicycle to work. Analysis by Wambalaba et al. [2004] indicates that the parameter of vanpool ridership with respect to fees is -0.026 to –0.148, which indicates that a one dollar decrease in vanpool price is associated with a 2.6 percent to 14.8 percent increase in the predicted odds of choosing vanpool with respect to drive-alone. York and Fabricatore [2001] estimate the price elasticity of vanpooling at about - 1.5, meaning that a 10 percent reduction in vanpool fares increases ridership by about 15 percent.

2.3.2 Strategies to Change Travel Behavior by Changing Travel Time

Travel time is identified as one of the most important variables that affect people’s mode choice, route choices, and departure time. Many TDM programs are designed to first change people’s travel time with intention to change travel behavior ultimately. Many studies, however, consistently demonstrate that commuters’ response to travel time are quite complex. The findings suggest that people put much more weight on travel time reliability than the simple measure of total time elapsed. In other words, it seems that people care more about arriving their destination on time than minimizing their travel time [Wachs, 1990].

TDM strategies that address changing commuters' travel time include: preferential parking for carpool and vanpool, compressed work week (CWW), flexible working hours, telecommuting, and high occupancy vehicle (HOV) lanes implemented by state or local government.

Preferential parking for vanpools or carpools is one strategy widely implemented. HOV lanes are designed to provide advantage to carpool, vanpool or buses by allowing them to bypass congestion on adjacent lanes for all other uses, which may save the travelers' in-vehicle time and provide desirable time reliability. Combined with priority parking locations, the total in-vehicle and out-of-vehicle time can be shortened although carpool, vanpool or buses have higher collection time.

It is well known that some commuters are willing to depart to work very early to avoid congestion on the way to work. Some others prefer to stay at work until the afternoon peak-hour is over. Many TDM strategies such as flexible work hours, compressed work week, and various other work hour variations are designed to reflect this phenomenon. Such programs are found to be very effective in some settings, able to reduce peak period congestion up to 20 percent in some applications [Barton-Aschman and Associates, 1981]. On the other side, Wachs [1990] argues that the benefits from these strategies could be quite localized since the effects of those programs on traffic stream dropped rapidly with the increase in distance from the worksite affected.

Telecommuting is another strategy that may fall under this category. For some commuters who live far way from their worksite, telecommuting is designed to allow them to use telecommunication technology to work at home or at a location close to home during regular work hours, rather than commuting to a conventional worksite, thus saving their driving time to work, and more importantly, eliminate some vehicle trips. Salomon [1985] concludes that the potential impact of telecommuting is complex and not necessarily completely beneficial. Later research, however, seems to reach consensus that on net, telecommuting reduces total trips, especially peak-period trips, and generates positive effect on the environment [Sampath et al., 1991; Hamer et al., 1992]. Choo et al. [2005] find that telecommuting has reduced annual VMT by less than 0.8 percent. They believe that, even with such small impacts, telecommuting appears to be far more cost-effective than public transit in terms of public sector expenditures for the same level of reduction of vehicle-trips achieved.

Shafizadeh et al. [2007] studied the cost and benefits of telecommuting and illustrate the conditions under which the business case for telecommuting is supported or weakened. Conditions for the employee (the telecommuter) are generally most favorable when: (1) the employer bears the equipment cost; (2) commute distances are above average; (3) the commute vehicle has below-average fuel economy; (4) travel time is highly valued; and (5) telecommuting is frequent. Conditions for the employer are most favorable when: (1) the telecommuter bears the equipment cost; (2) there is low telecommuter attrition; (3) the employee is highly productive on telecommuting days; (4) the employee's time is highly valued; and (5) telecommuting is frequent. For the employer, telecommuting is also favorable if parking and office space savings are realized.

2.3.3 Employer Support TDM Strategies

Most TDM programs are employer based and can be either mandatory or voluntary. In a mandatory TDM program, employers are required by their state or local governments to set up reduction goals of vehicle miles traveled (VMT) and to implement specific support strategies to achieve the goals. One way in which employers can try to persuade employees to consider traveling by alternative modes, rather than drive-alone, is to provide various types of support that make it easier and more attractive to use those modes. These support programs typically consist of measures that heighten awareness of the availability of other modes, provide information on their service or use, or generally make it easier and more attractive to employees to consider their use. These employer support programs generally do not include measurable time or cost incentives or disincentives. Rather, they serve to provide an improved set of conditions for employees to use an alternative, and provide incentives that are tangible and important, but not necessarily quantifiable by the employee [EPA 2005].

Many of the strategies in this category of programs are specific to the needs of the particular mode. These strategies include ride matching and preferential parking for carpooling and vanpooling, on-site transit information booths and pass sales for transit, sidewalk and shower facilities for people who bicycle to work. In addition to the mode-specific types of strategies, there are actions employers can take that are almost universal in their applicability across all of the alternative modes. Examples of these strategies include the following: (1) Employee Transportation Coordinators, generally persons who are trained to provide information or advice to employees regarding use of any alternative mode, in terms of where to go for information, company policy and benefits, etc. (2) Guaranteed Ride Home, a program to help an employee go back home by alternative means if it is necessary to work late or in event of a personal emergency. (3) Flexible Work Hours, a formal or informal policy that allows employees some flexibility over the official office hours in order to meet the schedule of the chosen alternative mode. (4) Promotions through marketing and other methods to increase awareness of a given mode or employer incentive or to provide prizes or awards for meeting some usage challenge.

As discussed above, most support-type strategies do not translate into changes in travel time or travel cost. While the impacts of those strategies on travel behavior are important and significant, they are complementary and interactive, rather than independent, and are relatively difficult to measure. In the Federal Highway Administration (FHWA)'s TDM model, the support-type strategies are therefore estimated by categorizing them to different program levels for each employer and then associating the program level with an incremental change in the mode share of the mode to which the program is applied [FHWA, 1993]. Through a case study of thirty worksites in the Puget Sound region affected by the Washington State Commute Trip Reduction (CTR) program, Hendricks [2004] finds that management support and an effective employee transportation coordinator (ETC) are not necessary for a successful work site trip reduction program if the work site is located in an area with access to high quality public transportation and employs lower-income staff who must choose transportation cost saving over time savings and convenience. They are necessary, however, for a successful work site trip reduction program if the work site is not located in an area with access to high quality public transportation.

2.3.4 Overall Effectiveness of TDM Strategies

As discussed above, the effectiveness of TDM strategies depends on the relationship between the incentives and/or disincentives to change traveler's travel cost and/or travel time and the propensity of travelers' response in a particular travel market. Effectiveness evaluations consist of empirical studies of TDM programs using aggregate data at the regional level or disaggregate data at the individual site level.

In a study conducted by the Environmental Defense Fund on the potential effect of a comprehensive package of demand management strategies (including road pricing) on vehicle miles traveled (VMT), researchers conclude that VMT levels could be lowered to 1990 levels by the year 2000 and another 10 percent reduction is expected by the year 2010 [Replogle, 1993]. Meyers [1997] reviews several successful applications of TDM actions to reduce urban congestion and enhance mobility. It seems that these studies agree that certain financial incentives or disincentives are the key for travelers to change their travel mode or travel behavior.

The Maryland Department of Transportation adopted a Concurrency Management Systems (CMS) approach that focused on implementing a package of congestion reduction and mobility enhancement actions in targeted transportation corridors. The actions implemented include: "(a) transportation demand strategies, (b) transportation systems management strategies that consist primarily of traffic operations improvements, (c) public transit improvements, (d) highway capacity improvements, (e) high occupancy vehicle lanes, (f) measures to encourage the use of non-motorized modes, and (g) growth management and activity center strategies that related to land use and development" [ITE, 1997]. They find that the strategies that work best in the targeted corridor are road pricing and parking cost change while other strategies targeted at relatively small travel markets have relatively small effect [GAO, 1997].

In summary, this section briefly reviews the origin and development of transportation demand management and focuses on the empirical evidence on various TDM programs and strategies. Current available empirical findings on the effectiveness of TDM programs suggest that TDM strategies have potentially important effects on travel demand. It seems that those strategies aimed at changing travelers' travel cost have noticeable effect. More empirical evidence, however, is needed to estimate the effectiveness of TDM programs based on real data collected at both worksite and corridor levels over a relatively longer period.

2.4 Modeling Framework of TDM Strategies

The state-of-the-art in travel demand analysis is quite advanced. The interest in travel demand management was originally spurred by a sustained national program of new facility constructions. Before the 1970's, travel demand analysis was used to improve the ability to make choices between large capital investments in different corridors and to evaluate highway projects of different capacities and operational characteristics. As the focus of transportation planning was shifted from highway capacity increase to travel demand management, the traditionally used travel demand models are not sensitive to travel time and cost variables and to transit, walk, and bike accessibility variables. Additionally, because those models are designed to predict traffic volume, they do not require a high level of accuracy. This makes the traditionally used model even less sensitive to TDM strategies [Wachs, 1990; Johnston and Rodier, 1994]. Because of the strict modeling requirements of the Clean Air Act, some of the Metropolitan Planning Organizations are updating their travel demand models to increase their sensitivity to TDM policies.

The following models are the widely used in TDM evaluation in the United States. A brief review of the models is provided as below.

2.4.1 Washington State TDM Effectiveness Estimation Methodology (TEEM) Model

The purpose of developing this model was to produce an analytical tool that could quantify the effectiveness of TDM and land use strategies in the Central Puget Sound Region. The model was created based on local data sources and can estimate the effectiveness of 20 TDM and land use strategies at a corridor or sub-area level. Each strategy is evaluated separately using different methodologies. The combined impacts can be evaluated based on the assumption of the interaction of different strategy.

The evaluation of the combined impacts of different strategies depends on the assumption of the interaction of the strategies. There are four main categories of strategy combination. In some cases, the cumulative effect of combining most strategies can be found by sequentially predicting the effect of one, then adjusting the baseline data and applying the next one. Strategies such as these are referred to as multiplicatively additive. Other strategies, when combined, affect different markets and the results can be combined directly. These are referred to as directly additive. This could include a strategy affecting only employee trips being combined with a strategy affecting only residential non-work trips. The third type of combination is strategies that conflict in ways that are not accounted for by readjusting the base shares. These are referred to as conflicting strategies and a correction factor must be specified to be able to estimate the combined effect of both. The final category of strategy combination is referred to as synergistic. When combined, they produce greater results because of their supportive nature than a direct addition of their impacts would suggest.

TEEM is designed to apply sensitivity factors to base mode shares incrementally when more than one strategy is being tested. By readjusting the base mode shares, the methodology can accurately represent the first two types of interactions above: directly additive and multiplicatively additive. If the strategies do not interact or affect the same markets and are directly additive, then no adjustment of the predicted changes is necessary at all. If they are multiplicatively additive, the readjusting of the base mode share provides an accurate assessment of the combined affect but the individual effects cannot be identified. The order in which they are tested does not affect the results. Only the conflicting and synergistic affects are not directly accounted for in TEEM. Users of TEEM need to be aware of when such interaction may be occurring and certain adjustments need to be made [WA DOT, 2006].

2.4.2 Environmental Protection Agency (EPA) COMMUTER Model

This is a model developed by Cambridge System, Inc. for the U.S. Environmental Protection Agency (EPA). The first version of the model was released in 2000 and the model was updated in 2005. The basic objective of the model is to assess or evaluate the emission impacts of various transportation control measure strategies. The methodology and procedure of the model are based on the Federal Highway Administration's Travel Demand Management Evaluation Model (FHWA TDM model).

In the COMMUTER model, the TDM strategies are classified into four categories: employer TDM support strategies, alternative work schedule, travel time improvement, and travel cost changes. The first two categories are analyzed using relational factors in look-up tables, with a normalization procedure applied to the adjusted shares to ensure that changes are proportionate across the available alternatives and do not allow final choices to exceed 100 percent. The strategies that involve changes to either travel time or cost are analyzed through the more rigorous logit pivot-point procedure [EPA, 2006].

The COMMUTER model estimates the combined impacts of different TDM strategies by performing the calculation through a sequencing order. The order in which the COMMUTER model performs its calculations of travel changes is as follows:

- It first calculates the changes due to Alternative Work Hours. This serves to readjust the travel population baseline to determine how many trips will be shifted to the off-peak period, and how many will remain in the peak period and be subject to application and analysis of the mode-choice oriented strategies.
- Next, mode shares of the remaining peak trips are readjusted to reflect the effects of the employer TDM support strategies.
- All time and cost related strategies are tallied up and brought into the logit pivot-point procedure, which is then applied to the revised mode share starting point from step 2.

2.4.3 CUTR Worksite Trip Reduction Model

This model was developed by the Center for Urban Transportation Research (CUTR) at the University of South Florida in 2004 using data based on several thousand worksite trip reduction programs from three urban areas in the United States (Los

Angeles, Tucson, and Washington State) that have had trip reduction requirements on employers for many years. Two approaches were used for the model building process: linear statistical regression models and non-linear neural network models. The linear statistical regression models were used as a benchmark for the validity and accuracy of the neural network models. Several phases were followed to build the neural network models. Models were built for each of the three datasets using a variety of approaches of handling the data, including variable selection, grouping of incentives, and the treatment of outliers. Models were also built after combining the data from the three urban areas into a single dataset. The only model to get better results simultaneously on all three cities' validation sets was a neural network model built with no variable selection on equally sampled combined data [CUTR, 2004].

2.5 Summary

This chapter reviews the origin and development of Transportation Demand Management, followed by a discussion of various strategies implemented by TDM programs. Empirical evidence regarding each category of strategies aimed at changing travel time, travel cost and other purposes is presented. Overall evaluation of TDM strategies is also reviewed. The last part of this chapter reviews the modeling framework of TDM programs and provides a brief discussion of three leading TDM evaluation models.

CHAPTER 3 AN EMPIRICAL ANALYSIS OF COMPRESSED WORK WEEK CHOICE

3.1 Introduction

The compressed work week (CWW), one of the alternative working schedule programs designed to reduce vehicle trip rates, is the focus of this chapter. Compressed work week allows employees to work their "regular" number of hours in shorter-than-normal days per week or per pay period. For example, employees may choose four 10-hour days with one day off, or nine nine-hour days with one day off every other week [Ronen and Primps, 1981; Giuliano and Golob, 1990; Tanaboriboon, 1994; Bhattacharjee et al., 1997]. In terms of TDM, compressed work week functions to reduce the commuter's travel frequency and change the time the work trips occur. If an employee works 4 days a week, 10 hours a day, she needs to leave home earlier and leave office later. Therefore, people working on compressed work week not only reduce the number of work trips, but also shift the work trips from peak period to non-peak period.

The first CWW program was implemented in Southern California in 1982. The interest in CWW was later reinforced by two public policy implementations in California. The first one was the *1989 Air Quality Management Plan,* which proposed to reduce work trips by 30 percent by the year 2010 using CWW and other tools. The second one was Regulation XV of the South Coast Air Quality Management, which requires employers with more than 100 employees at a single work site in Los Angeles, Orange

County, and the urban areas in Riverside and San Bernardino counties to submit plans to achieve higher vehicle occupancy ratios (ranging from 1.3 to 1.75 depending on areas) and lower vehicle trip rates, thus reducing air pollution and congestion [Mokhtarian, 1991].

The states of Washington and Oregon also passed similar laws. The Commute Trip Reduction (CTR) Law was passed by the Washington State legislature and incorporated into the Washington Clean Air Act in 1991. The goals of the program are to reduce traffic congestion, air pollution, and petroleum consumption through employer-based programs that decrease the number of commute trips made by people driving alone. It calls for a statewide multimodal plan and requires all state agencies to aggressively develop substantive programs to reduce commute trips by state employees. According to the CTR laws, the state's nine most populated counties (including the cities within those counties) are required to adopt CTR ordinances and provide support for local employers in implementing CTR. Employers are required to develop a commuter program designed to achieve reductions in vehicle trips and may offer benefits such as subsidies for transit fares, compressed work schedules, telecommuting opportunities, and more. More than 1,110 worksites and more than 560,000 commuters statewide participated in the CTR Program in 2005 [Washington State Department of Transportation, 2007].

Earlier studies on the compressed work week focus on the benefits and problems associated with its implementation [Allen and Hawes, 1979; Nollen, 1981; Ronen and Primps, 1981; Wachs, 1990]. In 1993, the Federal Highway Administration (FHWA) issued FHWA TDM Evaluation Model, which provides a guideline on evaluating the impacts of CWW. This model assumes a CWW participation rate of 22 percent for eligible office employees [Federal Highway Administration, 1993]. More recent studies focus on the impact of CWW on vehicle trip reductions [Barton-Aschman and Associates, 1981; Giuliano and Golob, 1990; Hung, 1996] and individual activity travel patterns [Sundo and Fujii, 2005].

Given the options of CWW from employers, what are the factors that determine commuters' decision to take the CWW is an important question that remains unanswered. This chapter identifies those factors that influence a commuter' choices of whether they participate in CWW or not. This chapter also analyzes the trend and participating rate based on a large sample. This study may help policy makers evaluate the effectiveness of TDM strategies and choose the most efficient ways to cut trip rates. The results from this study also have important applications in regional travel demand forecasting. By incorporating CWW into those models, their predictability of trip rates can be improved.

Analysis of the employee commute travel behavior survey data from 1993 to 2005 indicates that for the employees affected by the CTR program, the participation rate in CWW increased steadily from 14.5 percent in 1993 to more than 20 percent in 2005. While the major pattern of CWW is still working four days for 40 hours per week (4/40) (7.3 percent in 2005), the percentage of employees working for nine days at 80 hours per two weeks (9/80) doubled from 2.9 percent to 5.85 percent from 1993 to 2005.

To identify the factors that determine commuters' choice of CWW, I first apply a multinomial logit (MNL) model based on the 2005 data from the Washington State CTR database to estimate the employees work schedules choices. I find that an employer's promotion level of TDM programs is one of the key determinants of a commuter's choice to become involved in CWW. Commuters are more likely to participate in CWW programs the more that employers support and promote it. I also find that the number of CWW program years, a measure of how long the CWW program has been implemented, has a positive but not constant effect on CWW choices. Distance from home to work is another key factor that influences a commuter's decision about CWW. The longer the distance from home to work, the higher the probability that the employee will choose alternative work schedules. Employees' mode choices of the journey-to-work affect their choices of working on CWW schedules. Commuters using a single mode of transit and a shared ride are less likely to work on CWW schedules than those who simply drive alone to work, while commuters using mixed modes are more likely to work on a CWW schedule than those who drive alone. Additionally, employees' decisions to participate in CWW programs are also affected by their job titles and their employer's major business types.

To further examine the technical feasibility of the model, an ordered logit model is estimated based on the sub-sample of the employees with full options of work schedules and the results are compared with that of the MNL model. Overall, the results from the ordered logit model are consistent with the major findings from the MNL model.

The rest of this chapter is organized as follows. Section 2 introduces the dataset. Section 3 provides a brief descriptive analysis of participation rate trend of CWW. Section 4 presents the discussion of the determinants of the employee's work schedule choice. Section 5 presents the multinomial logit modeling of the CWW choice, including methodology, model specification, and discussion of the main results. Section 6 present the results of the ordered logit model. Section 7 presents the conclusion.

3.2 Data

The Washington State Commute Trip Reduction (CTR) program is an employer-based regional Transportation Demand Management (TDM) effort initiated in Washington State in 1991. The CTR law requires employers to implement programs that encourage alternatives to drive-alone commuting to their worksites. The CTR Law applies to all employers with 100 or more full-time employees arriving at work between 6:00 and 9:00 a.m. located in a county with a population greater than 150,000. By 2005, more than 560,000 employees working for more than 1100 worksites living in nine counties in Washington State were affected by this law. Employers affected by the CTR law are required to submit an Employer Annual Report & Program Description form to report the summary information on the programs they implemented. The affected employers are also required to measure employee commute behavior every two years to measure their progress toward their CTR goals.

The data are from the Washington State CTR Database. This database is designed to systematically organize and store the information collected in the Washington State CTR annual employer reports and biennial employee commute travel behavior survey conducted by the Washington State Department of Transportation. The employer annual report provides detailed information on employer's characteristics and the TDM programs implemented by the employer, such as:

- Worksite and employer information, including the organization name, worksite street address, Employer Transportation Coordinator's (ETC) information, total number of employees, total number of affected employees, business type, etc.

- Program promotion information, including list of CTR programs implemented or promoted by the employer, such as distribute CTR summary information, conduct transportation events, publish CTR articles, etc.
- Worksite characteristics, including the information of the accessibility the worksite has to a list of facilities, such as bus stops, shopping, child care, etc.
- Worksite parking information and parking management, including the total number of onsite/offsite parking spaces, parking charge for solo and HOV driver, availability of reserved/preferential HOV parking spaces, etc.
- Financial incentive and subsidies, including incentives/subsidies for transit, vanpool, carpool, walking, bicycling, etc.
- Site amenities, including the availability of covered/uncovered bicycle spaces/racks/lockers/cages, clothes lockers, showers, etc.
- Work schedule policy, including the availability (allowance) of compressed work week, telecommuting, and flexible work hours
- Other TDM programs availability. Include the availability of guaranteed/emergency ride home program, internal match service, etc.

The employee biennial commute travel behavior survey collects detailed information on employees' commuting travel behavior, such as:

- Work schedule
- Commute modal choice, including driving alone, carpool, vanpool, transit, motorcycle, walking, and bicycling
- Commute distance, including one way distance from home to worksite in miles

- Compress work week schedule, including work schedule of 5/40, 4/40, 3/36, 9/80, 7/80
- Telecommuting schedule, including the days regularly telecommuting per two weeks
- Job title
- Home zip code

The Washington State CTR database contains employers' data from 1995 to 2005 and employees' data for 1993, 1995, 1997, 1999, 2001, 2003, and 2005.

The Washington State CTR database is the only dataset that provides detailed information on TDM strategies and the corresponding employee commute travel behavior over time for tens of thousands of employees. According to the annual report issued by the Washington Department of Transportation on CTR law implementation, the coordinator in each worksite randomly send paper surveys to the employees every two years. The target response rate is 70 percent. The data analysis indicates that although the response rate varies, the overall response rate was as high as 77 percent in 2005. Among the total of 1100 worksites, more than 50 percent has a response rate above 80 percent. The total valid number of individual respondents is more than 200,000. Therefore, it is reasonable to believe the sample is representative of the population affected by the CTR laws. The relationship revealed between the explanatory variables and the CWW choices are also considered as reliable.

