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EVALUATION OF TRAVEL DEMAND MANAGEMENT STRATEGIES IN THE TRIP GENERATION PHASE OF A NETWORK-BASED MODELING APPROACH

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16. ABSTRACT

Current trip generation models are insensitive to the effects of travel demand management (TDM) strategies. To evaluate the potential effectiveness of TDM solutions, transportation professionals must rely largely on the results of case studies, which can not be generalized for areas other than the one in which the study was performed. To evaluate TDM strategies in a context that is sensitive to the unique characteristics of each urban area, TDM strategies should be incorporated into regional travel demand models.

Five TDM strategies affecting trip generation rates were examined: land-use strategies, pricing strategies, telecommunications, alternative work schedules, and on-site facilities. To analyze these strategies, household, person, and trip data from the Puget Sound Transportation Panel (PSTP) were used. Variables derived from the PSTP data that may help explain the impacts of these TDM strategies were evaluated for significance in trip generation models for the following purposes: home-based work, home-based shopping, home-based other, work-other, and other-other. The trip generation models were specified with Poisson and negative binomial regression techniques. After the models had been estimated, the significance of the variables representing the impacts of TDM strategies was analyzed and justified.

Many of the "TDM variables" were indeed significant in the trip generation models; however, in some cases, the significance of the variables can be attributed to factors that are not related to the effects of TDM strategies. For example, the effects of trip chaining appeared to have played a major role in the significance of certain variables. However, some variables appeared to explain the effects of certain TDM strategies quite well. With further research, the four-step modeling process may provide a viable mechanism for evaluating the impacts of TDM strategies on trip generation rates.

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LIST OF ABBREVIATIONS

AMOS - Activity-Mobility Simulator

AVR - Average vehicle ridership

CBD - Central Business District

DOT - Department of Transportation

DVRPC - Delaware Valley Regional Planning Commission

FHWA - Federal Highway Administration

FTA - Federal Transit Administration

GMA - Growth Management Act

GVRD - Greater Vancouver Regional District

HOV - High-occupancy vehicle

ISTEA - Intermodal Surface Transportation Efficiency Act

ITE - Institute of Transportation Engineers

LOS - Level of Service

MIS - Major Investment Study

MPO - Metropolitan Planning Organization

MWCOG - Metropolitan Washington Council of Governments

NEPA - National Environmental Policy Act

PEF - Pedestrian Environment Factors

PSRC - Puget Sound Regional Council

PSTP - Puget Sound Transportation Panel

TCM - Transportation Control Measures

TDM - Travel Demand Management

TRANSIMS - Transportation Analysis and Simulation System

TSM - Transportation Systems Management

UGA - Urban Growth Area

VMT - Vehicle miles traveled

WSDOT - Washington State Department of Transportation

CHAPTER 1: INTRODUCTION

PROBLEM STATEMENT

Transportation demand management (TDM) is a collection of strategies designed to regulate travelers' desire to use roads and highways and to encourage travelers to use modes of transportation other than driving alone. By applying tactics such as offering incentives for carpools, improving transit services, and charging tolls on highly congested routes, researchers hope that existing facilities can be used more efficiently.

TDM has recently been the focus of major research efforts because, in most cases, new freeway construction is no longer considered the most viable solution for reducing congestion. First, new construction requires massive amounts of funding, which is now much harder to obtain than in years past. Second, environmental research has exposed the harmful effects of emissions, noise, and water runoff due to freeways. Furthermore, residents in areas of proposed freeway construction have spoken out against new roadwork that may require condemnation of land and split their neighborhoods. In comparison, TDM is a relatively inexpensive, inobtrusive way to improve traffic flow.

Unfortunately, the consideration of TDM as a legitimate alternative to new freeway construction is difficult because methods for directly quantifying the benefits and costs of TDM strategies and comparing them to the corresponding impacts of new construction have not been well developed. Techniques for determining the impacts of new roadway construction are established and well understood by transportation practitioners, but the same can not be said for the impacts of TDM strategies. Although a number of case studies concerning the effectiveness of TDM strategies have been performed around the world, these studies provide only limited insight into the general effectiveness of TDM strategies. This lack of general information is due to the variation in the structure and characteristics of

cities around the world, as well as the variety of TDM strategies (and packages of strategies) that can be implemented. To effectively estimate the impacts of TDM strategies in a particular region, an approach is needed that considers the unique characteristics of the study area.

One possible method for evaluating TDM strategies is incorporating evaluation techniques within regional travel demand models. Because the effectiveness of TDM strategies varies dramatically from region to region and these models are developed for each urban area, they are a logical tool for evaluating the impacts of TDM strategies.

TDM strategies can affect each step of the traditional four-step estimation process used in regional travel demand models: trip generation, trip distribution, mode split, and trip assignment. This study will focused on the first step of the process, trip generation.

The product of this project as not a specific trip generation model that can be directly implemented to evaluate TDM strategies; instead, this project sought to explore the viability of using trip generation models to evaluate the effectiveness of TDM strategies and to provide a framework for future studies related to the incorporation of TDM strategies within the traditional four-step process.

REPORT ORGANIZATION

The remainder of this report is divided into six chapters. Chapter 2 briefly overviews the concepts that are central to this study, such as TDM, the major investment study process, and network-based modeling (the traditional four-step process). Chapter 3 discusses the relevant literature used as a basis for this study. Chapter 4 contains a detailed discussion of the specific objectives and methodologies used in this project. Chapter 5 presents the exact specification of the models estimated for this study. The elasticities of several of the significant variables in each model are examined in Chapter 6. Next, Chapter 7 details some of the weaknesses of the current modeling scheme and offers suggestions

for improvements. Finally, Chapter 8 draws conclusions regarding the findings and implications of this research.

CHAPTER 2: BACKGROUND

TRAVEL DEMAND MANAGEMENT

Travel demand management strategies recently have garnered much attention as possible alternative solutions to large-scale transportation projects. Compared to capital-intensive supply-side solutions, TDM strategies offer lower-cost alternatives for addressing transportation problems. TDM strategies also offer the ability to postpone expensive infrastructure investments by making better use of existing facilities. The Federal Highway Administration and Federal Transit Administrationhave advocated the evaluation of TDM alternatives in the major investment study (MIS) process, and the State of Washington has included TDM measures in the Washington State Transportation Policy Plan.

TDM is still a relatively new concept. In comparison to other transportation issues, there is a general lack of information about TDM, particularly in the area of TDM effectiveness. This lack of data has made the evaluation of TDM strategies difficult, especially when analysts try to compare the effects of TDM strategies with the effects of new highway capacity (WSDOT, 1996).

DESCRIPTION OF STRATEGIES

For analysis purposes, WSDOT has divided TDM strategies into six major categories (WSDOT, 1996):

- **Public Mode Support Strategies** include publicly provided alternatives to SOV travel and those services and facilities that encourage and support other modes.
- **Employer-Based Strategies** are private sector programs and services that encourage employees to change commuting patterns. The strategies include

incentives that make publicly provided modes more attractive, disincentives to solo commuting, and employer management policies that provide employees with flexibility in mode choices.

- **Pricing Strategies** are tax and pricing schemes that affect the cost of transportation and thereby provide monetary disincentives to people engaging in certain types of travel behavior.
- **Telecommunications Strategies** are emerging demand management solutions that are based in advanced telecommunications technologies.
- **Land-Use Strategies** are potentially the most effective long-term TDM strategies. They change densities, land use, urban design, and land-use mix to affect travel needs and patterns.
- **Public Policy and Regulatory Strategies** introduce restrictions and regulations to auto use and provide political support and guidance to new institutional relationships.

The specific strategies in each category are outlined in Table 1.