3.3 CWW Participation Trend for the Employees Affected by the WA CTR Laws

In this section, I provide a brief descriptive analysis of the CWW participation trend for the commuters affected by the Washington CTR programs from 1993 to 2005.

The results from this analysis may be used directly to evaluate the effectiveness of TDM strategies and help decision makers choose the most efficient ways to cut trips rates based on the primary business type of the employer and the job title of the employee.

The CWW participation rate, as shown in table 3.1, increased steadily from 14.5 percent in 1993 to about 20 percent in 2005. While the major pattern of CWW is still working four days 40 hours per week (4/40), the percentage of employees working on 9/80 (nine days 80 hours every two weeks) doubled from 2.9 percent in 1993 to 5.85 percent in 2005. The percentages of employees working on 3/36 (three days 36 hours per week), 7/80 (seven days 80 hour for very two weeks), and other CWW schedules have relatively slight increase or remain stable from 1993 to 2005. This may suggest that the options of 3/36, 7/80, and other CWW schedules are more jobs related. In other words, people working on 3/36, 7/80 and other CWW schedules are more likely to choose those schedules because of their job characteristics. For example, the regular work schedule of a firefighter consists of two 24-hour days per week, for an average of 8 days per month. The regular work schedule for a hospital nurse is three days 36 hours per week. For an average employee, the actual possible options of CWW schedules are 4/40 and 9/80.

Table 3.1 Percent of Employees by Work Schedule from 1993 to 2005

Program Year	Num of Employees	Percent of Employees by Work Schedules (%)					
		5/40	3/36	4/40	7/80	9/80	Other
1993	188714	85.53	1.82	6.30	0.66	2.90	2.78
1995	204832	83.47	1.73	7.64	0.75	3.64	2.77
1997	256510	81.53	2.35	7.99	0.95	4.15	3.03
1999	238113	82.87	2.07	8.06	0.63	3.55	2.82
2001	246322	82.01	2.16	9.39	0.78	3.51	2.14
2003	247239	80.87	2.50	8.10	0.61	4.94	2.99
2005	273957	79.97	2.29	7.34	0.66	5.85	3.89

In terms of job title, on average from 1993 to 2005, 17.2 percent of the sample is administrative support, 13.5 percent is craft/production/labor, 15 percent is management, 4 percent is sales/marketing, 6.9 percent is customer service, 35 percent is professional/technical, and around 8 percent is the other. For all job categories, CWW program participation rate has been steadily increasing. The employees with job title of craft/production/labor, professional/technical, and the other have the highest percentage of working on CWW schedules. Over the 12-year period from 1993 to 2005, the growth rate for participation of CWW schedule programs ranged from 14 percent to 57 percent, representing annual increase rate of 1.2 percent to 4.7 percent. The percentages of employees work on CWW schedules by job title from 1993 to 2005 are reported in Table 3.2.

Table 3.2 Participation Rate for CWW by Job Title from 1993 to 2005

Job Title	Avg. Num of Employees		Percent of Employees on Compressed Work Week (%)						
	N	%	1993	1995	1997	1999	2001	2003	2005
Administrative Support	32052	17.15	9.35	10.88	11.62	10.50	11.86	12.66	14.25
Craft/Production/Labor	25135	13.45	15.28	20.14	22.73	22.81	23.19	22.27	23.94
Management	27983	14.97	7.77	9.78	10.68	9.38	10.18	10.45	11.73
Sales/Marketing	7459	3.99	6.91	8.21	8.73	6.69	7.43	7.04	9.79
Customer Service	12799	6.85	13.33	13.91	15.25	12.75	15.48	16.09	17.46
Professional/Technical	66337	35.49	18.97	21.34	23.39	21.68	22.15	24.54	23.84
Other	15156	8.11	21.02	20.73	22.00	19.04	17.64	20.95	24.00

In terms of primary business type of the employer, on average from 1993 to 2005, around 19.9 percent of the sample works for government, 17.7 percent works for manufacturing, 14.3 percent works for health care, and 9.4 percent works for financial service industry. All other business types have lower than 10 percent of the sample size. For all of the business types with large sample size, the employees work for health care have the highest percentage of working on CWW schedules, 33.6 percent in 2005. The employees work for manufacturing have highest growth of participation rate, more than doubled from 10.8 percent in 1993 to 22.7 percent in 2005. The only business type that experienced a decrease in CWW participation rate is retail/trade. The participation rates of CWW by major business type from 1993 to 2005 are presented in Table 3.3.

The participation rates for each work schedule by job title and by primary business type for the year 2005 are reported in Table 3.4 and Table 3.5 respectively

Table 3.3 Percent of Employees on CWW by Employer Primary Business Type from 1993 to 2005

Primary Business	Avg. Num of Employees		Percent of Employees on Compressed Work Week (%)						
	N	%	1993	1995	1997	1999	2001	2003	2005
Agriculture, Forestry, Fishing, Mining	775	0.45	7.59	14.04	9.04	7.64	10.66	3.21	9.45
Finance, Insurance, Real estate	14632	9.38	5.40	5.79	6.65	8.25	10.51	11.17	9.90
Information Services/ Software/ Technical	11577	7.42	3.66	9.17	17.85	6.89	6.51	5.36	5.51
Professional/ Personal Services	8174	5.24	6.76	7.95	8.73	9.25	9.99	10.14	11.72
Retail/Trade	6796	4.36	11.1	11.87	9.28	7.26	7.45	6.63	7.96
Manufacturing	27540	17.66	10.76	15.07	18.36	19.12	21.22	22.66	24.29
Health Care	20413	14.28	26.33	27.46	29.16	30.80	29.82	30.79	33.61
Public Utility	7092	4.55	11.77	8.82	11.79	9.67	9.70	12.22	13.48
Military	11639	7.46	17.99	22.47	21.35	16.56	13.89	17.11	19.71
Construction	259	0.17	39.81	51.69	35.63	12.46	17.80	18.07	12.97
Transportation	3343	2.14	15.39	14.1	14.7	17.6	26.1	25.75	26.51
Government	28428	19.89	16.14	21.04	23.59	23.27	24.33	26.19	28.07
Education	5302	3.40	7.30	8.25	9.94	12.15	11.79	13.76	14.89
Other	5602	3.59	14.20	14.57	13.72	14.32	13.59	10.61	10.77

Table 3.4 Participation Rate for Each Work Schedule by Job Title in 2005

Job title	Num of Employees		Percent of Employees by Work Schedules (%)					
	N	%	5/40	3/36	4/40	7/80	9/80	Other
Administrative support	33718	13.09	85.75	1.95	4.67	0.33	4.89	2.41
Craft/Production/Labor	26582	10.32	76.06	1.34	13.35	1.14	4.17	3.94
Management	34644	13.45	88.27	0.78	3.60	0.27	4.79	2.30
Sales/Marketing	9179	3.56	90.21	1.50	2.35	0.58	2.93	2.43
Customer service	21640	8.40	82.54	2.28	7.17	0.67	4.43	2.91
Professional/Technical	115039	44.66	76.16	2.92	8.05	0.76	7.46	4.65
Other	16769	6.51	76.00	3.27	7.96	0.82	5.02	6.93

Table 3.5 Participation Rate for Each Work Schedule by Primary Business Type in 2005

Primary Business	Num of Employees		Percent of Employees by Work Schedules (%)					
	N	%	5/40	3/36	4/40	7/80	9/80	Other
Agriculture, Forestry, Fishing, Mining	1228	0.51	90.55	0.49	4.80	0.33	2.12	1.71
Finance, Insurance, Real estate	23783	9.79	90.10	1.19	4.16	0.13	2.83	1.59
Information Services/ Software/Technical	24644	10.14	94.49	0.66	2.02	0.13	0.72	1.98
Professional/ Personal services	14467	5.95	88.28	1.61	3.61	0.35	3.35	2.81
Retail/Trade	12196	5.02	92.04	0.72	2.57	0.20	2.55	1.92
Manufacturing	39393	16.21	75.71	1.01	11.30	0.78	5.59	5.61
Health Care	32919	13.55	66.39	8.73	8.62	2.20	6.35	7.72
Public Utility	7944	3.27	86.52	0.77	8.13	0.39	2.51	1.69
Military	9781	4.02	80.29	0.48	2.86	0.76	11.50	4.11
Construction	563	0.23	87.03	0.53	8.17	0	2.66	1.60
Transportation	5813	2.39	73.49	3.91	12.42	0.58	6.26	3.34
Government	51229	21.08	71.93	1.81	10.95	0.57	11.74	3.01
Education	10190	4.19	85.11	2.16	4.75	0.42	2.41	5.14
Other	8879	3.65	89.23	0.83	4.14	0.27	2.77	2.75

3.4 Determinants of Employee's Work Schedule Choice

There is no previous theoretical model or empirical work discussing the drive or constraints for CWW choices. Mokhtarian and Salomon (1994), however, presents a conceptual framework for modeling telecommuting choices, which I believe may also suitable for modeling the work schedule choice. Following this guideline, the determinants that affect commuter's choice of telecommuting would include (1) the commuter's job characteristics, (2) the commuter's journey-to-work travel characteristics, (3) the commuter's socio-demographic characteristics, (4) the attitudes of the employer towards CWW, and (5) the commuter's personal preference.

For employees working on certain type of jobs or for certain type of employers, working on compressed work schedules is mandatory rather than optional. For example, the regular work schedule for a hospital nurse is three days 36 hours per week. One of the typical work schedules for fire fighters is working three cycles of 24 hours on duty and 24 hours off duty followed by a 96-hour off period year round including weekends and holidays. Most emergency medical responders work a fixed 12-hour schedule, but some of them are assigned to a 24-hour on duty, 48-hour off duty schedule. An analysis of WA CTR data shows that, even for average employees, the participation rates of CWW vary dramatically for employees work on different jobs and/or for different industries.

It is highly expected that the longer the distance from home to work, the higher the probability that employee will choose alternative work schedules. The commuter's travel pattern, specifically the mode choice, is expected to affect the commuter's choice of CWW as well. The commuters' work schedule choices affect not only the frequency of the home-based work trip, but also the time at which the travel occurs. The employees working on compressed work week have to leave home earlier and leave the office later every workday. This may make the transit and shared-ride options less attractive, especially for those working on 3/36 and other CWW schedules.

The personal or family characteristics may also affect the employee's CWW choice. Because working on compressed work week leads to leaving home earlier and leaving the office later every workday, CWW may less attractive to employees that are responsible for taking care of a family. For the same reason, people from a family with young children may be less likely to work CWW.

The other important factor that directly affects the adoption of CWW is the supportiveness of employer. Whether the CWW is "encouraged", or it is only "allowed" is expected to play a significant role for commuters to make the decision whether to participate in CWW or not.

3.5 Multinomial Logit Modeling of Work Schedule Choices

The ultimate goal of this part of study is to develop and estimate a model that can be used to forecast the possibility of working on CWW schedules of an employee based on the characteristics of the employee and employer. This model can then be used to predict the number of employees work on different schedules at the levels of worksite or traffic analysis zone (TAZ). This model, built on a large sample, therefore, can not only be used to predict or evaluate the impact of a TDM program, but will also be able to used to improve the accuracy of the travel demand forecasting for a regional transportation model.

3.5.1 Methodology

The discrepancies of the work schedule for different employees are essentially the results of choice making from a set of mutually exclusive and collectively exhaustive alternatives. The theoretical framework that underpins the modeling of the choice made among or between a set of mutually exclusive options is random utility model [McFadden, 1973]. The decision maker is assumed to maximize her utility by evaluating the attributes associated with each of alternatives. The choice made by the decision-maker is determined by his preferences, attributes of alternatives, and other constrains. In the random utility model, each individual's utility for each choice is a function of observed influences and random influences. For example, individual *i*'s utility from choice *j* can be expressed as

$$U_{ij} = x_i' b_j + v_{ij} \tag{4.1}$$

where x is the vector of observed attributes and individual characteristics influencing choice for each option, and v_{ij} represents relevant but unobserved influences. Individual *i* choose option *j* if $U_{ij} > U_{ik}$ for all $k \neq j$. Under the three assumptions: (1) v_{ij} is independently distributed, (2) v_{ij} is identically distributed, and (3) v_{ij} is Gumbel-distributed with a location parameter η and a scale parameter λ, the probability of individual *i* choose option *j* is given by

$$P_{ij} = \frac{e^{\lambda x_i' b_j}}{\sum_j e^{\lambda x_i' b_j}} \tag{4.2}$$

The model is normalized by setting the coefficients of base option to be zero to remove the indeterminacy of the model [Greene, 2000]. The log-odds ratio is given by

$$\ln(P_i / P_{Base}) = x_i' b_j. \tag{4.3}$$

3.5.2 Model Specification

I used the 2005 employee data to estimate the logit model of CWW choices. The choice set includes: (1) working 5 days for 40 hours per week, denoted as 5/40, (2) working 3 days for 36 hours per week, denoted as 3/36, (3) working 4 days for 40 hours per week, denoted as 4/40, (4) working 9 days for 80 hours every two weeks, denoted as 9/80, (5) other CWW schedules, denoted as other.

The observed influences in the model included those variables available from both employer and employee surveys. From the employee survey, I used three variables, including commute distance from home to work, employee's job title, and employee's journey-to-work mode choice, to capture individual differences. The commute distance from home to work measures the one-way distance from an employee's home to his or her usual work site, including miles for errands or stops made daily on the way to work.

The employee's journey-to-work mode choice was divided into the single mode of driving alone, transit, shared rides, and mixed modes. WA CTR data report seven job titles: administrative support, craft/production/labor, management, sales/marketing, customer service, professional/technical, and other. Thus, I created seven dummy variables to reflect an individual's job title.

Four groups of variables were from the employer survey: business type, employer's TDM program promotion level, number of CWW program years, and the existence of multiple shifts at a worksite. 10 dummy variables were created to reflect the primary business of the employer: finance/real estate/insurance, information service or software, professional/personal service, retail/trade, manufacturing, health care, transportation, government, education, and other. Employer's TDM promotion level is an index used to measure the supportiveness of employers on employee's choice of TDM programs, and more specifically in this case, the choice of CWW schedules. This index was constructed to reflect the overall implementation of TDM strategies.

The number of CWW program years, defined as the number of years the CWW program has been implemented since 1995, was used to capture the effect of time on CWW choices. The effect of this variable was expected to be positive since it takes time for employees to understand the benefits of CWW programs and make transitions accordingly. The time effects were also expected to be not constant. Therefore, I created 11 dummy variables to reflect the number of years that had passed since the initial implementation of CWW programs. If a worksite started the CWW programs in 2005, the number of years would be zero, which is the base value for this variable and excluded from the regression. The last control variable is the existence of multiple shifts, a dummy variable reflecting whether a worksite requires multiple shifts. The detailed definitions of selected variables are presented in Table 3.6 (other variables are self-explanatory, therefore not reported).

TABLE 3.6 Selected Variable Definitions

Variable	Definition
Distance	One way distance in mile commute from home to work location
Shift	Does this worksite have multiple shifts? Shift=1, if Yes; Shift=0, Otherwise
Drive alone	=1, if drives alone to work for the whole week =0, otherwise
Transit	=1, if takes public transit to work for the whole week =0, otherwise
Shared rides	=1, if carpools or vanpools to work for the whole week =0, otherwise
Mixed modes	=1, if takes at least two different modes to work for the whole week =0, otherwise
Promotion Level	Employer TDM program promotion level =0, No CTR promotion =1, Post CTR promotional materials for employees, OR provide information about the worksite CTR program during new employee orientations or in hiring packets =2, All the above, PLUS: Conduct transportation events/fairs and/or participate in county/state CTR promotions/campaigns, OR send electronic mail messages about the CTR program =3, All the above, PLUS: Publish CTR articles in employee newsletters =4, All the above, PLUS: Distribute CTR information with employee paycheck

In 2005, there were about 273,000 valid observations from the employee commute travel behavior survey. There was, however, inconsistency about the availability of the CWW schedules between what was reported by employers and the choices made by employees. For example, for a certain worksite, an employer reported that no CWW program was available, while certain employees indicated they were on one of the CWW schedules. To determine the actual availability of each of the CWW options, I calculated the total number of employees working on each of the work schedules for each worksite based on the employee survey data. The results of this calculation were then compared with the information provided in the employer survey. For each of the CWW schedules, if the number of employees working on a particular CWW schedule was zero and the employer reported that this CWW schedule was not allowed, I assumed it was not available for all the employees working for this employer. Based on the results of this procedure, if none of the CWW schedules were allowed at the worksites, all of the observations (employees) working for this employer were excluded from the sample. The final sample size was 181,009.

3.5.3 Regression Results

The model was estimated based on 2005 sample. The results of multinomial logit regression model are presented in Table 3.7. Columns 2 to 5 report the coefficients for the CWW schedules of 4/40, 3/36, 9/80, and other. The base is the regular schedule of 5/40. The value of the log likelihood function at its maximum, *Log-L(β)*, is -102,164.4. The *R-Squared*, an informal goodness-of-fit index (reported by *LIMDEP*, the software I use to run the regression) that measures the fraction of an initial log likelihood value explained by the model, defined as *1-Log-L(β)/Log-L(0),* is 0.5614. The chi-square, a statistic used to test the null hypothesis that all the parameters are zero, defined as -*2(Log-L(0)- Log-L(β)),* is 277,23.02, which indicates that I can reject the null hypothesis that all the parameters are zero at the level of 0.001 or better.

Examining the coefficients in the models for the choices of CWW, it was first observed that the constant terms for the choices of 3/36, 4/40, 9/80, and other were all negative, suggesting that the average effect of those unobserved influence variables was in the direction of not participating in CWW. This was expected since around 80 percent of employees in the sample chose the regular schedule when they had the option to participate in the CWW program in 2005.

The coefficients of the one-way distance from home to work for all the choices of CWW schedules were positive and statistically significant at the level of 0.01 or better. This result suggests that all other things being equal, commuters have a higher probability to choose participating in CWW when the home-to-work distance is longer.

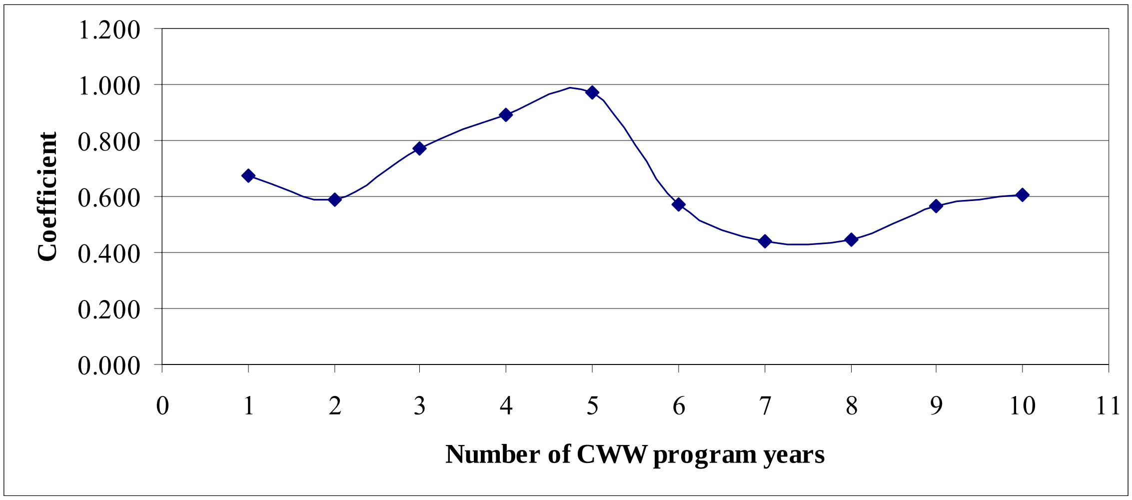
The coefficients of TDM promotion level for all the choices listed in the model were positive and statistically significant at the level of 0.01 or better. This finding suggests that employer's support of TDM strategies plays a very important role in commuters' choice of compressed work week schedules. As discussed above, the TDM program promotion is not specifically for the CWW promotion but for the whole TDM program. For CWW, the index of the employer TDM program promotion may be more likely to serve as the reflection of the attitude of the employer toward the employee's participation in CWW. In other words, this result shows that whether the CWW is "encouraged" or it is only "allowed" does matter for commuters trying to make the decision whether to participate in CWW or not. It also shows that the coefficient for the TDM promotion level in the utility of 4/40 is greater than the one for 9/80, which in turn, is greater than the one for 3/36. This means that increasing the TDM promotion level is associated with an increased preference for 4/40 and 9/80 compared with 3/36. This may again support the expectation that the 3/36 schedule is more job characteristics related, and therefore is less likely to be impacted by the employer's TDM promotion.

The coefficients of transit and shared ride were all negative and significant for all of the CWW choice categories at the level of 0.1 or better. This finding suggests that, compared with those who drive alone, people taking transit or carpooling or vanpooling are less likely to work on CWW schedules. It also shows that the coefficients of 3/36 and other are greater than those of 4/40 and 9/80. This suggests that among the CWW schedules, transit-commuters or carpoolers or vanpoolers are less likely to work on 3/36 than other CWW schedules. The commuters' work schedule choices affect not only the frequency of the home-based work trip, but also the time at which the travel occurs. The employees working on compressed work week have to leave home earlier and leave the office later every workday. This may make the transit and shared-ride options less attractive, especially for those working on 3/36 and other CWW schedules. It is interesting to see that the employees using mixed modes are more likely to work on CWW schedules compared with those who drive alone.

The coefficients of the number of CWW program years were all positive and statistically significant at the level of 0.01 or better. The non-constant coefficients also confirm the expectation that the time effect on CWW choices is not equal. Figure 3.1 illustrates the time effect, suggesting that CWW program implementation has increasing effect on CWW choices until it reaches its peak in year five. After year five, its marginal effect falls until year eight, after which, its marginal effect goes flat. It seems that CWW programs have larger effects during the first five years. This finding suggests that when evaluating the impacts of CWW on person trip reductions, how long the CWW programs have been implemented should be incorporated and their effects should not be the same.

The coefficients of multiple shifts for all the choices were positive and statistically significant at the level of 0.001 or better. This variable controls the characteristics that cannot be captured by job title and business type.

Figure 3.1 CWW Program Year Effect on CWW Choices



There are six dummy job title variables used in the regression. For those individuals who worked as administrative staff and managers, the coefficients were consistently negative and statistically significant, suggesting that commuters working under the above mentioned job title have a lower likelihood of choosing alternative work schedules than choosing a regular schedule compared with those with other job titles. This is not surprising considering their job characteristics. Managers supervise other people's work. When they are not around, some decisions may not be made on time and performance of other members under supervision may not be consistent, which may lower the overall efficiency of the worksite. Employees working as administrative support provide supportive work for managers. It is expected to see supporting staff work the same schedule as managers. This suggests that when Employer Transportation Coordinators (ETCs) at each worksite decide which programs to implement, they may consider the restrictions of job characteristics to improve the effectiveness of the programs they implement.

TABLE 3.7 Empirical Results for CWW Choices

Variable	3/36[a, b]	4/40[a,b]	9/80[a,b]	Other [a,b]
Constant	-6.257*** (36.0)	-4.503*** (38.8)	-4.148*** (35.0)	-4.437*** (34.7)
Distance	0.007*** (5.1)	0.011*** (14.7)	0.005*** (5.9)	0.003*** (3.0)
Promotion Level	0.117*** (4.5)	0.138*** (8.9)	0.127*** (7.5)	0.138*** (6.9)
Shift	0.405*** (6.8)	0.357*** (11.9)	0.365*** (12.2)	0.602*** (13.8)
Transit	-1.438*** (8.9)	-0.469*** (8.4)	-0.296*** (6.2)	-0.989*** (11.7)
Shared Ride	-1.185*** (8.6)	-0.130*** (3.1)	-0.073* (1.8)	-0.837*** (12.3)
Mixed Modes	1.782*** (46.1)	1.455*** (65.0)	0.720*** (27.6)	0.906*** (31.7)
Administrative Support	-0.484*** (6.0)	-0.521*** (10.0)	-0.143** (2.5)	-1.054*** (17.3)
Production/Labor	-0.091 (1.0)	0.576*** (11.9)	-0.248*** (3.9)	-0.572*** (9.5)
Management	-1.385*** (13.5)	-0.854*** (15.6)	-0.225*** (3.9)	-1.187*** (19.3)
Sales/Marketing	-0.335** (2.3)	-0.990*** (9.0)	-0.207** (2.1)	-0.776*** (7.5)
Customer Service	-0.309*** (3.6)	-0.058 (1.1)	-0.173*** (2.7)	-0.716*** (11.1)
Professional/Technical	0.070 (1.1)	0.122*** (2.9)	0.479*** (9.8)	-0.262*** (5.9)
Finance/Real Estate/Insurance	0.484*** (3.8)	-0.143** (2.6)	-0.741*** (12.4)	-0.493*** (6.2)
Information Service/Software	-0.359** (2.2)	-0.970*** (12.3)	-2.156*** (19.5)	-0.374*** (4.3)
Personal Service	0.984*** (7.3)	-0.202*** (2.9)	-0.431*** (6.3)	0.207** (2.5)
Retail/Trade	0.125 (0.7)	-0.412*** (5.1)	-0.659*** (8.1)	-0.152 (1.6)
Manufacturing	1.250*** (10.2)	0.925*** (20.9)	0.160*** (3.5)	0.936*** (16.3)
Health Care	2.198*** (20.3)	0.418*** (8.8)	-0.065 (1.4)	1.079*** (19.0)
Transportation	1.637*** (11.5)	0.529*** (7.3)	-0.306*** (3.2)	0.255** (2.4)
Government	1.121*** (10.0)	0.926*** (21.7)	0.798*** (19.9)	0.413*** (7.1)
Education	0.919*** (6.8)	-0.133* (1.9)	-1.062*** (11.7)	0.547*** (7.3)
CWW Year 1	0.675*** (6.9)			
CWW Year 2	0.590*** (6.1)			
CWW Year 3	0.770*** (8.2)			
CWW Year 4	0.890*** (9.1)			
CWW Year 5	0.974*** (10.1)			
CWW Year 6	0.572*** (5.3)			
CWW Year 7	0.438*** (4.5)			
CWW Year 8	0.445*** (4.7)			
CWW Year 9	0.565*** (6.1)			
CWW Year 10	0.604*** (6.5)			
N(R-Squared)	181,009 (0.5614)			
Log-L	-102164.4			
Chi-squared[94]	27723.02***			

[a] absolute value of z-statistics in parentheses.
[b] *2-tail significance at α = 0.10. **2-tail significance at α = 0.05. ***2-tail significance at α = 0.01.

There were nine business type variables used in the regression. The coefficients of information service/software were consistently negative, while those of manufacturing and government were consistently positive. Other business types had coefficients with mixed signs.

The coefficients of information service/software were negative and statistically significant at the level of 0.01 or better. This suggests that employees working for the information service industry, compared with people working in other business types, are less likely to choose alternative work schedules. A possible explanation for this finding may be that information service commuters are more likely to choose other TDM programs such as telecommuting since their jobs may be done at home or other locations close to their home. A data analysis using the WA CTR database confirms that, overall, 15 percent of commuters in this industry choose telecommuting at least one day per week compared with the average of less than 6 percent.

The coefficients of manufacturing were positive and statistically significant at the level of 0.01 or better on all CWW work schedules. This result suggests that people working in manufacturing have a higher probability of choosing alternative work schedules. This also implies that, for manufacturing employers, among the TDM programs that are aimed at reducing journey-to-work person trips, a CWW program may be a very effective method since manufacturing employees are more likely to be required to physically work at their worksites.

The coefficients on health care were positive and statistically significant at the level of 0.01 or better for the choice of 3/36, 4/40, and other CWW schedules, which suggests that employees working in the health care industry have a higher probability of choosing alternative compressed work schedules of 3/36, 4/40, and other schedules, compared with other business types. It also shows that the coefficient of 3/36 is greater than that of other and 4/40, which means among the CWW schedules, they are more likely to choose 3/36. As discussed above, in the health care industry, employees such as registered nurses are required to work the 3/36 schedule. The result captures this requirement. In the model, I only focus on the commuter's actual choices since I am not able to tell whether a commuter's choice of CWW is required by the employer or selected discretionally by the employee.

From the above analysis, it is reasonable to conclude that overall, an employee's job title and an employer's major business type are important determinants of an employee's decision about CWW. For certain business types, such as manufacturing, health care, and transportation, since their employees are more likely to be required to physically work at their worksites, CWW could be a very effective way to reduce person trip rates. For an industry like information service/software, since the jobs can be done at home or other places rather than a worksite, telecommuting may be a better program to reduce journey-to-work person trips.

As a final check on the analysis, I estimate the model using 80 percent of the 2005 sample and test the predictability of the model using the 20 percent of excluded sample. By comparing the predicted probability with the survey result, I feel confident that the model is able to predict the choices about CWW fairly well. The model predicts that 21.11 percent of employees would participate in CWW in 2005, 0.68 percent lower than the survey results. The prediction for 9/80 is 6.34 percent, while the survey result is 6.72. For all of the other CWW choices, the difference between model prediction and survey results are less than 0.15 percent.

The coefficients obtained from the multinomial regression were then applied to the 2003 survey data to predict the likelihood for CWW choices. Overall, I predicted that around 19.89 percent of employees who have the option chose CWW, compared with the survey result of 20.97 percent, which is very close. The model, however, over-predicts the choice of 9/80 and under-predicts the choice of 4/40. These differences are expected as a result of different datasets and changing CWW participation trends. As shown in Table 1, from 1993 to 2001, 4/40 had been the most popular CWW choice. After 2001, however, the choice of 9/80 had increased from 3.5 percent to 5.9 percent, while the participation rate for 4/40 decreased from 9.4 percent to 7.3 percent. Using 2003 data may not capture this trend accurately. Overall, I believe the model's predictability is satisfactory and the coefficients obtained from the regression may be incorporated to regional travel demand models for future trip rate forecasting. A Detailed comparison is reported in Table 3.8.

TABLE 3.8 Comparisons of the Model Predictions and Survey Results

CWW schedule	Average Compressed Work Week Percentage (%)			
	Program Year 2005*		Program Year 2003**	
	Model	Survey	Model	Survey
3/36	2.34	2.38	2.30	2.60
4/40	7.96	8.09	7.61	9.02
9/80	6.34	6.72	5.73	5.68
Other	4.47	4.60	4.25	3.66
Total CWW	21.11	21.79	19.89	20.97

*Based on the 20 percent of 2005 sample that is excluded from the model estimation
**Based on all of the 2003 sample

3.6 Ordered Logit Modeling of Work Schedule Choices

There are arguments, however, that the employee's choice of work schedules, including working 6 days (3/36), 7 days (7/80), 8 days (4/40), 9 days (9/80), and 10 days (regular hours) per two weeks, is ordinal discrete choice. For ordinal dependent variable, the appropriate model is ordered logit or probit regression. Differs from the multinomial logit model, which based on the random utility theory, in the ordered logit or probit model, the ordinal choice variable is assumed as the discrete realizations of an underlying, unobserved (or latent) continuous random variable (The detailed introduction about the ordered logit model is included in chapter 4). The choice set for each of the alternatives for the ordinal logtit or probit model, therefore, is fixed. This constitutes the major drawback for its application in modeling employee's work schedule choice, since most of the employees do not have the full options of the work schedules (less than 10 percent of CTR affected employees have the full options of compressed work week schedules).

To further examine the technical feasibility of the model, an ordered logit model is estimated based on the sub-sample of the employees with full options of work schedules and the results are compared with that of the MNL model. The regression results of the ordered logit model are reported in table 3.9.

The coefficients of commute distance, TDM promotion level, and the existence of multiple shifts are all positive and significant at the confidential level of 99 percent of better. These findings suggest that the longer commute distance, higher TDM promotion level, and the existence of multiple shifts at the worksite are likely to increase the possibilities the employee make the transition from working on regular hours to working on CWW and from working more days to working less days per two weeks (from 9/80 to 4/40 to 3/36). The coefficients for transit and shared ride are negative, for mixed modes is positive, while all of them are significant at the confidential level of 99 percent of better. Once again, it indicates that, compared with driving alone, the people using the single mode of transit and shared ride are less likely to work on CWW, while those using the mixed modes are more likely to work on CWW.

Although the interpretation of the coefficients of the ordered logit model is different from that of the multiple logit model, overall, we can still see that the results from the ordered logit model are consistent with the major findings from the MNL model.

Table 3.9 Ordered Logit Model for CWW Choices

Variable	Coefficient	z-statistics
Distance	0.009***	15.22
Promotion Level	0.118***	10.65
Shift	0.397***	18.38
Transit	-0.421***	-12.14
Shared Ride	-0.192***	-6.54
Mixed Modes	1.312***	81.81
Job title-Administration Support	-0.411***	-11.81
Job title-Production/Labor	0.387***	10.65
Job title-Management	-0.683***	-18.82
Job title-Sales/Marketing	-0.580***	-8.81
Job title-Customer Service	-0.179***	-4.83
Job title-Professional/Technical	0.240***	8.3
Business type-Finance/Real Estate/Insurance	-0.304***	-7.81
Business type-Information Service/Software	-1.479***	-23.14
Business type-Personal Service	-0.088*	-1.89
Business type-Retail/Trade	-0.588***	-10.04
Business type-Manufacturing	0.960***	27.68
Business type-Health Care	0.771***	24.75
Business type-Transportation	0.649***	12.03
Business type-Government	0.803***	27.26
Business type-Education	-0.220***	-4.51
Tele Year 1	0.450***	3.3
Tele Year 2	0.452***	3.36
Tele Year 3	0.463***	3.51
Tele Year 4	0.791***	5.89
Tele Year 5	0.770***	5.75
Tele Year 6	0.362**	2.54
Tele Year 7	0.345***	2.56
Tele Year 8	0.141	1.06
Tele Year 9	0.403***	3.07
Tele Year 10	0.354***	2.7
Cut Off Point 1	3.356	
Cut Off Point 2	3.953	
Cut Off Point 3	5.333	
Cut Off Point 4	5.591	
N (*Pseudo R2*)	13,637 (0.1089)	
Log likelihood (*LR chi2(31)*)	-85729.6(20963.5***)	

*2-tail significance at α = 0.10. **2-tail significance at α = 0.05. ***2-tail significance at α = 0.01.

3.7 Conclusion

This chapter analyzes the participation trend of CWW schedules and applies multinomial logit model to estimate the choices of CWW schedules using the Washington State CTR 2005 survey data. The data analysis indicated that for the employees affected by the CTR program, the participation rate in CWW increased steadily from 14.5 percent in 1993 to about 20 percent in 2005. While the major pattern of CWW was still working 4 days for 40 hours per week (4/40) (7.3 percent in 2005), the percentage of employees working 9 days for 80 hours per two weeks (9/80) doubled from 2.9 percent to 5.85 percent from 1993 to 2005.

A multinomial logit model is developed and developed to predict the employees' choice of CWW schedules. The model's predictability was analyzed by comparing the predicted result with the survey results. The difference was very small. I also used the 2003 data to verify the model. Again, the difference between the prediction and the survey result was reasonable. I found that employer's promotion level of TDM programs is one of the key determinants of a commuter's decision about CWW. Commuters are more likely to participate in CWW programs the more that employers support and promote it. Employees' journey-to-work mode choices also affect their choices of working on CWW schedules. Compared with those who drive alone, the commuters using a single mode of transit or shared ride are less likely to work on CWW schedules, while the commuters using mixed modes are more likely to work on a CWW schedule. I also found that the number of CWW program years, a measure of how long the CWW program has been implemented, have a positive but not constant effect on CWW choices. Distance from home to work is another key factor that influences commuter's decisions about CWW. Additionally, employees' decisions to participate in CWW programs are also affected by their job titles and their employer's major business types. Overall, those commuters whose jobs must be performed at their worksites are more likely to choose alternative work schedules when the option is available.

To further examine the technical feasibility of the model, an ordered logit model is estimated based on the sub-sample of the employees with full options of work schedules and the results are compared with that of the MNL model. Overall, the results from the ordered logit model are consistent with the major findings from the MNL model.

The commuters' work schedule choices affect both the frequency of their home-based work trips, but also the time at which the travels occur. The employee's choice of working on a compressed work week schedule not only helps reduce the number of work trips, but also helps shift the work trips from peak periods to non-peak periods. For example, an employee working four days a week will reduce his or her travel by two work trips per two weeks. Further, because of the expansion of daily work hours from eight hours to ten hours, the employee will have to leave home earlier and leave the office later, thus shifting his or her work trips from peak periods to non-peak periods. If enough employees choose to participate in compressed work weeks, peak period congestion may be alleviated.

The MNL model can easily be applied to evaluate the impacts of existing TDM programs. For metropolitan areas where a comprehensive commute trip reduction program is implemented but no detailed information on employee travel behavior is available, the MNL model can be applied to estimate the number of CTR affected employees working on compressed work schedules when employers' and employees' information on basic variables such as job title are readily available.

Furthermore, the MNL model may be incorporated into the regional transportation model to reflect the TDM impacts in the transportation planning process. For the area affected by the Washington State CTR program, the model can be directly used to predict the percentage of employees working on compressed work week schedules at the TAZ level for CTR affected employees. For other areas where detailed employer and employee data are not available, the model developed here may be simplified to use aggregate data at the TAZ level to predict the participation rate of compressed work week schedules. For example, I can use the average commute distance, the percentage of employers affected by TDM strategies, and the percentage of employees by job title and business type to estimate CWW participation rate. The projected percentage of employees working compressed work weeks then may be applied to adjust the number of home based work trips to reflect its impacts on the transportation system and, at the same time, to improve the accuracy of the regional planning model.

For the promotion of TDM programs, the estimates of the determinants of the CWW choices have important applications. TDM promotion agencies or ETCs should consider the job characteristics of employees and major business type of employers to identify suitable TDM strategies. Although CWW is not costly to implement, for certain industries, they may not work well.

CHAPTER 4 MODELING OF TELECOMMUTING CHOICES

4.1. Introduction

Telecommuting is designed to allow commuters to use telecommunication technology to work at home or at a location close to home during regular work hours, rather than commuting to a conventional worksite, thus saving their driving time to work, and more importantly, eliminating some vehicle trips, which may help reduce congestion. The concept of the "electric homeworker" first appeared in automation literature in 1957, but did not receive public attention until the oil crisis of the 1970's [Mahmassani et al., 1993]. As a feasible policy tool, telecommuting opportunities were first available to commuters in southern California in 1988 [Mokhtarian, 1991]. With the rapid development and widespread application of information technology, telecommuting options are available to many regular employees and are on the menu of TDM programs that more and more employers may choose to implement.

4.1.1 Previous Researches

Researchers' interest on telecommuting has been continuous and growing since its first implementation as a part of public policy to address transportation congestion in 1988. Most early research focused on the impact of telecommuting on household travel behavior. Many hypotheses have been formulated and tested [Mokhtarian, 1991; Pendyala et al., 1991]. Since most journey to work trips are made during the peak hour periods, telecommuters can reduce their work trips. This may lead to more flexibility when it comes to time budgeting and activity scheduling. If the assumption that commuters have a fixed budget of time for travel is correct, then saved time and money for telecommuters may lead to some undesirable effects, such as more home-centered trips or non-work trips. Another important impact of telecommuting is related to journey to work modal choices. For telecommuters, removal of some job related trips also lowers their probability of carpooling, vanpooling, or other alternative mode since telecommuters do not need to commute daily [Pendyala et al., 1991].

Although the impact of telecommuting remains an unsolved issue because of conflicting findings, it seems that most researchers agree that, on net, telecommuting reduces total trips, especially peak-period trips, and generates a positive effect on the environment [Hamer, 1991; Sampath et al., 1991; Quaid and Lagerberg, 1992]. This conclusion is supported by most recent evidence obtained by Choo et al. [2005]. They find that telecommuting reduces annual VMT by 0.8 percent or less. Their finding is based on a multivariate time series analysis of aggregate nationwide data spanning 1966 – 1999 for all variables except telecommuting and 1988-1998 for telecommuting. They conclude that although its impact is small, telecommuting appears to be far more cost-effective than public transit in terms of public sector expenditures.

Since the effectiveness of telecommuting as a strategy to reduce traffic congestion, energy consumption, and air pollution depends largely on the extent to which it is adopted by firms and accepted by employees, it is important to address the demand side of telecommuting. Mokhtarian and Salomon [1994] were the first to develop a conceptual model of individual choice in telecommuting. They illustrated the relationships between constraints, preferences, and choices faced by individuals and argued that individuals would choose to telecommute only if the constraints are not binding.

Most other studies are empirical analyses based on either the stated preference approach [Bernardino et al., 1993; Mahmassani et al., 1993; Mokhtarian and Salomon, 1995] or the revealed preference approach [Mannering and Mokhtarian, 1995; Mokhtarian and Salomon, 1997; Drucker and Khattak, 2000; Popuri and Bhat, 2003].

Findings based on the stated preference approach seem to be inconsistent. Mokhtarian and Salomon [1995] find that attitudinal factors are more important determinants than social-economic and demographic characteristics for telecommuting choices. However, the findings from Bernardino et al. [1993] suggest that attitudinal factors are not determinants of telecommuting choices. Their explanation is that since the employer decides to offer the option of telecommuting, employers are likely to make a telecommuting program more or less attractive based on their own interests. In addition to those arguments, Mahmassani et al. [1993] identify more factors that influence people's telecommuting decision including information input from employer, job redesign, fair evaluation of job performance, and promotion opportunities.

The studies based on stated preferences provide useful insights into the factors affecting telecommuting choice, but given the wide gap between preferring to telecommute and actually telecommuting, a better understanding of the telecommuting adoption decision would only be possible by analyzing the data from revealed preference surveys. As discussed in Mokhtarian and Salomon [1995], while 88 percent of the total 628 respondents preferred to telecommute, only 13 percent actually did. Findings from studies based on the revealed preference approach, however, are not consistent either.

Based on revealed preference survey data from three public agencies in California, Mannering and Mokhtarian [1995] explore the individual's choice of telecommuting frequency as a function of demographic, travel, work, and attitudinal factors through a multinomial logit model. They find that commuters are more likely to telecommute if they have a larger household size, small children at home, more vehicles in the household, a higher degree of family devotion, preference for working alone, familiarity with other telecommuters, or are male. Job related characteristics, such as distance and travel time to work, the amount of work time spent in face-to-face contact, and occupation type, however, are insignificant in determining the telecommuting frequency. Mokhtarian and Salomon [1997], find that commuters' awareness of telecommuting opportunities, management support, job suitability, technology, and other job related drives play important roles in commuter's choices of telecommuting. Based on a revealed preference survey collected in the New York metropolitan region, Popuri and Bhat [2003] apply a joint discrete choice model to estimate the home-based telecommuting choice and weekly home-based telecommuting frequency simultaneously. They find that individual demographics, work-related attributes, and household demographics are all significant determinants of telecommuting adoption and frequency.

4.1.2 Contribution of This Study

One of the common issues faced by most empirical studies on telecommuting is the data availability. Most previous studies are based on small samples and do not have a clear definition of the telecommuters or their actual telecommuting frequency. For example, in most studies applying the discrete choice model, the choice set are defined as frequently, infrequent, and rarely telecommuting, rather than the actual frequency. The commuters are not distinguished between those self-employed, those who do not have an office away from the home, and those who have a fixed office but telecommute regularly.

To strengthen the findings on telecommuting choices, this chapter develops an ordered logit model to estimate telecommuting choices based on a unique dataset with more than 90,000 observations. The employees' choices of telecommuting are made from a set of mutually exclusive and collectively exhaustive alternatives, including not telecommuting, telecommuting one day, two days, and three or more days per two weeks. To model the telecommuting choice and its frequency through a discrete choice model, the dependent variable, therefore, is an ordinal discrete choice. Although multinomial logit and probit models have been widely used in discrete choice modeling and in several earlier studies on telecommuting choices, they may not be appropriate because they fail to account for the ordinal nature of outcomes [Greene, 2000]. For ordinal dependent variables, ordered logit or probit regression is more appropriate.

The data was collected from the Washington State Commute Trip Reduction (CTR) program. In 2005, this dataset had more than 200,000 observations that have detailed information on employers characteristics and employees travel patterns. The dataset includes only those employees who work at a worksite with at least 100 full time employees with regular working schedules starting between 6:00 a.m. and 9:00 a.m. (inclusive) on two or more weekdays for at least twelve continuous months. This means the sample excludes the self-employed and other types of employees who do not have an office away from home. Furthermore, in this sample, the telecommuters are defined as those who regularly telecommute one or more days per two weeks. In other words, the employees who randomly or casually telecommute are not counted as telecommuters.