For additional information regarding specific details of each strategy, the reader is referred to *Transportation Demand Management: A Guide for Including TDM Strategies in Major Investment Studies and in Planning for other Transportation Projects* (WSDOT, 1996).

Table 1: Classification of TDM Strategies

Category	Strategy
Public Mode Support Strategies	Public Education and Promotion
	Area-Wide Ridematching Services
	Transit Services
	Vanpool Service
	Transit and Vanpool Fares
	Non-Motorized Modes
	High Occupancy Vehicle (HOV) Facilities
	Park and Ride Lots
Employer-Based Strategies	Monetary Incentives
	Alternative Work Schedules
	Commute Support Programs
	Guaranteed Ride Home
	Parking Management
	Facility Amenities
	Transportation Management Associations
Pricing Strategies	Gasoline Tax Increases
	Vehicle Miles Traveled (VMT) Tax
	Congestion Pricing
	Parking Tax
Telecommunications Strategies	Telecommuting
	Advanced Telecommunications
Land-Use Strategies	Development Impact Mitigation
	Mixed Land-Use, Jobs / Housing Balance
	Transit-Oriented / Pedestrian-Friendly Design
	Residential Density Increases
	Employment Center Density Increases
	Parking Management
	On-Site Amenities
Public Policy and Regulatory Strategies	Trip Reduction Ordinances
	Restricted Access to Facilities
	Support of New Institutional Relationships
	Increase of HOV Lanes Restriction to 3+
	Parking Restrictions

Source: WSDOT, 1996

EVALUATION METHODS

Attempts to evaluate the effectiveness of TDM strategies have centered around two basic methodologies:

- **Case Studies** are documented "before-and-after" scenarios involving the implementation of specific TDM strategies in a certain location. The travel behavior of people affected by the TDM measures after their implementation is compared to the travel behavior of the same group of people before the strategies were in place. These comparisons are possible through the application of surveys.
- **Empirical Models** are mathematical formulations that attempt to predict changes in travel behavior (reductions in vehicle miles traveled, mode split, etc.) due to TDM strategies. The calculations are based on before-TDM travel data and on user inputs regarding TDM characteristics such as the amount of participation in a carpool program, the time savings of an HOV facility, etc.

Studies that have used these methods have provided some effectiveness data, but in general, data are still relatively sparse. The issues concerning the methodologies used for generating data are discussed in Chapter 3.

MAJOR INVESTMENT STUDIES

DESCRIPTION OF PROCESS

A major investment study (MIS) is a process designed to aid in making better transportation planning decisions in metropolitan areas. An MIS is undertaken by a metropolitan planning organization (MPO) in conjunction with the state department of transportation (DOT) and other federal, state, and local agencies to determine the likely costs, benefits, and impacts of a proposed transportation investment.

The purpose of an MIS is to analyze a variety of strategies (including highway, transit, travel demand management, and multimodal options) to determine the best alternative for a transportation project. The MIS process is a collaborative venture,

requiring cooperation among all affected agencies, along with appropriate and effective input from the public.

The MIS process was developed in 1993 by the Federal Transit Administration (FTA) and Federal Highway Administration (FHWA) in compliance with the Intermodal Surface Transportation Efficiency Act (ISTEA). An MIS is required whenever a major metropolitan transportation investment is considered and when federal funds are potentially involved. A "major metropolitan transportation investment" is defined as a "high-type highway or transit improvement of substantial cost that is expected to have a significant effect on capacity, traffic, level of service, or mode share at the transportation corridor or sub-area scale" (National Transit Institute, 1995). This includes such projects as the new construction or extension of a partially controlled principal arterial, significant capacity expansion of a partially controlled principal arterial, construction or extension of an HOV facility or fixed-guideway transit facility, or the addition of lanes or tracks to a fixed guideway.