This probably explains why the telecommuting rate reported by the WA CTR data is dramatically lower than that reported by other studies. For example, Drucker and Khattak [2000] reported a total telecommuting rate of 14.3 percent from the 1995 National Personal Transportation Survey data, while the telecommuting rate based on WA CTR database was only 1.51 percent in 1995. In another study conducted by Popuria and Bhat [2003] based on 1997-1998 Regional Transportation Household Interview Survey in New York, the total telecommuting rate was 15.4 percent, compared with the results from WA CTR data in 1997 of 2.21 percent. I believe this strict definition may help generate more reliable results.

Finally, this study focuses on examining the effectiveness of telecommuting as a component of an integrated TDM program and predicting the telecommuting rate in the future. The empirical evidence may be applied to evaluate or predict the effectiveness of a TDM program. It may also be incorporated into local or regional travel demand forecasting models to better measure the overall performance of transportation systems. The findings from this chapter may also help policy makers when they consider implementing alternative combinations of TDM strategies.

The rest of this chapter is organized as follows: section 2 analyzes the telecommuting choices trend. Section 3 presents a brief discussion of the determinants of the telecommuting choice, followed by the introduction of modeling methodology, the model specification and results discussion in section 4. Section 5 provides conclusion.

4.2 Telecommuting Choices Trend Analysis

This section reports results from the data analysis of Washington State CTR data on telecommuting choices from 1993 to 2005. The results are based on valid observations in each year.

Table 4.1 Telecommuting Rate by Telecommuting Days per Two Weeks from 1993 to 2005

Year	Num of Employees	Percent of Employees by Telecommuting Days Per Two Weeks (%)										
		1	2	3	4	5	6	7	8	9	10	Total
1993	186467	0.36	0.27	0.09	0.08	0.06	0.02	0.01	0.02	0.01	0.05	0.97
1995	202965	0.66	0.45	0.10	0.10	0.06	0.03	0.01	0.03	0.01	0.05	1.51
1997	253653	0.81	0.77	0.15	0.16	0.09	0.05	0.02	0.04	0.02	0.11	2.21
1999	234343	1.16	0.92	0.29	0.30	0.21	0.10	0.05	0.12	0.06	0.28	3.49
2001	239969	1.13	1.00	0.25	0.28	0.14	0.09	0.04	0.07	0.02	0.22	3.24
2003	239882	1.46	1.49	0.37	0.45	0.20	0.14	0.05	0.11	0.04	0.25	4.57
2005	260992	1.68	1.80	0.49	0.60	0.27	0.22	0.10	0.19	0.09	0.38	5.83

Table 4.1 presents an overall picture of telecommuting choices made by CTR law affected employees. Although it is clear that the overall participation rate for telecommuting is still pretty low (5.83 percent in 2005), telecommuting has been gaining popularity consistently. In 1993, two years after the CTR law was passed, less than 1 percent of employees affected by this law chose to telecommute regularly, while in 2005, 5.83 percent of employees made the telecommuting choices, an increase of more than 500 percent.

Table 4.2 reports the participation rate for telecommuting by job title from 1993 to 2005. It is clear that the telecommuting rates vary dramatically for employees with different job titles. The employees working as sales/marketing have the highest telecommuting rate (10.57 percent in 2005), followed by professional/technical and management (8.72 percent and 6.88 percent in 2005). Employees working as administrative support, craft/production/labor, and customer service have telecommuting rates below 2 percent. They all experienced consistent growth of telecommuting choices from 1993 to 1995.

Table 4.2 Telecommuting Rate by Job Title from 1993 to 2005

Job Title	Avg. Num of Employees		Percent of Employees on Telecommuting (%)						
	N	%	1993	1995	1997	1999	2001	2003	2005
Administrative support	35837	15.98	0.24	0.40	0.81	1.77	1.28	1.39	1.80
Craft/Production/Labor	31110	13.87	0.14	0.21	0.27	1.03	0.35	0.50	0.60
Management	30857	13.76	1.33	2.33	3.33	4.74	4.60	5.81	6.88
Sales/Marketing	7966	3.55	3.31	2.73	4.80	5.38	7.08	8.93	10.57
Customer Service	14791	6.60	0.19	0.49	0.69	2.12	1.27	1.51	1.53
Professional/ Technical	84808	37.82	1.49	2.41	3.41	4.70	4.70	6.89	8.72
Other	18855	8.41	1.29	1.74	2.36	2.91	2.31	3.03	3.95

Table 4.3 presents the participation rate for telecommuting by employer's primary business type from 1993 to 2005. For those working for information service/software/technical, the telecommuting rate is 14.82 percent in 2005, more than double the average rate (5.83 percent in 2005). This is highly expected since they not only have the technology needed for telecommuting but they also have a lower requirement of worksite presence and personal interaction based on their job characteristics.

Manufacturing is noteworthy for its unexpectedly high telecommuting rate and its highest growth rate. This may be explained by the fact that industry evolution and globalization have changed the definition and nature of manufacturing. For one thing, more and more manufacturing jobs that require a physical worksite presence are moving overseas. Furthermore, the manufacturing industry is more and more high-tech related, making it more suitable for telecommuting.

Table 4.3 Telecommuting Rate by Primary Business Type from 1993 to 2005

Primary Business	Avg. Num of Employees		Percent of Employees on Telecommuting (%)						
	N	%	1993	1995	1997	1999	2001	2003	2005
Agriculture, Forestry, Fishing, Mining	958	0.45	0.00	0.51	0.50	0.23	0.33	0.37	1.72
Finance, Insurance, Real estate	21246	9.96	0.82	1.22	1.95	4.19	4.74	4.96	5.94
Information Services/ Software/Technical	13118	6.15	3.60	4.55	7.74	8.72	7.29	14.25	14.82
Professional/Personal Services	11167	5.23	1.36	2.78	3.90	5.07	5.05	5.12	7.69
Retail/Trade	9159	4.29	0.43	0.69	0.96	2.08	3.36	3.74	4.93
Manufacturing	36493	17.10	0.35	0.70	0.90	1.94	1.62	4.39	7.31
Health Care	30151	14.13	0.73	1.07	1.78	2.66	2.44	2.88	3.23
Public Utility	8518	3.99	3.91	3.29	5.15	7.58	6.24	6.41	7.10
Military	17744	8.32	0.16	0.53	0.56	1.39	0.75	0.69	0.72
Construction	332	0.16	0.33	2.03	0.30	0.68	0.85	2.01	0.72
Transportation	4847	2.27	0.84	1.47	1.37	2.13	2.01	2.39	2.32
Government	45038	21.11	1.22	1.93	2.28	3.03	2.65	3.20	3.23
Education	7358	3.45	2.17	3.16	3.96	5.04	6.01	7.06	8.71
Other	7243	3.39	1.05	1.03	1.67	2.79	2.90	4.01	3.99

Table 4.4 reports telecommuting participation rates by job title and telecommuting days per two week for program year 2005. Table 4.5 presents the telecommuting choices participation rate by employer's major business type and telecommuting days per two weeks for program years 2005.

Table 4.4 Telecommuting Rate by Job Title and Telecommuting Days per Two Weeks in 2005

Job title	Num of Employees		Percent of Employees on Telecommuting (%)										
	N	%	1	2	3	4	5	6	7	8	9	10	Total
Administrative support	33320	13.15	0.40	0.52	0.12	0.14	0.08	0.08	0.04	0.12	0.02	0.28	1.80
Craft/Production/Labor	25920	10.23	0.08	0.11	0.04	0.05	0.11	0.03	0.01	0.01	0.02	0.14	0.60
Management	34136	13.47	2.77	2.14	0.60	0.51	0.27	0.15	0.11	0.10	0.05	0.18	6.88
Sales/Marketing	9039	3.57	3.32	2.91	0.97	1.06	0.66	0.29	0.22	0.30	0.09	0.74	10.57
Customer Service	21326	8.42	0.24	0.28	0.11	0.09	0.18	0.05	0.04	0.10	0.03	0.41	1.53
Professional /Technical	10000	44.75	2.40	2.79	0.73	0.99	0.36	0.37	0.16	0.28	0.15	0.48	8.72
Other	16242	6.41	0.92	1.07	0.32	0.47	0.25	0.16	0.04	0.21	0.06	0.44	3.95

Table 4.5 Telecommuting Rate by Primary Business Type and Telecommuting Days per Two Weeks in 2005

Primary Business	Num of Employees		Percent of Employees on Telecommuting (%)										
	N	%	1	2	3	4	5	6	7	8	9	10	Total
Agriculture, Forestry, Fishing, Mining	1163	0.49	0.69	0.77	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.72
Finance, Insurance, Real estate	23384	9.82	1.64	1.67	0.41	0.47	0.27	0.19	0.09	0.27	0.12	0.83	5.94
Information Service/ Software/Technical	24450	10.27	4.77	4.26	1.38	1.58	0.60	0.50	0.23	0.35	0.24	0.91	14.82
Professional/ Personal Services	14211	5.97	2.60	2.67	0.66	0.61	0.28	0.18	0.04	0.13	0.05	0.47	7.69
Retail/Trade	11984	5.03	2.39	1.33	0.32	0.44	0.10	0.08	0.07	0.06	0.04	0.12	4.93
Manufacturing	38135	16.01	1.42	1.75	0.65	0.99	0.57	0.50	0.26	0.43	0.25	0.50	7.31
Health Care	32468	13.63	0.95	0.97	0.22	0.28	0.13	0.11	0.05	0.13	0.04	0.36	3.23
Public Utility	7787	3.27	2.32	2.25	0.51	0.72	0.22	0.31	0.13	0.19	0.06	0.39	7.10
Military	9552	4.01	0.17	0.20	0.03	0.12	0.09	0.02	0.00	0.01	0.02	0.06	0.72
Construction	557	0.23	0.36	0.18	0.00	0.00	0.00	0.18	0.00	0.00	0.00	0.00	0.72
Transportation	5701	2.39	0.95	1.02	0.14	0.07	0.04	0.02	0.00	0.00	0.00	0.09	2.32
Government	50552	21.23	0.94	1.38	0.22	0.32	0.10	0.08	0.04	0.07	0.01	0.07	3.23
Education	9418	3.96	2.00	3.31	0.88	1.19	0.42	0.27	0.12	0.22	0.04	0.25	8.71
Other	8763	3.68	1.15	1.27	0.30	0.24	0.19	0.09	0.08	0.15	0.02	0.50	3.99

4.3 Determinants of Telecommuting Choices

Mokhtarian and Salomon (1994) developed a behavioral model of the individual choice to telecommute. In their paper, they identified the constraints and drives of telecommuting choices. They defined constraint as a factor that prevents the choice to telecommute while drive is a factor that motivates commuters to begin telecommuting. Key constraints for telecommuting choices are categorized as “relating to awareness of telecommuting options, the organization, job, and psychological factors.” If employees lack awareness of telecommuting choices or misunderstand their options, they are not likely to telecommute. The organization related constraints mainly involves lack of support from employers and/or managerial disapproval. The job related constraints include job unsuitability, unavailable technology, and/or high cost. The above mentioned three categories are external constraints and may be changed through public policy, company policy, marketing strategies, and technology improvement in telecommunication technology. Psychological constraints are internal factors, thus individual related. Personal interaction needs, household interaction problems, lack of discipline, risk aversion, and perceived commute benefits can also prevent commuters from telecommuting.

Among the potential factors that may motivate commuters to telecommute, they identify the key drives as work related, family related, leisure related, ideology related, and travel related. Work related drives include the desire to be more productive, independent, and flexible. Family and leisure related drives include the desire to have more time with other family members and have more leisure time by saving time to drive to work. Ideology related drives include certain peoples' belief that telecommuting can help protect environment by driving less. If a commuter has a long distance from home to work, or the work related commute is burdensome, these two factors both work as drives.

Given the data availability, the variables included in this empirical analysis include the majority of constraints and drives. I use TDM promotion activities, the allowance of flexible start/end work time, and the time the employer transportation coordinator spends on TDM promotion to measure supportiveness from employers, which may capture organization related constraints. The number of years the telecommuting have been allowed at the worksite may capture the awareness constrain. I include individual employees' job titles and work schedules to capture job related constraints. The commute mode choice will be used to capture the travel related drive. The commute distance, whether the worksite is located in downtown area, and the average property value by ZIP code in which the commuter reside can measure the family and leisure related drives. I believe the variables of employer's major business type and the existence of multiple shifts at the worksite can measure the work related drives.

4.4 Modeling the Telecommuting Choices

The major objective of this chapter is to examine the effectiveness of telecommuting as a component of an integrated TDM program and explore the possibility of estimating a model that can be used to predict the telecommuting rate in the future. I estimate the determinants of employees' telecommuting choices using an ordered logit model. In this section, I begin with methodology, followed by model specification and discussions of major findings.

4.4.1. Methodology

The employees' choices of telecommuting are made from a set of mutually exclusive and collectively exhaustive alternatives, including not telecommuting, telecommuting one day, telecommuting two days, and telecommuting three or more days per two weeks. To model the telecommuting choices through a discrete choice model, the dependent variable, therefore, is an ordinal discrete choice. For ordinal dependent variables, the appropriate model is ordered logit or probit regression. Although multinomial logit and probit models are widely used in discrete choice modeling, they may not be appropriate because they fail to account for the ordinal nature of outcomes [Greene, 2000]. For the computation simplicity, I use ordered logit in this chapter.

In the ordered logit model, the ordinal choice variable, denoted as y, is assumed as the discrete realizations of an underlying, unobserved (or latent) continuous random variable y^*. The latent y^* is a linear combination of some predictors, x, plus a disturbance term, ε, which has a logit distribution.

$$y^* = \beta x + \varepsilon \tag{4.1}$$

where β is the coefficient vector.

The observed choice variable y is assumed to be determined by the latent continuous variable y^* as follows:

$$y_i = j \quad \text{if } \delta_{j-1} \leq y^* \leq \delta_j,\ j = 1,2,\ldots J \tag{4.2}$$

where δ are unknown thresholds or cutoff points in the distribution of y^* with $\delta_0 = -\infty$ and $\delta_J = +\infty$. In this study, the dependent variable telecommuting choices are ordered variable with four categories: (1) no telecommuting (j = 1); (2) telecommuting one day per two weeks (j = 2); (3) telecommuting two days per two weeks (j = 3); (4) telecommuting three or more days per two weeks (j = 4).

Assume the probability that employee i reports her telecommuting choice of j given a vector of observed influence variables x is $P_i = P(y_i = j / x_i)$, then

$$\begin{aligned} P_i(y_i = j / x_i) &= P(\delta_{j-1} < y^* < \delta_j) \\ &= \mathrm{P}(\delta_{j-1} < \beta x_i + \varepsilon_i < \delta_j) \\ &= \mathrm{P}(\delta_{j-1} - \beta x_i < \varepsilon_i < \delta_j - \beta x_i) \\ &= \phi(\delta_j - \beta x_i) - \phi(\delta_{j-1} - \beta x_i) \end{aligned}$$

where $\phi(\varepsilon)$ is the cumulative probability distribution of ε.

To estimate this model use maximum likelihood estimation (MLE), the log-likelihood is simply:

$$\ln L = \sum_{i=1}^{N} \sum_{j=1}^{J} Q_{i,j} \ln(\phi_{i,j} - \phi_{i,j-1})$$

where L is the likelihood function, $Q_{i,j}$ is an indicator variable which equals 1 if y_i=j and 0 otherwise, $\phi_{i,j} = \phi(\delta_j - \beta x_i)$, and $\phi_{i,j-1} = \phi(\delta_{j-1} - \beta x_i)$.

Based on the assumption of logit distribution of ε, the so-called proportional odds model (POM) is then

$$\frac{P(y \leq j/x)}{P(y > j/x)} = \exp(\delta_j - \beta x),\ j = 1,2\ldots4 \tag{4.3}$$

where $P(y \leq j/x)$ is the conditional probability of choosing at most *j-1* days per two weeks given a vector of observed influence variables *x*, $P(y > j/x)$ is the probability of choosing more than *j-1* days, β is a column vector coefficients. This model assumes that β does not depend on *j*. In other words, the slope of log odds ratio are the same across the categories of dependent variable. This means the separate equations for each category differ only in the intercepts.

While the proportional odds model is easy to estimate and straight forward in interpretation, the assumption of parallel slope, also called proportional odds assumption, is not necessary realistic. For example, the impact of distance on telecommuting choice may vary by the number of telecommuting days. The feasibility of the proportional odds assumption can be tested using the Wald Tests, which tests the hypothesis that the coefficients in each independent variable are constant across categories of the dependent variable. If this assumption does not hold, generalized ordered logit model should be applied by allowing the slope change in response to choices.

The generalized ordered logit model can be written as

$$P(y_i > j) = \frac{\exp(\delta_j + x_i\beta_j)}{1 + \exp(\delta_j + x_i\beta_j)},\ \mathrm{j = 1, 2, ...J - 1} \tag{4.4}$$

From (4.4), it can be shown that the probabilities that *y* will take on each of the values from 1 to *J* is given as below

$$
\begin{aligned}
P(y_i = 1) &= 1 - \frac{\exp(\delta_j + x_i\beta_j)}{1+\exp(\delta_j + x_i\beta_j)} \\
P(y_i = j) &= \frac{\exp(\delta_{j-1} + x_i\beta_{j-1})}{1+\exp(\delta_{j-1} + x_i\beta_{j-1})} - \frac{\exp(\delta_j + x_i\beta_j)}{1+\exp(\delta_j + x_i\beta_j)}, \text{ j = 2,..., J - 1} \qquad (4.5) \\
P(y_i = J) &= 1 - \frac{\exp(\delta_{J-1} + x_i\beta_{J-1})}{1+\exp(\delta_{J-1} + x_i\beta_{J-1})}
\end{aligned}
$$

When J = 2, the generalized ordered logit model is the same as binomial logit model. When J >2, the generalized ordered logit model becomes "equivalent to a series of binary logistic regressions where categories of dependent variable are combined" [Williams 2007, pp. 2]. In this case, for j = 1, the generalized ordered logit model is equivalent to contrast choice 1 with choices 2, 3, and 4. For j = 2, the contrast is between sum of choices 1 and 2 against choices 3 and 4. For j = 3, it is choice 1, 2, and 3 versus choice 4.

4.4.2. Model Specification

I apply the ordered logit model to estimate the relationship between telecommuting choices and a group of observed influences to those decisions. The observed influences in the model include those variables available from both employer and employee surveys. From the employee survey, except the telecommuting choices, I use four variables, including commute distance from home to work, the employee's job title, travel pattern, and work schedule to capture individual differences. The commute distance from home to work measures the one-way miles from employee's home to her usual work site, including miles of errands or stops made daily on the way to work. Washington State CTR data report seven job titles: administrative support, craft/production/labor, management, sales/marketing, customer service, professional/ technical, and the other. Thus, I created seven dummy variables to reflect individual's job title. The employee's journey-to-work mode choice was divided into using the single mode of driving alone, transit, shared rides, and using the mixed modes. The dummy variable of work schedule is defined to measure if the employee works on compressed work week.

Seven groups of variables are from the employer survey: total number of full time employees, primary business type, employer's TDM program promotion activities, number of hours the Employer Transportation Coordinator (ETC) spent on CTR program promotion, the existence of multiple shift at the worksite, the availability of flex time policy to allow employees to vary their start and end times, and the number of years the telecommuting program has been implemented since 1995. Nine dummy variables were created to reflect the primary business of the employer: finance service (including real estate and insurance), information service or software, manufacturing, health care, public utility, transportation, government, education, and other.

Through a factor analysis among the thirteen employer TDM promotion activities, four of them are selected to reflect the employer's TDM promotion, including distributing CTR information, conducting transportation events, publishing CTR articles, and sending electronic mail messages about the CTR program. Although the TDM program promotion activities and the times the Employer Transportation Coordinator (ETC) spent on CTR promotion (ETC hours) are not specifically for telecommuting promotion but for the whole TDM program, it is reasonable to expect that the higher degree of supportiveness from the management for TDM choices, the higher participation rate for telecommuting from the employees.

Table 4.6 Selected Variable Definitions

Variable	Definition
Distance	One way distance in mile commute from home to work location
Total Employees	Total number of full time employees
TDM Promotion Activities	Distribute Summary of TDM Program: Distribute a summary of your worksite's CTR program to employees? =1, Yes =0, Otherwise Conduct Transportation Events: Conduct transportation events/fairs and/or participate in county/state CTR promotions/campaigns? =1, Yes =0, Otherwise Publish CTR Articles: Publish CTR articles in employee newsletters? =1, Yes =0, Otherwise Send CTR info through email: Send out the CTR information through email? =1, Yes =0, Otherwise
ETC Hours	The average number of hours the Employer Transportation Coordinator spent on CTR promotion
Average Property Value	The average property value by ZIP code in which the commuter reside
Shift	Does this worksite have multiple shifts? Shift=1, if Yes; Shift=0, otherwise
Flex Time	Does your organization offer flex time (allow employees to vary their start and end times)? Flex time=1; Flex time =0, otherwise
Drive Alone	=1, if drives alone to work for the whole week =0, otherwise
Transit	=1, if takes public transit to work for the whole week =0, otherwise
Shared Rides	=1, if carpools or vanpools to work for the whole week =0, otherwise
Mixed Rides	=1, if takes at least two different modes to work for the whole week =0, otherwise
Work Schedule	=1, if works 5 days per week =0, otherwise

The number of telecommuting program years, defined as the number of years the telecommuting program has been implemented, or allowed, since 1995, is used to capture the effect of time on telecommuting choices. The effect of this variable is expected to be positive since it takes time for employees to understand the benefits of telecommuting program and make transitions accordingly. I also expect the time effect is not constant. Therefore, I created 11 dummy variables to reflect the number of years from the initial implementation of telecommuting program rather than use one continuous variable of number of years. If a worksite started the telecommuting program in 2005, the number of the year is zero, which is the base value for this variable and excluded from the regression. I also tried to capture the difference of employer's location by using a dummy variable to reflect whether the worksite is located in the downtown area or not.

I use the average property value of the ZIP code in which the employee resides to serve as a proxy to capture employee's social economic information. The property value includes the "land value and the building value". The data are from King County appraiser's web site [King County Department of Assessment, 2005]. The detailed definitions of selected variables are presented in Table 4.6 (other variables are self-explanatory, therefore not reported).

In 2005, there are about 200,000 valid observations from employee commute travel behavior survey. There is, however, inconsistency about the availability of the telecommuting choices between that reported by employers and the choices made by employees. For example, for certain worksite, employer reports that no telecommuting program is available, while certain employees indicate that they regularly telecommute certain days per two weeks. To determine the actual availability of the telecommuting options, I calculated the total number of employees working on telecommuting for each worksite based on the employee survey data. The results of this calculation are then compared with the information provided in the employer survey. If the number of telecommuting employees is zero and the employer reported that telecommuting is not allowed, I assume that telecommuting is not allowed for all employees working for this employer. Otherwise, it is allowed.