An MIS is not necessary under the following conditions:

- If a potential project lies completely outside of a metropolitan area
- If a potential project lies within a metropolitan area but federal funding will not be involved in the project implementation

However, if a potential investment lies partially within the bounds of a metropolitan area and is subject to federal funding during implementation, an MIS is required for the portion of the project within the metropolitan area.

Current metropolitan planning regulations state that each MIS must include the following elements:

- a cooperative and collaborative process for establishing the range of alternatives to be studied and the factors to be addressed

- an evaluation of the effectiveness and cost-effectiveness of alternative investments or strategies in attaining local, state, and national goals and objectives
- consideration of the direct and indirect costs of alternatives and factors such as mobility improvements; social, economic, and environmental effects; safety; operating efficiencies; land use and economic development; financing; and energy consumption
- a proactive public involvement process that provides opportunities for the public and various interests to participate
- documentation of the consideration given to alternatives and their impacts.

Furthermore, Executive Order 12893 on Principles of Federal Infrastructure Investments states that major investment studies will include "a systematic analysis of expected benefits and costs, utilizing both quantitative and qualitative measures as appropriate." It is important to note, however, that an MIS is used to make decisions regarding design concept and scope. This procedure is not used to determine the final design. Therefore, it is highly unlikely that costs and benefits of each alternative will have to be computed with high accuracy. Instead, alternatives should be compared in relation to each other to determine the most effective strategy, with the final design analysis to come later.

There is no formal step-by-step procedure for conducting an MIS. FTA and FHWA officials intentionally designed the process in this manner to allow local officials to tailor the process to their specific needs. In the past, the FTA and FHWA have had a more dominant role in project analysis, such as requiring their approval at key points in the process. In an MIS, however, the FTA and FHWA guide the process rather than "policing" it. The MIS is designed to be highly collaborative, encouraging all affected parties to provide input throughout. The intention is for everyone to reach a consensus decision

regarding the project after deliberating all the alternatives. If this common solution is reached, implementation of the project will be much more smooth than if court intervention is needed to decide the future of the proposal.

Although no formal guidelines dictate how to conduct an MIS, a general framework does exist. The MIS process consists of five major stages:

1. Initiation
2. Development of an initial set of alternatives
3. Screening of and decision regarding a detailed set of alternatives
4. Analysis, refinement, and evaluation of the alternatives
5. Selection of the preferred investment strategy

The elements of each of these stages are discussed below.

1. Initiation

At the outset of the process, all affected parties, including the MPO, state DOT, transit operator(s), FTA, FHWA, affected local officials, environmental and resource agencies, and operators of other major modes of transportation should cooperatively develop a work plan for the duration of the process. This plan should result from an initial meeting of all parties involved in the project in which the current mobility needs and problems are discussed, along with goals and objectives of the project. Although the MPO often initiates the process, any party deemed acceptable to those involved can lead the effort.

2. Development of an initial set of alternatives

After the initial inter-agency meeting, development of the initial set of alternatives should begin. This is a key point in the process for public involvement, which can take the form of public hearings, open houses, mailouts, and others. At this point, all conceivable alternatives should be available for consideration. This includes any ideas advanced by the

public. The techniques that will be used to evaluate the alternatives should also be discussed at this stage.

3. Screening of and decision regarding a detailed set of alternatives

After all ideas for strategies have been received, the screening process to decide on a detailed set of alternatives can begin. This process does not involve a complicated evaluation of each alternative but rather the elimination of the alternatives that are obviously not feasible or are impractical. This screening is based on major criteria such as engineering constraints, environmental issues, and cost.

4. Analysis, refinement, and evaluation of the alternatives

After a consensus on a detailed set of alternatives has been reached, the analysis, refinement, and evaluation of alternatives can begin. In addition to the alternatives developed as a result of this process, the National Environmental Policy Act (NEPA) requires that a "no-build" alternative be considered, and the FTA and FHWA require that a transportation systems management (TSM) alternative be considered. Each alternative should be examined according to the following considerations:

- environmental impact analysis
- land-use analysis
- conceptual engineering and costing
- travel demand forecasting
- transportation/traffic impacts
- operations planning and costing
- service planning
- financial analysis.