Table 4.7 Ordered Logit Model (POM) for Telecommuting Choices

Variable	Coefficient	z-statistics
Distance	0.0294***	24.2
Total employees	-0.000025***	3.92
Downtown	0.2150***	5.21
Distribute Summary of CTR Program	0.4511***	4.55
Conduct Transportation Events	0.1868***	3.38
Publish CTR Articles	0.2021***	5.53
Send CTR info through email	0.2930***	4.90
ETC hours	0.0025**	2.39
Average property value	1.91e-7**	2.11
Shift	-0.1788***	5.22
Flex time	0.1785***	2.91
Transit	-0.4988***	8.82
Shared rides	-0.3686***	6.72
Mixed rides	-0.2855***	8.21
CWW schedule	-0.7368***	22.40
Job title-Administration Support	-0.7987***	7.87
Job title-Production/Labor	-1.8804***	12.26
Job title-Management	0.5176***	6.56
Job title-Sales/Marketing	0.8784***	9.85
Job title-Customer Service	-0.7583***	6.44
Job title-Professional/Technical	0.7562***	10.27
Business type-Finance/Real Estate/Insurance	-0.1344**	2.32
Business type-Information Service/Software	0.4824	9.00
Business type-Manufacturing	0.4725***	9.52
Business type-Health Care	-0.4834***	7.52
Business type-Public Utility	0.2476***	3.20
Business type-Transportation	-0.5261***	4.39
Business type-Government	-0.4524***	8.06
Business type-Education	0.8701***	10.48
Tele Year 1	1.0529***	4.37
Tele Year 2	0.9400***	3.99
Tele Year 3	1.0511***	4.49
Tele Year 4	0.8712***	3.75
Tele Year 5	0.9992***	4.28
Tele Year 6	1.2317***	5.36
Tele Year 7	0.2970	1.11
Tele Year 8	0.8654***	3.65
Tele Year 9	0.7067***	3.07
Tele Year 10	0.7319***	3.24
Cutoff Point1	4.7481	
CutoffPoint2	5.1611	
CutoffPoint3	5.7935	
N (*Pseudo R2*)	92,321(0.0859)	
Log likelihood (*LR chi2(117)*)	-5503(0.000)	

*2-tail significance at α = 0.10. **2-tail significance at α = 0.05. ***2-tail significance at α = 0.01.

Table 4.8 Brant Test of Parallel Odds Assumption

Variable	Chi-square	p>Chi-square
ALL	966.07	0.000
Distance	3.89	0.143
Total employees	21.21	0.000
Downtown	1.12	0.572
Distribute Summary of CTR Program	0.52	0.770
Conduct Transportation Events	3.41	0.182
Publish CTR Articles	30.45	0.000
Send CTR info through email	0.96	0.618
ETC hours	1.38	0.502
Average property value	2.03	0.363
Shift	121.60	0.000
Flex time	5.17	0.075
Transit	7.63	0.022
Shared rides	15.82	0.000
Mixed rides	65.73	0.000
CWW schedule	0.95	0.622
Job title-Administration Support	3.13	0.209
Job title-Production/Labor	0.16	0.921
Job title-Management	46.53	0.000
Job title-Sales/Marketing	6.14	0.046
Job title-Customer Service	9.66	0.008
Job title-Professional/Technical	15.81	0.000
Business type-Finance/Real Estate/Insurance	1.67	0.433
Business type-Information Service/Software	1.40	0.496
Business type-Manufacturing	30.58	0.000
Business type-Health Care	1.95	0.377
Business type-Public Utility	0.94	0.626
Business type-Transportation	8.15	0.017
Business type-Government	23.98	0.000
Business type-Education	8.96	0.011
Tele Year 1	1.83	0.400
Tele Year 2	2.10	0.350
Tele Year 3	3.84	0.147
Tele Year 4	2.45	0.294
Tele Year 5	0.68	0.711
Tele Year 6	3.62	0.163
Tele Year 7	0.68	0.711
Tele Year 8	1.70	0.428
Tele Year 9	1.61	0.447
Tele Year 10	2.96	0.228

Based on the availability of the detailed property value data, I only include the records for which the employee's home zip code is within the King County. After combining the two dataset, the final sample size is 92,321.

The model specification is guided by a series of tests. The model is estimated using the econometric software STATA 9.0. I first run a proportional odds model (POM) based on equation (4.3). The regression results of the POM appear in table 4.7. I then apply the Brant test (Wald Tests) in STATA to see whether the common slope assumption is violated. The results of Brant test are reported in table 4.8. It is clear, from the Brant test, that the parallel regression assumption is violated for the overall model and for most of the variables. Therefore, I use generalized ordered logit model to estimate the model based on equation (4.4). The model is estimated based on 2005 sample.

4.4.3 Regression Results

The generalized ordered logit model regression results are reported in Table 4.9. Columns 2 to 4 report the coefficients for the choices of telecommuting one or more days, two or more days, and three or more days per two weeks. The value of the log likelihood function at its maximum is -28835.7. The chi-square, a statistic used to test the null hypothesis that all the parameters are zero, defined as $-2(Log\text{-}L(0)- Log\text{-}L(\beta))$, is 6361.91 with a degree of freedom of 117, which indicates that we can reject the null hypothesis that all the parameters are zero at the level of at least 0.001.

Examining the coefficients in the models for the telecommuting choices, it is first observed that the constant terms are all negative, suggesting that the average effect of those unobserved influence variables is in the direction of not telecommuting or telecommuting fewer days. This is fully anticipated since around 93 percent of employees in the sample chose commute to their worksites when they have the option to telecommute. Additionally, majority of telecommuters only telecommute one or two days per two weeks.

Beginning with the effect of journey to work distance, it is not surprising that employees commuting longer distances are 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. The coefficients of distance are statistically significant at the level of 0.001 or better.

The coefficients for the three dummy variables that measure the employee's journey-to-work mode choice are all negative and statistically significant at the level of 0.001, which suggests that compared with commuters who using the single mode of driving alone, employees using single mode of transit and shared ride, or using mixed modes are more likely to not telecommute or telecommute fewer days. I realize that employees' journey-to-work modal choice and telecommuting choice may be jointly determined by some unobserved influences. It may also be possible that an employee's telecommuting choices may affect his journey-to-work modal choice. If this is the case, then the variables of employee's modal choice may be endogenous. It is, however, very difficult to find suitable instrumental variables to correct this potential problem. I feel confident that even these variables may bias the result, the bias is not significant given the model prediction results discussed later.

The impact of an employee's work schedule is significant. People working on compressed work weeks are less likely to work on telecommuting.

The employer's supportiveness toward the CTR program, reflected by the three dummy variables representing the employer's TDM promotion activities, the number hours the ETC spend on promoting CTR program, and the allowance of flexible start/end work time at the work site, as expected, has positive and significant impacts on employee's telecommuting choice. The three dummy variables of employer's TDM promotion activities have positive coefficients and statistically significant at the level of 0.001 or better for all of the telecommuting choice categories. The coefficients of flexible time are positive for all choice categories and significant for telecommuting one or more days and two or more days. The number of hours the Employer Transportation Coordinator works is significant for telecommuting one or more days. The last variable in this group is the number of ETC hours spent on TDM programs. The results suggest that, although the employer's TDM promotion may not be specifically focused on telecommuting but rather a reflection of the employer's supportiveness to the whole CTR program, the employer's positive attitude to the TDM program does have significant impacts on employee's telecommuting choice. It also suggests that the impact of employer's CTR supportiveness on employee's telecommuting choice most likely happens on encouraging employee from not telecommuting to telecommuting rather than from telecommuting less frequently to more frequently.

The eleven dummy variables, representing the number of years the telecommuting program has been implementing since 1995, are created to reflect the awareness of the employee on telecommuting program. Except year seven, which has a positive but not statistically significant coefficient, all other year dummy variables have a positive coefficient and statistically significant at the confidential level of 95 percent or better for the first two categories. This suggests that the number of program years has a positive impact on employee's choice of telecommuting one or two days per two weeks. On the other hand, most coefficients for the last category, telecommuting three or more days, are not statistically significant. As to the values of the coefficients of the year dummy variables, as expected, they are not constant but follow a similar pattern for the three telecommuting categories. Overall, the coefficients are increasing for the first six years and begin to decrease from year seven while the coefficients are still positive. This suggests that telecommuting program implementation year has an increasing effect on telecommuting choices until it reaches its peak in year 6, after which its marginal effect falls or goes flat.

The impact of worksite location is positive and significant which means the employees working on downtown area are more likely to telecommute. The impact of employer size, the total number of employees, is negative and significant.

It is interesting to see that people living in an area with higher property value area are significantly more likely to telecommute. This may suggest that telecommuting is more suitable for the high-end job.

Among the six job titles included in the regression, the coefficients of administrative support, production/labor, and customer services are negative and statistically significant at the level of at least 0.001 for all categories. These results suggest that employees with the job titles mentioned above are less likely to telecommute at all or telecommute fewer days if telecommuting. This finding may be explained by their job characteristics. While administrative staffs provide direct support for management and production workers at factories or other facilities produce goods, both have a need to physically work at the worksite.

The coefficients of management have positive signs but are not statistically significant for the choice of telecommuting three or more days per two weeks. This result suggests that managers are more likely to make the transition from not telecommuting to telecommuting but are less likely to telecommute three or more days, which is reasonable considering their job characteristics.

Table 4.9 Generalized Ordered Logit Model for Telecommuting Choices

Variable	One Day +[a,b]	Two-Day +[a,b]	Three-Day+[a,b]
Distance	0.0292(23.87)***	0.0305(21.88)***	0.0302(16.78)***
Total employees	-0.00002(3.57)***	-0.00004(5.35)***	-0.00005(4.89)***
Downtown	0.2075(5.02)***	0.2437(4.90)***	0.2342(3.28)***
Distribute Summary of CTR Program	0.4500(4.54)***	0.4788(4.15)***	0.5962(3.80)***
Conduct Transportation Events	0.1902(3.44)***	0.2213(3.29)***	0.0585(0.64)***
Publish CTR Articles	0.1942(5.30)***	0.2797(6.32)***	0.4745(7.77)***
Send CTR info through email	0.2910(4.86)***	0.2676(3.73)***	0.2152(2.15)***
ETC hours	0.0021(2.03)**	0.0018(1.53)	0.0021(1.26)
Average property value	2.07e-7(2.34)**	7.35e-8(0.67)	2.77e-7(0.21)
Shift	-0.2151(6.28)***	-0.4394(0.28)	-0.1005(1.85)*
Flex time	0.1800(2.93)***	0.1602(2.13)**	0.0229(0.23)
Transit	-0.4888(8.63)***	-0.5674(8.17)***	-0.6693(6.70)***
Shared rides	-0.3521(6.41)***	-0.4416(6.77)***	-0.6261(6.72)***
Mixed rides	-0.2617(7.50)***	-0.3851(9.17)***	-0.5575(9.22)***
CWW schedule	-0.7288(22.04)***	-0.7279(19.71)***	-0.7793(17.23)***
Job title-Administration Support	-0.7959(7.84)***	-0.8506(7.27)***	-0.7842(5.47)***
Job title-Production/Labor	-1.8421(12.01)***	-1.9084(11.44)***	-1.8998(9.77)***
Job title-Management	0.5403(6.84)***	0.2852(3.10)***	0.0277(0.24)
Job title-Sales/Marketing	0.8859(9.92)***	0.7448(7.18)***	0.6348(4.93)***
Job title-Customer Service	-0.7587(6.44)***	-0.6851(5.32)***	-0.4241(2.77)***
Job title-Professional/Technical	0.7590(10.30)***	0.6837(8.13)***	0.4564(4.33)***
Business type-Finance/Real	-0.1373(2.37)**	-0.1418(2.00)**	-0.0295(0.30)
Business type-Information	0.4934(9.18)***	0.4707(7.37)***	0.5002(5.77)***
Business type-Manufacturing	0.4483(9.00)***	0.5208(8.72)***	0.8096(10.16)***
Business type-Health Care	-0.4723(7.34)***	-0.5600(7.06)***	-0.6157(5.49)***
Business type-Public Utility	0.2456(3.17)***	0.2432(2.58)***	0.3379(2.59)***
Business type-Transportation	-0.5208(4.35)***	-0.4560(3.11)***	-1.0614(3.74)***
Business type-Government	-0.4419(7.86)***	-0.3568(5.41)***	-0.6130(6.02)***
Business type-Education	0.8723(10.46)***	0.8959(9.46)***	0.6930(5.28)***
Tele Year 1	1.0475(4.34)***	1.3732(4.05)***	0.9070(2.06)***
Tele Year 2	0.9530(4.04)***	1.1797(3.56)***	0.6440(1.50)***
Tele Year 3	0.9895(4.22)***	1.4584(4.43)***	1.2423(2.93)***
Tele Year 4	0.8501(3.66)***	1.2714(3.88)***	1.0401(3.47)***
Tele Year 5	1.005(4.31)***	1.1541(3.48)***	0.6601(1.54)
Tele Year 6	1.1884(5.71)***	1.6267(5.01)***	1.1663(2.80)***
Tele Year 7	0.2883(1.07)	0.5720(1.56)	0.2101(0.45)
Tele Year 8	0.8459(3.56)***	1.2656(3.79)***	1.0058(2.34)**
Tele Year 9	0.7077(3.08)***	1.0173(3.12)***	0.6440(1.54)
Tele Year 10	0.7283(3.22)***	1.1112(3.45)***	0.6173(1.49)
Constant	-4.73(18.00)***	-5.5337(15.37)	-5.4984(11.78)
N (*Pseudo R2*)	92,321(0.0994)		
Log likelihood (*LR chi2(117)*)	-28835.725(0.000)		

[a] absolute value of z-statistics in parentheses.
[b] *2-tail significance at $\alpha = 0.10$. **2-tail significance at $\alpha = 0.05$. ***2-tail significance at $\alpha = 0.01$.

Among the eight employer's major business types, the coefficients of information service/software, manufacturing, public utility, and education are positive and statistically significant at the level of 0.01 or better. The coefficients on transportation, health care, and government are negative and statistically significant. This finding suggests that employer's major business type can be considered either as a drive or a constraint affecting commuter's telecommuting choices.

As a final check, I estimated the model based on randomly selected 80 percent of the total sample and used the other 20 percent to test the model's predictability. The model is also tested using 2003 data. The results are reported in Table 4.10.

From Table 4.10, it is clear that, overall, the prediction is very close to the survey result. The model predicts that 7.461 percent of commuters choose to telecommute at least one day per two weeks in 2005, while the survey result is 7.102 percent. When using the 2003 data, the model over-predicts the percentage of telecommuters. This is fully anticipated since the telecommuting programs have been more and more acceptable to both employers and employees over time, a trend illustrated in Table 4.1.

Table 4.10 Comparison of the Model Predictions and Survey Results

Days/2 Weeks	Average Percentage of Employees on Telecommuting (%)			
	Program Year 2005		Program Year 2003	
	Model	Survey	Model	Survey
0 Day	92.539	92.898	92.814	94.313
1 Day	2.315	2.075	2.217	1.936
2 Days	2.149	2.195	2.079	1.966
3 + Days	2.997	2.832	2.890	1.785
Total Telecommuting	7.461	7.102	7.186	5.687

4.5 Conclusion

This chapter analyzes the participation trend for telecommuting and applies a generalized ordered logit model to estimate the impacts of journey to work distances and mode choice, employer's supportiveness towards the CTR program and the number of years telecommuting has been allowed, employee's job characteristics, work schedule, and average household property value, and employer's major business types and worksite location on employee's telecommuting choice.

The data analysis indicates that although, overall, the participation rate of regularly telecommuting one or more days per two weeks for the CTR affected employees is still pretty low (5.83 percent in 2005), telecommuting has been gaining popularity consistently. During the period from 1993 to 2005, among those affected by the CTR law, the percentage of employees choosing to regularly telecommute at least one day every two weeks increased more than 5 times. I also find that the telecommuting rates vary dramatically for the employers with different primary business types and for the employees with different job titles.

I apply a generalized ordered logit model to estimate the employee's telecommuting choices. Telecommuting is categorized into not telecommuting, telecommuting one day, two days, and three or more days per two weeks. I find that commuters with a longer distance from home to work are more likely to make transition from not telecommuting to telecommuting and telecommuting more days if already choosing to do so. The people using the single mode of driving alone are more likely to telecommute compared with those using the single mode of transit or shared rides, as well as those using mixed modes.

The employer's supportiveness toward the CTR program, reflected by the three dummy variables representing the employer's TDM promotion activities, the number hours the ETC spend on promoting CTR program, and the allowance of flexible start/end work time at the work site, as expected, has positive and significant impacts on employee's telecommuting choice.

The employees' awareness of the telecommuting program, represented by the number of year the telecommuting has been allowed, has positive but not constant impacts on the employee's adoption of telecommuting.

Job characteristics, including job title and work schedule, serve as either drive or constraint for employees' telecommuting choice.

The employees' telecommuting choices are also affected by their employer's other business characteristics, such as worksite location, total number of fulltime employees, the existence of multiple shifts at the worksite, and employer's major business type.

The model is evaluated by estimating the model using randomly selected 80 percent of 2005 data and comparing the model's predictions with the survey results using the 20 percent of excluded sample. The model is also tested using 2003 data. For the 2005 data, the model prediction of the overall telecommuting rate is 6.344, very close to the survey result of 6.377. The differences between the model predictions and the survey results for all three categories of telecommuting are less than 2 percent. For the 2003 data, the model over-predicts the telecommuting rate (5.650 percent versus 4.70 percent). Since the telecommuting rates of the CTR affected employees changed significantly from 2003 to 2005 (4.57 percent versus 5.83 percent), the model's over prediction of telecommuting is fully expected and suggests that commuter's preference is changing in favor of telecommuting over time, a factor that cannot be captured by the model.

As elaborated in chapter 3, the results of this chapter can be used to evaluate the impacts of a telecommuting program, a component of an integrated TDM program, and to identify the effectiveness of the TDM strategies. More importantly, they may be incorporated into the regional transportation model to reflection the impacts of TDM on transportation planning process and, at the same time, to improve the accuracy of the regional planning model.

CHAPTER 5 AN INTEGRATED MODEL OF TDM IMPACTS ON JOURNEY TO WORK MODE CHOICES

5.1 Introduction

One of the major objectives of the employer-based Commuter Trip Reduction (CTR) program is to reduce vehicle trips by implementing programs that encourage alternatives to drive-alone commuting to worksites [Washington State DOT, 2007]. Therefore, the impacts of the implemented TDM programs on a commuter's modal choice could be an important measure of TDM effectiveness.

Although the commuter's travel behavior in terms of travel mode choice has been studied extensively, there is no empirical work that estimates the combined effects of a TDM program on an individual's modal choice. Most previous research of TDM impacts was worksite-based, retrospective, focusing on one or more aspects of TDM strategies, and based on small samples.

5.1.1 TDM Strategies Evaluation Literature Review

In a case study conducted by Mehranian et al. [1987], two downtown companies are compared to clarify the effect of parking cost on journey-to-work modal choices. The two companies are located at the same site, and their employees have access to the same parking facilities. The major differences are the employer's policy on subsidization of parking cost. One company provided a partial parking subsidy to about one-third of its employees and no financial assistance to carpoolers, vanpoolers, transit users. The other company had a more complex system of subsidies to its employees, providing varying levels of support for solo drivers, carpoolers, vanpoolers, and transit riders. Although the second company spent far more money on promotion of ridesharing, the two companies have almost the same percentage of drive-alone. They find that the second company's complex subsidies to different modes shifted transit use to vanpooling and carpooling. Although the second company spent much more money on the promotion of ridesharing, its majority of commuter subsidies are used to subsidize the parking costs of solo drivers, which counters the effectiveness of its original effort of promoting ridesharing and transit use. They conclude that, for the employers that already subsidize the parking of solo drivers, it is more cost-effective to promote ridesharing and transit use by eliminating parking subsidies to solo drivers than it is to offer additional subsidies to other alternative modes.

Brownstone and Golob [1991] investigate the effect of certain incentives implemented to increase journey to work ridesharing using the greater Los Angeles area data based on an ordered probit discrete choice model. They find that female full timers and those employees who have larger household sizes with multiple workers, longer commutes, and larger worksite are more likely to rideshare. Their simulation model suggests that policy tools such as providing all carpool and vanpool with reserved parking, ridesharing subsidies, guaranteed rides home, and high-occupancy vehicle lanes would reduce drive-alone commuting between 11 and 18 percent.

Peng et al. [1996] investigate the effect of parking prices on urban journey-to-work modal choices using travel activity data from Portland, Oregon. The results from their nested multinomial logit model suggest that parking prices have a significant influence on commuters' mode choices. They find that parking prices have divergent impacts on commuters using different modes and/or with different residential locations. Compared with central city transit users, suburban transit users are more sensitive to parking price changes. Vanpoolers and carpoolers are less responsive to parking prices than solo drivers. For suburban residents, those driving alone and ridesharing to work are less responsive to parking prices than are central city residents. Employment location also plays an important role in mode choice. Employees working in suburban areas are more likely to drive and less likely to use transit. While increased transit service alone has a fairly small effect on transit use, combined efforts of increasing parking price and improving transit service simultaneously provides an effective means of reducing solo driving and increasing transit use.

Several researchers look at the effect of land-use policies on modal choices. Cervero [1996] explores how mixed land-uses affect the commuting choices in large urban areas based on data from the 1985 American Housing Survey. The effects of land-use environments on mode choice are modeled using binomial logit analysis. It appears that mixed land-use policies may help to provide alternatives to driving, although the effect is likely to be small. Bento et al. [2003] also look at the effect of urban form on journey to work mode choices using the 1990 national personal transportation survey data and find most urban spatial characteristics have no significant effect on commuter's choice individually.

Kuppam et al. [1999] carry out an analysis using the 1991 wave of the Puget Sound Transportation Panel data set to investigate the effects of attitudinal and preference variables on commuter's mode choices. They find that demographic variables and attitudinal variables are extremely important in explaining mode-choice behavior, but the latter have more explanatory power.