There are no fixed guidelines regarding the appropriate level of detail in an MIS analysis, but ideally the expected costs and benefits of each alternative candidate should be quantified as much as possible to ease decision-making. At this point, alternatives should be further refined to optimize costs and benefits.

5. Selection of the preferred investment strategy

The refinement and evaluation of each alternative should continue until one preferred investment strategy has been chosen. This is obviously the most important decision, and it should be made with input from all affected parties, including the public.

Once the preferred strategy has been selected, it is incorporated into the Metropolitan Transportation Plan. When funding becomes available, the project development stage is entered. After this work has been completed, the project can be implemented.

Reasoning for Incorporating TDM Strategies Within an MIS

At the federal level, the ISTEA legislation of 1991 has made major changes to the process for allocating federal funds to transportation projects. The MIS process is designed to identify all "reasonable alternative strategies" for addressing transportation needs, and the FTA and FHWA strongly suggest that TDM strategies be represented in the evaluation process.

At the state level, the State of Washington Transportation Commission has given TDM and TSM strategies major roles in Washington state's transportation policy. Policies related to TDM and TSM contained within the "Washington State Transportation Policy Plan 1993 Report to the Legislature" include the following:

> "State and local agencies should establish procedures to ensure that system efficiency improvements are analyzed as components of, or alternatives to, new road and highway development."

> "State, regional and local funding rules should be changed to allow TDM/TSM projects to compete equally with more traditional transportation projects such as adding lanes to a highway." (WSDOT, 1996)

The Washington Transportation Plan assumes that 22 percent of growth in the number of trips over the next 20 years will be accommodated by TDM strategies. According to WSDOT, "This directs us as transportation professionals to look at things in new ways— to expand our thinking. Reviewing TDM alternatives within the MIS process provides just such an opportunity, both within and outside of the department." (WSDOT, 1996)

WSDOT is hopeful that the development of TDM alternatives will enable a side-by-side comparison of "alternative" solutions with traditional "build" options: "We must look seriously at the trip reduction potential of demand management strategies and highlight for our decision makers the aggressive measures that might be required as an alternative to capital investments." (WSDOT, 1996)

Furthermore, a long-range goal of WSDOT is to ensure compatibility between the MIS process and the department's priority programming process. The preferred alternative selected in the MIS process should also meet the benefit/cost criteria of Priority Programming. The department would like to modify the Priority Programming process to de-emphasize capital-intensive solutions, so that "alternative" strategies such as TDM will receive more funding. WSDOT anticipates that including TDM (and TSM) strategies will result in higher benefit/cost ratios and higher project ranking for state funding (WSDOT, 1996).

NETWORK-BASED MODELING

Urban travel demand forecasting has been defined as "the art of predicting travel behavior and demand for a specific future time frame, based on a number of assumptions."

(National Highway Institute, 1994) Network-based modeling is a methodology commonly used in urban travel demand forecasting, and the "traditional four-step process" is a subset of network-based modeling that has been the primary modeling tool for the past 25 years (Rutherford, 1991). The "traditional four-step process" consists of the following steps:

- trip generation
- trip distribution
- mode choice
- trip assignment.

A description of each of these steps follows. Because the focus of this project was on trip generation, the first step of the process receives a more lengthy discussion.

TRIP GENERATION

Trip generation is the first of the four basic phases in the traditional travel demand forecasting process. The number of trip ends in each zone is determined in this step and is then used to distribute trips in the trip distribution phase (National Highway Institute, 1994). The output of trip generation analysis is a table of trip ends by zone (Rutherford, 1991). One of these trip tables is generated for each trip purpose and is then used as input to the trip distribution phase.