In a discrete choice experiment of road pricing and parking charges conducted in Greater Vancouver suburb areas based on a sample of 548 commuters who drove alone to work at the time of experiment, Washbrook et al. [2006] find that increases in drive-alone costs will bring about greater reductions in single-occupancy-vehicle (SOV) demand than increases in SOV travel time or improvements in the times and costs of alternatives beyond a base level of service. This study designs a customized discrete choice experiment and asks the participants to choose between drive-alone, carpools, or take a hypothetical express bus service. Attributes coefficients based on the experiments are then used in a predictive model to estimate commuters' responses to various policy-oriented combinations of charges and incentives. The authors believe this is a cost-effective way for policymakers to evaluate choices to lower SOV.

5.1.2 Limitations of the Worksite Based Analysis Method

As stated in Chapter 2, most of the TDM models, including EPA's COMMUTER model, CUTR's worksite reduction model, and Washington State's TEEM model, are worksite based. The worksite-based approach estimates changes in mode split at an aggregate, worksite level by treating the worksite as the analysis unit. Although most of commute trip reduction programs are employer-based, using worksite as the analysis unit to evaluate the effectiveness of the TDM strategies has limitations.

Firstly, calculation of the aggregate mode split is highly affected by some factors that are hard to control or measure, for example the survey response rate. The non-respondents are generally treated as having the same distribution of mode shares as that of valid respondents. There are other arguments, however, that people driving alone are less likely to answer the questionnaire. Based on this assumption, some studies treat the non-respondents as driving alone, or treating the non-respondents as driving alone when the response rate is less than certain amount, e.g. 70 percent. Since the impact of the TDM on the worksite's mode split is relatively low, the bias induced by the calculation could be significant.

Secondly, some of the important determinants of mode choice, such as travel time and travel cost, can only take average value at the worksite level, while those variables are meaningful only from the perspective of individuals. The worksite-based approach also fails to catch varieties of the individual trips, which is critical when the study focuses on quantifying the impact of reduced individual trips. In addition, the worksite based approach reduces the number of observations (worksites) available from which to make the estimates. This is especially important when the study area is a sub-area, such as downtown or corridor area.

5.1.3 Modeling the Impacts of an Integrated TDM Program on Mode Choice

An employer-based TDM program generally includes different strategies. For most of the strategies, their impacts are more interactive than independent. For example, an internal or external ride match program will be more effective if combined with reserved high occupancy vehicle (HOV) parking space or HOV parking charge discount. Focusing on only one aspect of TDM strategies without controlling of the availability of other TDM programs may result in omitted variable bias.

Among the various methodologies applied in human behavior study, the discrete choice model has been widely used in the transportation community to study the travel-related human behavior, specifically, the traveler's mode choice and departure time choice. The Washington State CTR dataset provides detailed information on TDM strategies and the corresponding employee commute travel behavior for hundreds of employers and tens of thousands of employees. This makes it possible, for the first time, to perform a systematic discrete choice analysis of integrated TDM impacts on individual employee's mode choices.

In this chapter, a nested logit model is applied to estimate the determinants of modal choices for the CTR affected employees and evaluate the impacts of various TDM strategies on commuter's modal choices based on a large sample of about 60,000 observations.

The model is a two-level nested logit model. The first nest includes motor, transit, non-motor. In the second nest, motor is divided into drive-alone and shared riding. The mode shares of each of the alternative are: motor, 74.18 percent (drive-alone, 60.61 percent; shared ride, 13.57 percent); transit, 22.29 percent; and non-motor, 3.52 percent.

Based on the nested logit model, the elasticity and marginal effects of finance incentives and TDM support and promotion programs are further calculated to evaluate the quantitative impacts of various TDM strategies on the modal choices.

Commuter mode choice has been studied extensively. Generally, the factors that have been examined and proven to be relevant to commute mode choice include (1) commuter's sociodemographic characteristics, such as age, gender, income, household composition and car ownership, and so on; (2) connection information between the origin and destination, such as travel time and travel cost by modes, and so on; (3) land-use characteristics of the origin and destination, such as location, population density, accessibility to transit services and parking facility, availability of sidewalk and bike lane, and so on; and (4) other factors, such as travelers' subjective perceptions of and feelings toward modes as well as their lifestyle.

In this chapter, the data obtained from the employer annual report includes the characteristics of employer, the worksite land-use, and the TDM program implemented at the worksite. The data from the employee travel behavior survey include commuter's mode choice, job title, commuting distance, and work schedule. The detailed travel information for both transit and auto between the commuter's zip code and the commuter's worksite within King County are extracted from Google transit (www.google.com/transit) through a computer program. The average property value of the commuter's home zip code, used as a proxy for the commuter's household income, is obtained from King County appraiser's website (http://www.metrokc.gov/assessor/download/download.asp). Since the transit connection information is only available for King County Metro, this study will focus on the worksites located within King County and employees residing King County, including the Seattle urban area and other suburban and rural areas. Since more than 60 percent of the employers affected by the Washington State CTR program are located in King County, the utilization of this sub-sample will not affect the accuracy of the model.

The result of this part of study will not only provide a comprehensive, reliable quantitative and qualitative assessment of the impacts of TMD strategies on the affected commuters' mode choice, but will also explore the framework of a mode choice model that includes the TDM components. This mode choice model may further be incorporated into the regional transportation model to reflect the impact of the TDM on the regional transportation planning process.

5.2 Methodology

5.2.1 Nested Logit Model

Utility-based choice or choice based on the relative attractiveness of competing alternatives from a set of mutually exclusive alternatives is called a discrete choice situation. Discrete choice models are interpreted in terms of an underlying behavioral model, the so-called random utility maximization (RUM) model. The decision-maker chooses the alternative with the highest utility. Characteristics of the decision-maker and of the choice alternatives determine the alternatives' utilities.

Discrete choice decisions in the context of random utility theory are usually modeled and estimated with the multinomial logit model (MNL), or standard logit model, because of its closed choice probabilities and straightforward of interpretation. The MNL, however, assumes independence of irrelevant alternatives (IIA), i.e. the ratio of the choice probabilities of two alternatives is not dependent on the presence or absence of other alternatives in the model.

In a standard logit model, for any two alternatives *i* and *k*, the ratio of the probabilities of individual *n* choosing *i* over *k* is

$$\frac{p_{ni}}{p_{nk}} = \frac{e^{V_{ni}} / \sum_{j=1}^{J} e^{V_{nj}}}{e^{V_{nk}} / \sum_{j=1}^{J} e^{V_{nj}}}$$

$$= \frac{e^{V_{ni}}}{e^{V_{nk}}} = e^{V_{ni} - V_{nk}}$$

where J is the number of alternatives and V_{nj} is the utility of alternative j for individual n.

This ratio does not depend on any alternatives other than i and k. That is, the relative odds of choosing i over k are the same no matter what other alternatives are available or what the attributes of the other alternatives are. Since the ratio is independent other than alternatives, it is said to be independent of irrelevant alternatives, or IIA.

The IIA property is the direct result of the basic assumption on which the MNL has been established, that is, the error term of the utility function is independently identically Gumbel-distributed. While the IIA property is realistic in some choice situations, it is clearly inappropriate in others.

To overcome this restrictive substitution assumption between alternatives, various extensions of the MNL exist, all with the general solution of allowing correlations between the alternatives' error terms. The idea of the nested logit model lies in the grouping of similar alternatives into nests and thus creating a hierarchical structure of the alternatives (Ben-Akiva and Lerman, 1985; Train, 2003). The error terms of alternatives within a nest are correlated with each other, and the error terms of alternatives in different nests are uncorrelated.

The nested logit model, also known as the generalized extreme value (GEV) model, structured logit, and sequential logit, was first derived by Ben-Akiva [1973], as an extension of the multinomial logit model designed to capture correlations among alternatives. The nested logit model has become an important tool for the empirical analysis of discrete outcomes and has been widely applied in transportation modal choice studies (Train, 1980; Bhat, 1997). Its popularity comes from two facts: (1) it relaxes the restrictive assumption of the independence of irrelevant alternatives (IIA) of conditional logit model, and (2) it uses a closed-form likelihood function, which enables straightforward and fast computation. Therefore it is considered analytically tractable compared to multinomial probit and mixed logit.

The nested multinomial logit model is a more generalized multinomial logit model. It allows researchers to specify a structure that categorizes the alternatives into groups (nests) by assuming that alternatives in each group are similar in an unobserved way, thus creating a hierarchical structure of the alternatives (Ben-Akiva and Lerman, 1985; Train, 2003). The error terms of alternatives within a nest are correlated with each other, and the error terms of alternatives in different nests are uncorrelated.

For simplicity, assume a two-level nesting structure. Suppose there are J alternatives categorized into K nests: N_1, N_2… N_K. Suppose $y = j$ is the observed choice selected and alternative j is an element of nest N_k, then the probability that $y = j$ for individual n is given by

$$P_n(y = j) = P_n(y \in N_k).P_n(y = j \mid y \in N_k) \tag{5.1}$$

where $P(y \in N_k)$ is the marginal probability of choosing an alternative in nest N_K, and $P(y = j \mid y \in N_k)$ is the conditional probability of choosing alternative j given that an alternative in nest N_k is chosen. In other words, the probability of alternative j in the N_k nest results from the product of the marginal choice probability of nest N_k and the conditional choice probability for alternative j within nest N_k. Both marginal and conditional choice probabilities are standard logit models.

Without loss of generality, the observed component of utility can be decomposed into two parts: (1) a part labeled x that is constant for all alternatives within a nest and (2) a part labeled γ that varies over alternatives within a nest. Utility of alternative j for individual n can be written as

$$U_{nj} = x_{nk} + \gamma_{nj} + \varepsilon_j \tag{5.2}$$

for $j \in N_k$, where x_{nk} depends only on variables that describe nest N_k. These variables differ over nests but not over alternatives within each nest. γ_{nj} depends on variables that describe alternative j . These variables vary over alternatives within nest N_k.

The marginal and conditional probabilities can be expressed as

$$P_n(y \in N_k) = \frac{e^{x_{nk} + \lambda_k I_{nk}}}{\sum_{l=1}^{K} e^{x_{nl} + \lambda_l I_{nl}}} \tag{5.3}$$

$$P_n(y = j \mid y \in N_k) = \frac{e^{\gamma_{nj} / \lambda_k}}{\sum_{j \in N_k} e^{\gamma_{nj} / \lambda_k}} \tag{5.4}$$

where

$$I_{nk} = \ln \sum_{j \in N_k} e^{\gamma_{nj} / \lambda_k}$$

According to (5.1), the probability of $y = j$ for individual n is given by

$$\begin{aligned} P_n(y = j) &= P_n(y \in N_k).P_n(y = j \mid y \in N_k) \\ &= \frac{e^{x_{nk} + \lambda_k I_{nk}}}{\sum_{l=1}^{K} e^{x_{nl} + \lambda_l I_{nl}}} \cdot \frac{e^{\gamma_{nj} / \lambda_k}}{\sum_{j \in N_k} e^{\gamma_{nj} / \lambda_k}} \end{aligned} \tag{5.5}$$

where I_{nk}, often called inclusive value of nest $N_{K,}$ is the log of the denominator of the conditional probability model. It links the marginal probability model and the conditional probability model by bringing information from the lower model into the upper model. The coefficient λ_k on I_{nk} in the marginal model, often called the log-sum coefficient λ_k, reflects the degree of independence among the unobserved portions of utility for alternatives in nest N_k , with a lower λ_k indicating less independence (more correlation).

The parameters of a nested model can be estimated by standard maximum likelihood techniques. Substituting the choice probabilities of Expression (5.5) into the log-likelihood function gives an explicit function of the parameters of this model.

Instead of performing maximum likelihood, nested logit models can be estimated consistently (but not efficiently) in a sequential fashion, exploiting the fact that the choice probabilities can be decomposed into marginal and conditional probabilities. This sequential estimation is performed "bottom up." The lower models (for the choices of alternative within a nest) are estimated first. Using the estimated coefficients, the inclusive value is calculated for each lower model. Then the upper model (for choice of nest) is estimated, with the inclusive value entering as explanatory variables.

5.2.2 Elasticities of Logit Model

Elasticities measures how the independent variables response to the change in the determining factors. For the discrete choice model, it is the percentage change in the probability of choosing one of the alternatives due to a 1-percent change in some attribute that is an independent variable in the model. For a discrete choice model, the coefficients are not directly tied to the elasticities and it is necessary to distinguish between disaggregate and aggregate, direct and cross elasticities.

A disaggregate direct elasticity represents the percentage change in an individual's choice probability of choosing alternative i due to a 1-percent change in the value of some attribute that is an independent variable in the utility function of alternative i.

The formula of a disaggregate direct elasticity is:

$$
\begin{aligned}
E_{x_{ink}}^{Pn(i)} &= \frac{\partial P_n(i)}{\partial x_{ink}} \cdot \frac{x_{ink}}{P_n(i)} \\
&= \frac{\partial \log P_n(i)}{\partial \log x_{ink}} \\
&= [1 - P_n(i)]\, x_{ink}\, \beta_k
\end{aligned}
\tag{5.6}
$$

where $P_n(i)$ denotes the possibility of individual n choose alternative i, x_{ink} is the k attribute in the utility function of alternative n for the individual i. β_k is the coefficient of attribute k.

A disaggregate cross elasticity represents percentage change in an individual's choice probability of choosing alternative i due to a 1-percent change in the value of some attribute that is an independent variable in the utility function of alternative j.

The formula of a disaggregate cross elasticity is

$$
\begin{aligned}
E_{x_{ink}}^{Pn(i)} &= \frac{\partial P_n(i)}{\partial x_{ink}} \cdot \frac{x_{ink}}{P_n(i)} \\
&= \frac{\partial \log P_n(i)}{\partial \log x_{ink}} \\
&= -P_n(j)\, x_{jnk}\, \beta_k
\end{aligned}
\tag{5.7}
$$

where $i \neq j$.

It is clear that the logit model has uniform cross elasticities, that is, "the cross elasticities of all alternatives with respect to a change in an attribute affecting only the utility of alternative j are equal for alternatives $i \neq j$" [Ben-Akiva and Lerman, 1985, pp. 111-112].

For a two-level nested logit model, the direct elasticity, which is defined as the percentage change in individual's choice probability of choosing alternative k in branch l

due to a 1-percent change in the value of some attribute *r,* that is an independent variable in the utility function of alternative *k* in the branch *l*, is computed as:

$$E_{x(r)|k,l}^{P(k,l)} = x_r \Big| k,l * \beta_r \Big| k,l * \{[1 - P(k|l)] + [1 - P(l) * P(k|l)] * \tau_l\} \qquad (5.8)$$

where $x_r|k,l$ is the value of the attribute *r* in the utility function of alternative *k* in branch *l,* $\beta_r|k,l$ is the coefficient of the attribute *r*, *P(k|l)* is the conditional probability of choosing alternative *k* given branch *l* is chosen, *P(l)* is the probability of choosing branch *l,* τ_l is the coefficient of Inclusive Value for branch *l.*

The cross elasticity, which is defined as the percent change in an individual's choice probability of choosing alternative *k* in branch *l* du1 to 1-percent a change in the value of some attribute *r*, that is a variable in utility function of alternative j in branch *i*, is calculated as:

$$E_{x(r)|j,i}^{P(k,l)} = -x_r \Big| j,i * \beta_r \Big| j,i * P(k|l) * [1 + P(l) * \tau_l] \qquad (5.9)$$

where $l \neq j, l = i$ or $l \neq i$

While the disaggregate marginal effects measure the responsiveness of an individual's choice probability to a change in the value of some attribute, in most cases people are more interested in the responsiveness of some group of decision makers. Aggregate elasticities measure the summarized responsiveness of a group of decision makers to the changes in the value of some attribute, rather than that of any individual response. There are different ways, however, to summarize the group responsiveness, including averaging the individual sample observations, using the sample means of the data, and calculating a weighted average. For the first method, the aggregate elasticities are simply the average of disaggregate elasticities. Observations receive equal weigh in the average. One problem that can arise using this method is that if an observation in the sample has an extreme configuration of attributes for some reason, then the elasticities for that observation can be extremely large, which in turn will cause the average to be huge. For the second method, the elasticities are computed just once at the sample means of the attributes. The weighted average method calculates the aggregated elasticities as weighted average of the individual level elasticities using the choice probabilities as weights, that is,

$$E_{x_{jk}}^{\overline{P}(i)} = \frac{\sum_{n=1}^{N} P_n(i) E_{x_{jnk}}^{P_n(i)}}{\sum_{n=1}^{N} P_n(i)} \tag{5.10}$$

where N is the number of decision makers in the group.

"By this construction, if an individual probability is very small, the resulting extreme value for the elasticities is multiplied by a very small probability weight, which offsets the extreme value" [Greene, 2002, pp. N3-24]. In this dissertation, the elasticities are calculated using the weighted average method.

5.3 Data and Variable Definition

5.3.1 Mode Share Trend for The CTR Affected Employees

Once again, the major data sources for this part of study come from Washington State CTR dataset, which was described in detail in Chapter 3. The dependent variable is journey-to-work mode choice. The mode shares from 1993 to 2005 based on CTR affected employee in King County and in all of the nine counties are presented in Table 5.1 and 5.2 respectively. In 1993, 64.79 percent of employees in King County and 74.52 percent of all of CTR affected employees drove alone. This share then declined to 58.27 and 68.64 percent respectively in 2001, after which, it rebounded to 63.28 and 70.02

percent in 2005. Although the shares of drive alone were higher based on the whole sample of CTR affected employees, the trend was the same. Despite the rebound, the shares of drive alone in King County and for the entire CTR affected employee are lower than the state share of 74.3 percent and national average of 77 percent in 2005. It seems that the share of non-motor remains relatively stable. The significant changes come from carpool, vanpool, and transit, especially, from vanpool and transit. At the peak of 2001, for the CTR affected employees within King County, the transit share increased 5 percent from 1993 while the vanpool share more than doubled. This is expected since, for most commuters, the alternatives of walking and bicycling are constrained by some factors, such as commute distance and the weather in Puget Sound area, and is less sensitive to the CTR strategies.

While the reason for the rebound of the driving alone share after 2001 remains unknown, from the perspective of CTR strategies, it may suggest the existence of some kinds of "Program Tiredness," which means as the CTR strategies are being implemented, people are getting used to the stimulation and they are becoming less and less sensitive. It may also suggest that the same type of CTR strategies may have different impacts at different time period.

Table 5.1 Mode Shares Trend for CTR Affected Employees in King County

Program Year	Num of Employees	Mode Share (%)				
		Drive Alone	Carpool	Vanpool	Transit	Non Motor
1993	71,691	64.79	14.68	0.97	16.40	3.16
1995	95,812	60.75	15.46	1.63	19.12	3.04
1997	104,013	59.55	15.59	2.63	19.11	3.12
1999	98,804	58.83	16.00	1.83	20.06	3.29
2001	109,671	58.27	15.21	2.11	21.41	2.99
2003	110,763	60.93	13.93	2.65	19.42	3.07
2005	133,681	63.28	13.09	2.48	18.12	3.02

Table 5.2 Mode Shares Trend for the Entire CTR Affected Employees

Program Year	Num of Employees	Mode Share (%)				
		Drive Alone	Carpool	Vanpool	Transit	Non Motor
1993	176,722	74.52	13.33	1.10	8.40	2.64
1995	192,525	69.67	15.06	1.40	10.96	2.91
1997	235,009	68.54	15.36	2.36	10.60	3.14
1999	194,975	68.78	14.99	1.41	11.50	3.32
2001	222,584	68.64	14.42	1.69	11.95	3.30
2003	208,486	69.71	13.47	2.04	11.93	2.86
2005	231,322	70.02	12.87	2.17	11.99	2.95

5.3.2 Variable Definition

The variables in the utility function of the nested logit model include (1) characteristics of the employer, including business type, total number of employees, and the existence of multiple shifts at the worksite; (2) parking management information at the worksite, including parking charge for SOV and HOV, ratio of onsite parking spaces to total number of employees, and the existence of reserved parking spaces for HOV; (3) employer paid financial subsidies for alternative modes, including the subsidy for transit, carpool, vanpool, bike, and walk; (4) employer TDM support/promotion strategies/activities, including the availability of guaranteed ride home program, the availability of company fleet vehicle for carpooling or vanpooling, and the promotion activities of distributing program summary material, sending program information through email, conducting transportation event, and publishing TDM articles in employee newsletter; and (5) amenities and land-use characteristics at the worksite, including area type (downtown, rural, other), existence of sidewalk, bike-lane, and onsite restaurant, and existence of onsite covered bike locker, cloth locker, and showers. The above variables are obtained from the employer annual report.

Parking management is one of the handy tools that the employers can lean on to achieve their CTR goal. I use the ratio of number of onsite parking spaces to the total number of employees, rather than the absolute number of parking spaces to measure the accessibility to the parking facility. In addition to the parking charge for SOV and HOV parking, I include the HOV parking charge discount, which is defined as the difference between the SOV parking charge and that of HOV, to measure the impacts of discounted HOV parking.

The financial subsidies to the alternative modes include cash incentives, gift card incentives, free passes for transit, and reimbursement of travel costs. It does not include the parking discount provided for HOV parking.

The variables from the employee travel behavior survey include commuter's job title, work schedule, and commuting distance.

The detailed travel information for both transit and motor between the commuter's home ZIP code and the commuter's worksite are extracted from Google transit (www.google.com/transit). A computer program is designed to search the travel information between each of the worksite-home pair for total more than 44,000 pairs. For driving, the results of the searching include travel time and distance. For transit the searching results include first walk time, first in-vehicle time, transfer time and second in-vehicle time if need transfer, and last walk time. Currently, in Washington State, the Google transit service only is available for King County Metro, which includes the Seattle metropolitan area. Therefore, this study will focus on the worksites located within King County and the employees residing King County, including the Seattle urban area and other suburban and rural areas. Since more than 60 percent of the employers affected by the Washington State CTR program are located in King County, the utilization of the sub-sample will not affect the accuracy of the model.

Table 5.3 Variable Definitions

Variable	Description*
Total Employees	Total number of employees.
	Primary business of the organization.
Finance	=1, if Finance, Insurance, Real estate; =0, if Otherwise (13.3%)
Info Service	=1, if Information services/Software/Technical; =0, if Otherwise (9.4%)
Personal Services	=1, if Professional/Personal Services; =0, if Otherwise (8.6%)
Manufacture	=1, if Manufacturing; =0, if Otherwise (7.1%)
HealthCare	=1, if Health Care; =0, if Otherwise (16.3%)
Public Utility	=1, if Public Utility; =0, if Otherwise (13.7%)
Military	=1, if Military; =0, if Otherwise (2.4%)
Transportation	=1, if Transportation; =0, if Otherwise (2.9%)
Government	=1, if Government; =0, if Otherwise (17.4%)
Education	=1, if Education; =0, if Otherwise (2.7%)
Other	=1, if Other; =0, if Otherwise (5.6%)
Shift	Does this worksite have multiple shifts? =1, if Yes (78.8%) =0, if Otherwise
	Job title of the employee
Administrative Support	=1, if Administrative Support; =0, if Otherwise (13.7%)
Management	=1, if Management; =0, if Otherwise (14.1%)
Technical	=1, if Professional/Technical; =0, if Otherwise (46.9%)
Production/Labor	=1, if Craft/Production/Labor; =0, if Otherwise (8.0%)
Customer Service	=1, if Customer Service; =0, if Otherwise (7.6%)
Sales/Marketing	=1, if Sales/Marketing; =0, if Otherwise (4.0%)
Other	=1, if Other; =0, if Otherwise (5.7%)
CWW	Does the employee work on compressed work week schedules? =1, if yes (16.9%) =0, if otherwise
Telecommuting	Does the employee work on telecommuting? =1, if yes (5.7%) =0, if otherwise
Commute Distance	On way distance in mile commute from home to worksite

*In the parenthesis is the percentage of the observations with observed value equal to 1 for the dummy variables

Table 5.3 Variable Definitions (Cont')

Transit In-Vehicle Time	Transit travel in vehicle time
Transit Out-Vehicle Time	Transit travel out vehicle time
Transit Transfer Times	Transit travel number of transfers
Avg. Property Value	Average property value in dollar of the ZIP code in which the commuter resides
Onsite Parking Charge	Parking charge for single occupant vehicles ($/space/month)
Onsite Parking Ratio	The ratio of total number of onsite parking spaces to total number of employees
Reserved HOV Parking	Worksite reserved HOV parking space(s) availability. =1, if reserved HOV parking space(s) available (71.7%) =0, if otherwise
HOV Parking Discount	Difference between SOV parking and HOV parking ($/space/month)
Subsidy	Monthly transit, HOV, or bicycle/Walk subsidy employer paid per participating employee ($/employee/month)
Flextime	Does your organization offer flex time (Allow employees to vary their start and end times)? =1, if yes (90.8%); =0, if otherwise
GRH	Is the guaranteed emergency ride home program available at this worksite? =1, if yes (89.1%); =0, if otherwise
Distribute Material	Does the employer distribute a summary of the worksite's CTR program to employees? =1, if Yes (96.4%); =0, if Otherwise
CTR Events	Does the employer conduct transportation events/fairs and/or participate in county/state CTR promotions/campaigns? =1, if Yes (87.8%); =0,if Otherwise
CTR Email	Does the employer send out the CTR information through email? =1, if Yes (91.5%); =0, if Otherwise
CTR Article	Dose the employer publish CTR articles in employee newsletters? =1, if Yes (42.9%); =0, if Otherwise

*In the parenthesis is the percentage of the observations with observed value equals to 1 for the dummy variables

Table 5.3 Variable Definitions (Cont')

HOV Fleet Vehicle	Availability of employer provided fleet vehicle for carpool =1, if Yes (2.8%) =0, Otherwise
Downtown	Is the worksite located in the downtown area? =1, if Yes (32.1%) =0, if No
Sidewalk	Worksite sidewalks availability. =1, if sidewalks is available onsite or within 1/4 mile (84.1%); =0, if otherwise
Restaurants	Worksite restaurants/cafeteria availability. =1, if restaurant/cafeteria is available onsite or within ¼ mile (75.7%); =0, if otherwise
Covered Bicycle Racks	Worksite covered bicycle spaces, cages, racks or lockers availability =1, if available onsite (80.4%) =0, if Otherwise
Lockers	Worksite clothes lockers availability =1, if available onsite (76.4%) =0, if Otherwise
Showers	Worksite showers availability =1, if available onsite (78.3%) =0, if Otherwise

*In the parenthesis is the percentage of the observations with observed value equals to 1 for the dummy variables

Table 5.4 Summary Description of Data (Continuous variables)

Variable	Mean	Std. Dev	Minimum*	Maximum
Total Employees	1,842.24	2,560.74	53	11,488
Commute Distance	11.84	8.02	1	55
Onsite Parking Charge	56.17	85.55	0 (58.77%)	310
Onsite Parking Ratio	0.52	0.37	0 (9.27%)	1
HOV Parking Discount	16.88	34.63	0 (72.44%)	280
Transit Subsidy	36.52	28.12	0 (16.88%)	144
HOV Subsidy	11.31	20.88	0 (66.41%)	185
Bike/Walk Subsidy	5.87	13.33	0 (78.44%)	100
Avg. Property Value	347,925	143,427	109000	1,988,184
Transit In-Vehicle Time	35.50	21.80	1	143
Transit Out-Vehicle Time	19.10	13.31	2	101
Transit Transfer Times	0.71	0.71	0 (43.07%)	4

*In the parenthesis is the percentage of the observations with observed value equals to 0

I use the average property value of the ZIP code in which the employee resides, combined with the employee job title, to serve as a proxy for the employee's socio-economic information. The property value includes the "land value and the building value." The data are from the King County appraiser's web site [King County Department of Assessment, 2005]. The detailed variables definitions are presented in Table 5.3. Descriptive data statistics are reported in Table 5.4.

5.4 Model Specification

A nested logit model is applied to estimate the determinants of modal choices for the CTR affected employees and evaluate the impacts of various TDM strategies on commuter's modal choices based on a large sample of about 60,000 observations.

The model specified in equation 5.5 imposes no restriction on the inclusive value parameters. However, as one of the discrete choice models, the nested logit model is derived from the random utility theory. The theory foundation of random utility theory is utility maximization. For nested logit estimation, the model is consistent with the utility maximization if and only if the inclusive value parameter lies between zero and one. Some normalization is required for the nested logit model to satisfy the inclusive value parameter restriction. Normalization is simply the process of setting one or more scale parameters equal to unity, while allowing the other scale parameters to be estimated. Generally, a nested logit model can be normalized in two different ways to produce the desired results. For a two level nested logit model, it can be normalized by either setting the scale parameter at the top level equal to one or setting the scale parameter at the bottom level equal to one. In this study, I apply the second way of normalization to specify the model, which is, normalizing the scale parameter at the branch.

The model is a two-level nested logit model. The first nest includes motor, transit, and non-motor. In the second nest, motor is divided into drive-alone and shared riding. The mode shares of each of the alternative are: motor, 74.18 percent (drive-alone, 60.61 percent; shared ride, 13.57 percent); transit, 22.29 percent; and non-motor, 3.52 percent. Figure 5.1 exhibits the structure of nested logit model. Figure 5.2 depicts the mathematic specification of the model.

Determining a traveler's choice set is always a problem that is theoretically straightforward but practically difficult. Theoretically, a traveler's choice set consists of every mode whose probability of being chosen exceeds zero. Practically, however, the traveler's choice set only contains the modes whose probabilities of being chosen are large enough to be practically significant. There are no rigorous analytic methods for assigning choice sets to travelers. The accuracy of the definition of a traveler's choice set largely depends on the availability of the traveler's personal information and the information on mode accessibility. The Washington State CTR data shows that less than one percent of travelers taking transit need to transfer three or more times, less than five percent need to transfer two or more times. For the travelers riding bicycle, more than 97 percent commute 20 or fewer miles one way. Therefore, in this dissertation, the drive alone and shared ride are assumed to be available to all travelers. Transit is assumed to be available only to the travelers for whom the maximum number of transfer times is less than two. Non-motor is assumed to be available to the commuter for whom the one way commuting distance is less than 20 miles.

Figure 5.1 Nested Logit Model Structure

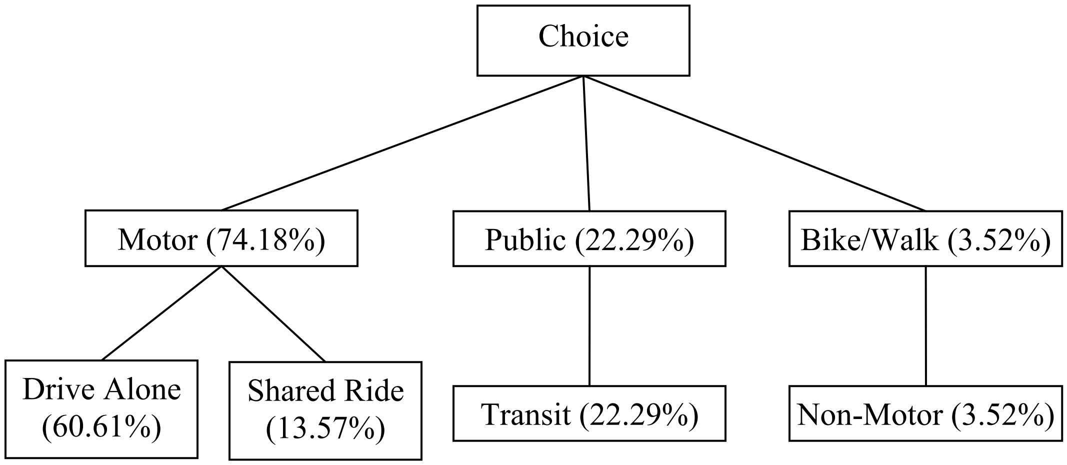


Figure 5.2 Mathematical Specification of the Nested Logit Model

1. Utility Functions

U(Drive Alone) = α_1*Onsite Parking Charge + α_2*Onsite Parking Ratio

U(Shared Ride) =β_0 + β_1*Commute Distance + HOVP*HOV Parking Discount
+ ReservedHOVParking*Reserved HOV Parking + β_2*Subsidy
+ β_3*Total Employees + β_4*Avg. Property Value + β_5*Downtown
+ β_6*CWW + β_7*Telecommuting + β_8*Shift + Flextime*Flextime + GRH*GRH
+ Distribute*Distribute Material + CTREmail*CTR Email
+ CTREvents*CTR Events + CTRArticle*CTR Article
+ β_9*Administrative Support + β_{10}*Labor + β_{11}*Manager + β_{12}*Sales
+ β_{13}*Technical + β_{14}*Finance + β_{15}*Information + β_{16}*Manufacture
+ β_{17}*Health + β_{18}*Public Utility + β_{19}*Transportation + β_{20}*Government
+ β_{21}*Education + Restaurant*Onsite Restaurant + HOVFleet*HOV Fleet Vehicle

U(Transit) =γ_0 + InVehicleTime*Transit In-Vehicle Time
+ OutVehicleTime*Transit Out-Vehicle Time + γ_2*Subsidy
+ γ_3*Total Employees + γ_4*Avg. Property Value + γ_5*Downtown + γ_6*CWW
+ γ_7*Telecommuting + γ_8*Shift + Flextime*Flextime + GRH*GR
+ Distribute*Distribute Material + CTREmail*CTR Email
+ CTREvents*CTR Events + CTRArticle*CTR Article
+ γ_9*Administrative Support + γ_{10}*Labor + γ_{11}*Manager + γ_{12}*Sales
+ γ_{13}*Technical + γ_{14}*Finance + γ_{15}*Information + γ_{16}*Manufacture

$+ \gamma_{17}$*Health + γ_{18}*Public Utility + γ_{19}*Transportation + γ_{20}*Government
$+ \gamma_{21}$*Education + Restaurant *Onsite Restaurant + Sidewalk*Sidewalk

U(Non-Motor) =λ_0 + λ_1*Commute Distance + λ_2*Subsidy + λ_3*Total Employees
$+ \lambda_4$*Avg. Property Value + λ_5*Downtown + λ_6*CWW + λ_7*Telecommuting
$+ \lambda_8$*Shift + Flextime*Flextime + GRH*GR
+ Distribute*Distribute Material + CTREmail*CTR Email
+ CTREvents*CTR Events + CTRArticle*CTR Article
$+ \lambda_9$*Administrative Support + λ_{10}*Labor + λ_{11}*Manager + λ_{12}*Sales
$+ \lambda_{13}$*Technical + λ_{14}*Finance + λ_{15}*Information + λ_{16}*Manufacture
$+ \lambda_{17}$*Health + λ_{18}*Public Utility + λ_{19}*Transportation + λ_{20}*Government
$+ \lambda_{21}$*Education + Restaurant *Onsite Restaurant
+ CoveredBike*Covered Bicycle Rack + Lockers*Onsite Lockers
+ Showers*Onsite Showers + Sidewalk*Sidewalk

2. Conditional Probabilities

$$\text{P(Drive Alone | Motor)} = \frac{\exp(U_{\text{Drive Alone}})}{\exp(U_{\text{Drive Alone}}) + \exp(U_{\text{Shared Ride}})}$$

$$\text{P(Shared Ride | Motor)} = \frac{\exp(U_{\textit{Shared}\ \text{Ride}})}{\exp(U_{\text{Drive Alone}}) + \exp(U_{\text{Shared Ride}})}$$

P(Transit | Pubic) = 1

P(Non-Motor | Bike/Walk) = 1

3. Inclusive Values

$$IV_{\text{Motor}} = \ln[\exp(U_{\text{DriveAlone}}) + \exp(U_{\text{SharedRide}})]$$

$$IV_{\text{Pulic}} = U_{\text{Transit}}$$

$$IV_{\text{Bike/Walk}} = U_{\text{Non-Motor}}$$

4. Branch Probabilities

$$\text{P(Motor)} = \frac{\exp(\tau_{Motor} * IV_{\text{Mootr}})}{\exp(\tau_{Motor} * IV_{\text{Mootr}}) + \exp(\tau_{Public} * IV_{\text{Public}}) + \exp(\tau_{Bike/Walk} * IV_{Bike/Walk})}$$

$$\text{P(Public)} = \frac{\exp(\tau_{Public} * IV_{\text{Public}})}{\exp(\tau_{Motor} * IV_{\text{Mootr}}) + \exp(\tau_{Public} * IV_{\text{Public}}) + \exp(\tau_{Bike/Walk} * IV_{\text{Bike/Walk}})}$$

$$\text{P(Bike/Walk)} = \frac{\exp(\tau_{Bike/Walk} * IV_{\text{Bike/Walk}})}{\exp(\tau_{Motor} * IV_{\text{Mootr}}) + \exp(\tau_{Public} * IV_{\text{Public}}) + \exp(\tau_{Bike/Walk} * IV_{\text{Bike/Walk}})}$$

5. Choice Probabilities

P(Drive Alone) = P(Motor)* P(Drive Alone | Motor)

P(Shared Ride) = P(Motor)* P(Shared Ride | Motor)

P(Transit) = P(Public)

P(Non-Motor) = P(Bike/Walk)

5.5 Regression Results

The model is estimated using LIMDEP 8.0. After combining all of the data from different source, the final sample size is 62,346. Table 5.5 reports the nested logit regression results.

The value of the log likelihood function at its maximum is - 50763.5. The chi-square, a statistic used to test the null hypothesis that all the parameters are zero, is 26532.76 with 81 degrees of freedom, which indicates that we can reject the null hypothesis that all the parameters are zero at the level of at least 0.001. The *R-Squared*, an informal goodness-of-fit index that measures the fraction of an initial log likelihood value explained by the model, defined as *1-Log-L(β)/Log-L(0),* is 0.495.

The inclusive value coefficients of τ for alternatives to shared-ride, transit, and non-motor are 2.648, 2.567, and 2.166 respectively and statistically significant at the level of at least 0.001. This statistic suggests the nested logit model is appropriate and necessary to estimate the commuter's journey-to-work mode choice.

Examining the coefficients in the models for the mode choices, it is first observed that the constant terms are all negative, suggesting that the average effect of those unobserved influence variables is in the direction of drive-alone. This is anticipated since more than 60 percent of commuters drive alone to work.

Commute distance is a variable in the utility function of shared-ride and non-motor used to measure the travel impedance. The coefficient on commute distance in the shared-ride equation is positive and statistically significant at the level of at least 0.001, which suggests that the longer the commute distance, the more likely commuters choose to share rides to work. On the other hand, the coefficient in the non-motor equation is negative and statistically significant at the level of at least 0.001, indicating that commuters with longer commute distance are less likely to bicycle or walk.

For transit, instead of using distance, three variables of transit in-vehicle time, transit out-vehicle time, and transit transfer times are used as the measurement of travel impedance. Out-vehicle time includes walking to a bus stop, waiting for a vehicle, and transfer time, and walking from a bus stop to the final destination. The coefficient of transit in-vehicle time is positive and statistically significant at the level of at least 0.001. The coefficients of transit out-vehicle time and transit transfer times are negative and statistically significant at the level of at least 0.01. These findings suggest that commuters are less likely to use transit to work if they have to wait longer for a transit to come or walk long distance to transit stops or they cannot arrive at their destination non-stop. The positive sign suggests that transit use is not negatively affected by transit in-vehicle time. The positive sign on transit in-vehicle time, together with the findings that out-vehicle time and transfer time have a negative impact on transit use, implies that commuters are more responsive to increases in out-of-vehicle time than in-vehicle time, a conclusion drawn by Domencich et al. [1972] and Small [1992]. The positive coefficient of transit in-vehicle may also be explained by the wide variety of transit services available to the residence. For people who have better access to transit service and can reach their worksite non-stop, transit use may not be a bad choice considering it is cost-effective and not very time-consuming.

The number of total employees is used to control for the size of the worksite. The coefficients of this variable are positive and statistically significant at the level of at least 0.1 for all of the three alternative modes. This result suggests that worksite size has a positive effect on commuters' alternative mode choices, which may be explained by the facts that it is easier for commuters to have a good match to share ride in large companies or organizations and that commuters in large worksites may have better access to transit use since public transportation stops are generally located in the places with high employment density.

The dummy variable, the existence of multiple shifts, is used to control for whether the worksite has multiple shifts. The coefficients of shift for the choices of transit and non-motor are negative and statistically significant at the level of at least 0.01. It is negative but not significant for shared ride. This result suggests that commuters in worksites with multiple shifts are less likely to use transit, bicycle, or walk to work. Possible explanations are that transit services may be not available for certain shifts or it is not very safe to walk or bicycle during night shifts.

There are four variables used to capture differences in employers' policy on parking cost and parking space supply. Parking charge is the variable used only in the equation of drive-alone. The coefficient on parking charge is negative and statistically significant at the level of at least 0.001. This result is expected and once again confirms that parking charges do have positive and significant impacts on employers' choice of using the alternative modes.

HOV parking discount measures the difference of the SOV parking charge and HOV parking charge. It is only defined for the alternative of shared ride. The coefficient of HOV parking discount is positive and statistically significant at the level of at least 0.05. This result confirms that HOV parking discount has positive and significant impacts on commuters' choices of carpool and vanpool.

I use the onsite parking ratio, which is defined as the ratio of the total onsite parking spaces to the total number of employees, rather than the total number of onsite parking spaces, to measure the employer's parking facility supply. It only enters into the utility function of drive-alone. The coefficient on the onsite parking ratio is positive and statistically significant at the level of 0.001, which suggests that the higher the ratio of onsite parking space to the total number of employees, the higher the likelihood for commuters to drive alone to work. If the onsite parking space is limited, it may increase the time that commuters spending on locating an onsite parking space or even force the commuter to park on the offsite parking facility, which in turn increases the out-of-vehicle time for driving alone. Consequently, it may encourage the commuter to use the alternatives to driving alone.

Reserved HOV parking is a dummy variable indicating whether reserved parking space is available for high-occupancy vehicles. It only enters into the utility function of shared ride. The coefficient of this variable is positive and statistically significant at the level of at least 0.01, which suggests that the existence of reserved parking spaces has significant positive impacts on a commuter's choice of carpooling ad vanpooling.

Table 5.5 Nested Logit Regression Results

Variable	Drive Alone [a, b]	Shared Ride [a,b]	Transit [a,b]	NonMotor [a,b]
Constant	-	-1.881*** (20.5)	-0.848***(10.0)	-0.834***(8.0)
Commute Distance	-	0.022*** (14.2)	-	-0.158***(10.0)
Total Employees	-	$5.2e^{-5}$***(8.6)	$5.0e^{-6}$*(1.7)	$1.8e^{-5}$***(3.0)
Shift	-	-0.029 (0.8)	-0.045***(2.8)	-0.097***(2.9)
Parking Charge	-0.001***(-9.7)	-	-	-
Onsite Parking Ratio	0.646***(16.9)	-	-	-
HOV Parking Discount	-	0.001**(2.0)	-	-
Reserved HOV Parking	-	0.0315*** (5.7)	-	-
Subsidy	-	0.005***(11.0)	0.001***(4.0)	0.004***(4.6)
Avg Property Value	-	$-8.0e^{-7}$***(7.5)	$1.02e^{-8}$(0.2)	$2.6e^{-7}$***(3.2)
CWW	-	-0.132***(3.9)	-0.134***(7.3)	-0.055*(1.8)
Telecommuting	-	-0.161***(2.9)	-0.174***(6.0)	-0.102*(1.8)
Flextime	-	0.235*** (9.3)	0.235*** (9.3)	0.235*** (9.3)
GRH	-	0.120***(5.7)	0.120***(5.7)	0.120***(5.7)
Distribute Material	-	0.300***(7.1)	0.300***(7.1)	0.300***(7.1)
CTR Events	-	0.159***(7.7)	0.159***(7.7)	0.159***(7.7)
CTR Email	-	0.262***(9.3)	0.262***(9.3)	0.262***(9.3)
CTR Article	-	0.014(1.0)	0.014(1.0)	0.014(1.0)
HOV Fleet Vehicle	-	0.333***(5.3)	-	-
Transit In-Vehicle Time	-	-	0.003***(7.7)	-
Transit Out-Vehicle Time	-	-	-0.004***(7.1)	-
Transit Transfer Times	-	-	-0.044***(4.0)	-
Downtown	-	0.308***(7.5)	0.664***(12.8)	0.21***(5.4)
Sidewalk	-	-	0.044***(3.1)	0.044***(3.1)
Onsite Restaurant	-	0.118***(7.2)	0.118***(7.2)	0.118***(7.2)
Covered Bicycle Racks	-	-	-	0.139***(2.9)
Showers	-	-	-	0.088**(2.2)
Lockers	-	-	-	0.096**(2.3)
Job-Administrative Support	-	0.011(0.3)	0.066***(3.1)	-0.091**(2.0)
Job-Production/Labor	-	0.266***(5.1)	0.029(1.0)	0.082(1.4)
Job-Management	-	-0.518***(11.0)	-0.530***(12.0)	-0.351***(6.1)
Job-Sales/Marketing	-	-0.338***(4.9)	-0.435***(9.5)	-0.308***(4.1)
Job-Professional/Technical	-	-0.146***(3.9)	-0.119***(6.1)	0.064*(1.8)
Business-Finance/Real Estate/Insurance	-	0.073*(1.7)	0.051***(2.4)	-0.088(1.9)*
Business-Information Service/Software	-	-0.227***(3.9)	0.008(0.3)	-0.018(0.3)
Business-Manufacturing	-	-0.412***(9.1)	-0.429***(9.6)	-0.059(1.1)
Business-Health Care	-	-0.203***(4.5)	-0.007(0.3)	-0.001(0.0)
Business-Public Utility	-	-0.106(1.2)	-0.050(1.4)	0.048(0.5)
Business-Transportation	-	-0.349***(4.5)	-0.064*(1.7)	-0.442***(3.5)
Business-Government	-	-0.153***(3.7))	0.047***(2.4)	-0.095**(2.3)
Business-Education	-	-0.251***(3.0)	0.104***(2.9)	0.093(1.5)
τ	-	2.648***(15.2)	2.567***(13.2)	2.166***(10.3)
N(R-Squared)	62,346 (0.49515)			
Log-L	-50763.5			
Chi-squared[81]	26532.76***			

[a] absolute value of z-statistics in parentheses.
[b] *2-tail significance at $\alpha = 0.10$. **2-tail significance at $\alpha = 0.05$. ***2-tail significance at $\alpha = 0.01$.

Alternative modes financial subsidy is one of the most popular strategies employers resort to achieve their CTR goals. For the sample I used to estimate the model, 83.12 percent of employees work for an employer providing transit subsidy, 33.59 percent providing carpool or vanpool subsidy, 21.56 providing bike or walk subsidy. The alternative modes financial incentives include cash incentives, gift card incentive, free pass for transit, and other reimbursements of out-of-pocket travel costs. It does not include the parking discount provided for HOV parking. Transit subsidy, HOV subsidy, and Bicycle-Walk subsidy are generic variables entering the utility functions for each of the alternative modes, the subsidy for drive alone is assumed to be 0. The coefficients of the subsidies are positive and statistically significant at the level of at least 0.001 for all of the alternative modes, suggesting financial subsidy could be an effective tool to encourage alternative modes use. The specific impacts of the financial incentive to a commuter's mode choice will be discussed in the next section.

The dummy variables of CWW and telecommuting are used to capture the employees' difference of their work schedules. They are both entered into the utility functions of the alternative modes. The coefficients of CWW and telecommuting are negative and statistically significant at the level of at least 0.01 for the shared ride and transit and at the level of at least 0.1 for the non-motor. This result suggests that when employers work on compressed work schedules or telecommuting, they are more likely to drive alone. When employees work on CWW, they need to work longer hours and leave home earlier and reach home late. This makes it harder for them to match the schedules of others to make a shared ride. Since most transit service varies in peak-hour and non-peak periods, it is not surprising that CWW workers are less likely to use transit.

Flexible time is a dummy variable to reflect the availability of the option whether employers allow commuters vary their start and end work time. The coefficients of flexible time are positive and statistically significant at the level of at least 0.001. The effect of flexible time is assumed to be the same across mode choices[1]. This result suggests that when offering flexibility to commuters to start and end their work, they are more likely to use alternative modes to drive alone. While this result is expected, it is important to know the positive impact is significant. We will also see in the next section that the elasticities of flexible on decreasing the drive alone use is even larger than some other TDM strategies, such as guaranteed ride home program. Since flexible time is easy to implement and cost-effective to employers, it should be recommended to the employers as one of the effective and efficient strategies to achieve the CTR goals.

The variable of guaranteed ride home program enters the utility functions of all of the alternative modes and assumed to have the same impacts across the alternative models. The variable of HOV fleet vehicle measures the availability of employer provided fleet vehicles for carpool or vanpool. It only enters into the utility function of shared ride. As expected the coefficients for both of the variables are positive and significant at the level of at least 0.01.

Four dummy variables are used to measure the employer's TDM promotion activities, including distributing CTR information, conducting transportation events, publishing CTR articles, and sending electronic mail messages about the CTR program.

[1] When allowing this variable to have different marginal effect across modes, the coefficients are very close.

Their effects are assumed to be the same across the alternative modes. Except publishing CTR articles, which is positive but not significant, the coefficients of the other three variables are all positive and statistically significant at the level of at least 0.001.

A dummy variable downtown is used to control for the location of the worksite. The coefficient on downtown is positive and statistically significant for all of the alternative modes, suggesting employees working in downtown areas are more likely to share ride, transit, bicycle, or walk to work. There are several reasons that induce the commuters working downtown to be more likely to take the alternative modes. Firstly, the downtown area may have better access to the public transportation system and many other amenities. Secondly, because of peak period congestion, auto use to downtown areas may associate with it a high degree of travel time unreliability. The uncertainty about arrival time may induce downtown workers to leave from home earlier. This extra time may be viewed as a source of disutility to the urban traveler.

Sidewalk and onsite restaurant are two dummy variables controlling for the land-use design of the worksite. Restaurant indicates whether a restaurant is available onsite or within 0.25 miles from the worksite. Sidewalk enters the utility function of transit and non-motor and its impact on these two modes are assumed to be the same. The coefficient on sidewalk is positive and statistically significant at the level of at least 0.01. The coefficients on onsite restaurant are positive and statistically significant at the level of at least 0.01. These two findings suggest that land-use designs that are pedestrian friendly in the areas of high employment density may also play a positive role in helping achieving CTR goals.

Covered bicycle racks, showers, and lockers are the three non-motor specific variables to indicate whether employers provide such facilities to help bicycling or walking employees. The impacts of the three variables on non-motor using are positive and statistically significant.

Five dummy variables are used to reflect employees' job title. The coefficients of management and sales/marketing are negative and statistically significant at the level of at least 0.01, suggesting that managers and employees with the job title of sales/marketing are more likely to drive alone to work. The coefficients of administrative support and professional/technical dummy variables have mixed signs. Employees working as administrative support are more likely to use transit and less likely to bicycle or walk to work, while professional/technical commuters are more likely to use non-motor and less likely to use shared ride and transit commuting to work. The coefficients of production/labor are positive but only statistically significant for shared ride, suggesting production/labor workers are more likely to share ride to work. From the above results, it is clear that a commuter's journey to work mode choice is affected by his or her job characteristics. This suggests that when encouraging an alternative mode to drive-alone, employers should consider their job characteristics and provide incentives tailored to commuters with different job characteristics.

There are eight dummy variables used to capture employer's major business type. The coefficients of manufacturing, health care, and transportation are negative for all of the alternative modes, suggesting that compared to other industry, commuters in the three above industries are more likely to drive alone. The coefficients of other dummy variables have mixed signs.

5.6 Elasticity and effect Analysis

One of the major objectives of this chapter is to measure the quantitative impacts of the TDM strategies on a commuter's journey to work mode choice. For the continuous variables, the quantitative impacts are measured as elasticities, which, for a discrete choice model, is the percentage change in the probability of choosing one of the alternatives due to a 1-percent of change in some attribute that is an independent variable in the model. For the dummy variable, the effect is measured as the change in the probability of choosing one of the alternatives with and without the strategy. The direct and cross aggregate elasticities of the continuous variables on a commuter's mode choice are calculated according to equation 5.8, 5.9, and 5.10. Table 5.6 reports the elasticities of the strategies whose impacts are statistically significant. The effect of a dummy variable for each observation is simply the difference of the possibility of choosing an alternative when the dummy variable equals to one and equals to zero. The aggregate impact of a dummy variable is the average of all of the observations. Table 5.7 reports the effects of the dummy variables whose impacts are statistically significant.

Parking charge is the variable only entered into the utility function of driving alone. The direct elasticity of - 0.281 and cross elasticities of 0.086, 0.307, 0.150 suggest that when the parking charge increases by 10 percent, commuter's likelihood to drive alone falls by 2.81 percent; shared ride, transit, and non-motor increase by 0.86, 3.07, and 1.50 percent respectively. The empirically derived as well as modeled parking price elasticities of demand from various empirical analyses generally range from - 0.1 to - 0.6, with -0.3 being the most frequently cited value [Vaca and Kuzmyak, 2005].

Onsite parking ratio measures parking space supply from employer. Its direct elasticity for drive-alone is 0.317, while its cross elasticities for shared ride, transit, non-motor are - 0.190, - 0.471, and - 0.394 respectively. If an employer decreases the ratio of number of onsite parking spaces to total number of employees by 10 percent, a commuter's likelihood to drive alone decrease by 3.17 percent; shared ride, transit, and non-motor increase by 1.90, 4.71, and 3.94 percent respectively.

The direct elasticity of HOV parking discount is 0.065, suggesting that when the parking discount to high occupancy vehicles increases by 10 percent, a commuter's likelihood to commute by shared-ride increase by 0.65 percent.

Alternative modes financial subsidy is one of the most popular strategies employers use to achieve their CTR goals. In order to evaluate the cost effectiveness of a commute trip reduction program, it is essential to accurately measure the quantitative impacts of the alternative modes financial subsidies. It is interesting to see that the subsidy elasticities for transit and shared ride reported in this dissertation are relatively lower than the price elasticities reported in the literature. For example, the direct elasticity of subsidies provided to share-riders is 0.509, suggesting that when the subsidies to shared riders increases by 10 percent, the likelihood for commuters to share ride increases by 5.09 percent. York and Fabricatore [2001] estimate the price elasticity of vanpooling at about 1.5. The direct elasticity of transit subsidy is 0.108, while Transport Research Library [TRL, 2004] calculates that bus fare elasticities average around 0.4 in the short-run, - 0.56 in the medium run, and - 1.0 over the long run. Metro rail fare elasticities are 0.3 in the short run and 0.6 in the long run. This might be explained by fact that the subsidy only covers part of the out-of-the-pocket travel cost of transit and shared ride. The direct elasticity of subsidies to non-motor is 0.233, suggesting that when the subsidies provided to non-motor users increase by 10 percent, commuter's likelihood to use non-motor to work increases by 2.33 percent.

Reserved HOV parking and HOV fleet vehicle are two dummy variables entered into the utility function of shared ride to measure the non-monetary supportiveness of the shared ride program. If the employer provides reserved parking to high occupancy vehicles, the commuter's likelihood to share ride to work increases by 2.248 percent and the likelihood of driving alone decrease by 0.747 percent. If HOV fleet vehicle is available to shared riders, commuter's likelihood to share ride to work increases by 4.858 percent.

If flexible time is allowed, a commuter's likelihood of using share ride, transit, and non-motor increases by 1.195 percent, 4.817 percent, and 0.733 percent, respectively.

Table 5.6 Elasticities for Selected Continuous Variables

Variable	Drive Alone	Shared Ride	Transit	Non-Motor
Parking Charge	-0.281*	0.086**	0.307**	0.150**
Onsite Parking Ratio	0.317*	-0.190**	-0.471**	-0.394**
HOV Parking Discount	-0.065**	0.109*	-0.074**	-0.041**
Subsidy Shared Ride	-0.359**	0.460*	-0.236**	-0.167**
Subsidy Transit	-0.080**	-0.019**	0.066*	-0.036**
Subsidy Non-Motor	-0.330**	-0.069**	-0.148**	0.252**

*Direct elasticities, **Cross elasticities

Table 5.7 Effects for Selected Dummy Variables

Variable	Drive Alone	Shared Ride	Transit	Non-Motor
Reserved HOV Parking	-0.747	2.248	-1.334	-0.167
Flextime	-6.745	1.195	4.817	0.733
GRH	-3.563	0.574	2.597	0.392
Distribute Material	-0.849	0.154	0.603	0.0918
CTR Events	-0.775	0.122	0.567	0.086
CTR Email	-0.472	0.075	0.345	0.052
HOV Fleet Vehicle	-1.776	4.858	-2.730	-0.351

5.7 Conclusion

This chapter focuses on the impacts of an integrated commute trip reduction program on commuting mode choice. A nested logit model is developed to estimate the employees' commute mode choices. In particular, the effect of TDM promotion activities and support strategies, parking management, worksite amenities, and alternative modes subsidies are examined. Furthermore, the elasticities of the financial incentives, the parking management programs, the TDM support programs, and the TDM promotion activities are calculated to measure the quantitative impacts of the TDM strategies.

A trend analysis of Washington State Commute Trip Reduction program shows that the mode shares of driving alone decline from 74.52 percent in 1993 to 68.64 percent in 2001 for the CTR affected employee. After 2001, the share of driving alone rebounded to 70.02 percent in 2005. Despite the rebound, the shares of driving alone for the CTR affected employees are significantly lower than the state average of 74.3 percent and national average of 77 percent in 2005. The significant differences come from carpool, vanpool, and transit, especially, from vanpool and transit.

Although what causes the rebound of share of drive-alone after 2001 remains unknown, from the perspective of CTR strategies, it may suggest the existence of some kinds of "program fatigue," which means as the CTR strategies being implemented, people are getting used to the stimulation and they are becoming less and less sensitive. It may also suggest that the same type of CTR strategies may have different impacts at different time period.

From the nested logit model, it is confirmed that, overall, the impacts of the TDM programs on commuter's choice of the alternative modes are positive and statistically significant.

In particular, from the perspective of parking management, it shows that if the SOV parking charge increases by 10 percent, a commuter's likelihood to drive alone falls by 2.81 percent, while shared ride, transit, and non-motor increase by 0.86, 3.07, and 1.50 percent respectively. If the employer decreases the ratio of number of onsite parking spaces and total number of employees by 10 percent, the commuter's likelihood to drive alone decrease by 3.17 percent, while shared ride, transit, and non-motor increase by 1.90, 4.71, and 3.94 percent respectively. When the parking discount to high occupancy vehicles increases by 10 percent, a commuter's likelihood to commute by shared-ride increases by 1.09 percent. If employer provides reserved parking to high occupancy vehicles, commuter's likelihood to share ride to work increases by 2.248 percent and the likelihood of driving alone decrease by 0.747 percent. If HOV fleet vehicle is available to shared riders, a commuter's likelihood to share ride to work increases by 4.858 percent.

As for the alternative modes financial subsidies, the direct elasticities of shared mode, transit, and non-motor are 0.460, 0.066, and 0.252, respectively, and their elasticities on driving alone are - 0.359, - 0.080, - 0.330 The financial subsidy elasticities for transit and shared ride reported in this dissertation are relatively lower than the price elasticities reported in literature. A possible explanation might be that subsidies only cover part of the out-of-the-pocket travel cost of transit and shared ride. This means a one percent increase in the subsidy is worth less than one percent increase in transit or carpool or vanpool fare and, consequently, has a smaller less impact on a commuter's commuting mode choice.

The quantitative impacts of TDM promotion activities and support strategies are also examined. The findings suggest that when encouraging alternatives to drive-alone, it is important that employers provide certain associated services, which may not only provide the physical help the commuter needed but also signal the supportiveness from the management and provide peace of mind to potential users.

The model developed in this chapter can be applied directly to estimate or predict the mode shares for the TDM affected employee. The derived elasticities can be used to evaluate the quantitative impacts of the individual strategies. Additionally, in order to achieve the goals to reduce the share of drive-alone, employers may consider different combinations of strategies to implement depending on their major business type and detailed job characteristics.

CHAPTER 6 CONCLUSION

This dissertation focuses on an overall evaluation of the Commute Trip Reduction program implemented in Washington State. In particular, I investigate the impacts of Travel Demand Management strategies implemented by the employers on commuter's travel behavior from three aspects. First, I examine the important determinants of employees' compressed work weeks schedule choice and how TDM promotions and strategies affect their decision to participate in CWW. Second, I develop models to examine the effectiveness of telecommuting as a component of an integrated TDM program and to predict the telecommuting rate and telecommuting frequency in the future. Finally, I apply a nested logit model to evaluate the quantitative impacts of various TDM strategies on commuters' journey-to-work mode choices.

6.1 Contribution

In this thesis, although I use different methodology to address the impact of TDM on commuters' travel behavior from different perspectives, the models I build are an integrated modeling effort to evaluate and forecast the effectiveness of an existing TDM. A direct measurement of the effectiveness of a CTR program is the number of vehicle trips or peak period vehicle trips reduction. Based on the number of reduced vehicle trips, other measurements, such as the reduction of delay, travel time, and fuel consumption and emission, can then be derived. Generally, a comprehensive employer based CTR program achieves the goal of vehicle trip reduction through implementing worksite-based

TDM strategies that focus on changing the commuter's mode choice, travel time choice, and travel frequency choice. In particular, compressed work week and telecommuting programs are aimed at changing commuter's travel frequency and travel time, which help reduce the number of person trips or peak period person trips. Employer's TDM support strategies and financial incentives or disincentives strategies are implemented to encourage employees to use alternative modes of drive-alone and reduce the vehicle trips. An integrated procedure of the employer-based TDM effectiveness evaluation, therefore, consists of estimating the number of employees working on compressed work week and telecommuting and the percentage of employees shifted from driving alone to the alternative modes. The models developed in this dissertation can be applied to address these three issues.

The evaluation of the effectiveness of the employer-based TDM program can be categorized to evaluating an existing program based on the employee travel behavior survey and predicting or estimating the impacts of a program based on survey data on TDM program implemented by employer. For an existing employer-based TDM programs that both the employer promotion data and employee travel behavior information are available, such as the Washington State CTR program, the evaluation process generally consists of calculating and comparing the vehicle trip rate or vehicle miles traveled for each employer before and after the implementation of TDM strategies. For most of other employer-based TDM programs, where the employee travel behavior information is not available, the program assessment procedure normally includes applying the TDM models to estimate or predict the vehicle trip rate change based on employer program implementation data.

The models developed in this dissertation can easily be applied to evaluate the impacts of existing TDM programs. For metropolitan areas where a comprehensive commute trip reduction program is implemented but no detailed information on employee travel behavior available, the models can be applied to estimate the quantitative impacts of TDM strategies on mode share and the number of CTR affected employees working on compressed work schedules and telecommuting when employers' and employees' information on basic variables such as job title are available.

Furthermore, the models may be incorporated into the regional transportation model to reflect TDM impacts in the transportation planning process. For the area affected by the Washington State CTR program, the models can be directly used to predict the percentage of employees working on compressed work week schedules and telecommuting at the TAZ level for CTR affected employees. For other areas where detailed employer and employee data is not available, the model developed here may be simplified to use aggregate data at the TAZ level to predict the participation rate of compressed work week schedules and telecommuting. For example, we can use the average commute distance, the percentage of employers affected by TDM strategies, and the percentage of employees by job title and business type to estimate CWW and telecommuting participation rate. The projected percentage of employees working compressed work weeks and telecommuting then may be applied to adjust the number of home based work trips to reflect its impacts on the transportation system and, at the same time, to improve the accuracy of the regional planning model. Similarly, the nested logit model, that incorporated the TDM strategies, can be applied to reflect the impacts of TDM strategies on mode shares.

As for the activity based travel demand model, the CWW and telecommuting models can be applied as sub-models to estimate the job related activities. For example, they can be applied to estimate how many workers will actually go to work and how many will work at home or stay home because of telecommuting and CWW.

Finally, the effectiveness of the TDM strategies is one of the important factors that determine the prospect of success of an integrated TDM program. This dissertation identifies effective TDM strategies based on the employee's job related characteristics and personal information through modeling the TDM impacts on commuting travel behavior. The findings may help policy makers evaluate the effectiveness of TDM strategies and choose the most efficient ways to reduce trips rates.

6.2 Major Findings

Based on the analysis of the impact of Transportation Demand Management programs on commuter's Compressed Work Week choice, telecommuting choice, and journey to work mode choices, the major findings are summarized as following:

- Job characteristics and employer's major business type are important factors that affect commuter's choice on CWW, telecommuting, and journey to work mode. This finding suggests that when considering effective ways to promote TDM programs that help achieve CTR goals, transportation planners and CTR coordinator in each worksite should identify industry characteristics and group commuters based on their job characteristics. Certain combinations of TDM strategies should be tailored to reflect the difference in job requirements, which may work better than providing a uniform TDM program for everyone.

- TDM promotion activities play an important role in changing commuter's travel behavior. In this thesis, four TDM promotion activities are identified to have positive and significant effects on commuter's choices of CWW, telecommuting, and using alternative modes to driving alone to work. CTR coordinators should review their TDM promotion activities to see whether they can do more or switch to some more effective ways to communicate with CTR affected employees. I find distributing CTR information regularly, sending CTR program summary and information to employees by email, publishing CTR articles regularly, and conducting transportation event are effective ways to help employees understand the TDM program benefits and employer's supportiveness, and take actions accordingly.
- TDM promotion should be a continuous effort to promote CTR goals. When the number of TDM promotion years is used in regression, I find the time effect of TDM promotion is not constant. I also find that, while the drive alone share declined significant from 1993 to 2001 for the CTR affected employees, it began to rebound after 2001. This finding may suggest that transportation planners in government agencies and CTR coordinators may need to adjust their promotion efforts from time to time based on their survey results.
- Financial incentives and disincentives are important determinants of commuter's journey to mode choices. In particular, subsidies to share-ride, transit, and non-motor have significant positive effects on commuter' choice of using alternative to drive alone. Parking management, including parking charge, discount parking charge for HOV parking, and reserved parking spaces for HOV parking has significant positive impacts on reducing driving alone. Services or amenities offered by employers such as guaranteed

ride home, providing HOV fleet vehicle, complementary facilities for bicyclers or walkers are also effective to help reduce driving alone.

- To achieve CTR goals to reduce vehicle trips, besides employer-based strategies, coordination and cooperation from other government agencies are also important components of an overall effort. For example, land use design to include certain amenities and land use policies to allow mixed use of employment, business, and residential may also help to achieve the CTR goals.

6.3 Future Research

Since TDM is a long term process, it is important to track individual commuter's travel behavior changes over time. A panel study of a large sample of individual commuters on their CWW, telecommuting, and mode choices will be a more effective way to estimate effectiveness of TDM programs. More importantly, this may have very important policy implementation to identify strategies that work better over time.

The other limitation of this research is data restriction. Although the Washington State Commute Trip Reduction dataset provides a large sample of individual observations, the data do not have commuters' personal information, such as gender, age, household size, and household income. To reduce omitted variable bias, I have to introduce some proxy to capture the commuter's difference in social status and household characteristics. It will dramatically increase the accuracy of the models should some basic personal information such as commuters' age range and household characteristics be available.

Most of TDM strategy information, such as the parking charge, alternative modes subsidies, and the implemented TDM promotion activities, is reported by the Employer

Transportation Coordinators at employer level. If the data can be collected at the employee level, it will significantly increase the accuracy of those data, consequently, the accuracy of the models.

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