BASIC CONSIDERATIONS

By examining household and land-use characteristics, the process of trip generation explains the relationships between measures of urban activity and travel behavior (National Highway Institute, 1994). To predict future amounts of travel, current relationships between urban activity and trip-making characteristics must be understood and quantified. If the urban activity forecasts are accurate and the relationship between urban activity and

trip-making remains the same, then predictions based on these relationships will be accurate (Rutherford, 1991).

In the trip generation phase of travel demand forecasting, the planner is concerned specifically with the number of trip ends. A trip end is defined as the beginning or ending (origin or destination) of a trip; thus each trip has two trip ends (Rutherford, 1991). Trip ends are also considered to be either productions (the home end of a home-based trip or the origin of a non-home-based trip) or attractions (the location of an out-of-home activity) (DKS Associates, 1994).

The effects of urban activity on trip generation are usually described in terms of amount of activities and character of activities. Measures of the amount and character of activities are provided by the urban activity forecasts and are input to the trip generation phase. Transportation system variables, derived from descriptions of the highway and transit networks, can also be used in trip generation; however, they generally have not been included in practice up to this point because strong relationships have not yet been discovered (Rutherford, 1991).

Classification of Trips. Generally, a separate trip generation model is run for each trip purpose. The reason for making a trip affects the number of trips generated, and this effect is shown through the use of different variables and coefficients of variables in the trip generation models for each trip purpose. Traditionally, the number of productions and attractions for each zone have been evaluated using three trip purposes:

- home-based-work (HBW)
- home-based-other (HBO)
- non-home-based (NHB).

Recently, the use of additional purposes, such as home-based shopping and home-based school, has become more widespread. However, the use of additional categories should be justified by local needs (Rutherford, 1991).

Data Requirements. To develop accurate trip generation models, a large number of data is needed. Most of the necessary data needed relate to the amount and character of urban activity. Typically, these data come from large-scale household travel surveys and inventories of existing land-use characteristics. Census data are also a valuable source of information for transportation planners.

1. Amount of Urban Activity

The amount of urban activity and travel behavior are obviously related. Generally, a zone with a larger number of households or employees will generate more trips than a zone with fewer households or employees. Therefore, establishing the amount of urban activity is a key element in trip generation analysis (Rutherford, 1991).

The amount of urban activity is usually stated in terms of a measure, such as the number of employees, households, or amount of retail sales in a zone (Rutherford, 1991).

2. Character of Urban Activity

Measures of the amount of activity usually are not enough to describe the relationship between activities and travel. The character of the activities must also be considered (Rutherford, 1991).

For residential land uses, character is described in terms of socioeconomic and demographic variables such as household size, household income, and vehicle availability. Generally, high-income or large families make more trips than low-income or small families. In addition, three-car families generally make more trips than one-car families (Rutherford, 1991).

For non-residential activities, character reflects the type of activity, such as industrial, retail, and commercial. In general, the number of trips a major shopping center generates is usually higher than the number of trips a warehouse of the same size generates (Rutherford, 1991).

Common Variables. Common variables used to estimate trip productions include the following:

- household size
- number of workers
- income
- auto ownership.

In addition, land-use factors such as residential density and the distance of the zone from the central business district (CBD) are also included in some models (Harvey and Deakin, 1993).

Common variables used to estimate trip attractions include the following:

- employment levels by occupation type
- floor space by business type.

Also, accessibility to the work force, represented by travel times, although rare in modeling applications in the United States, is found in some applications overseas (Harvey and Deakin, 1993).

Other Considerations. It seems logical that the level of service provided by the transportation system would impact trip generation rates. One might expect areas with excellent freeways and high-quality transit service to generate more trips than areas with poor facilities. However, strong relationships between trip generation and the transportation system have not been proven, and therefore, variables to describe the transportation system are seldom included in trip generation analysis (Rutherford, 1991).

The same is true for the cost of travel. Although it seems logical that the cost of travel would have a definite impact on trip generation rates, this relationship has yet to be included in trip generation models.

Trip generation relationships are often developed with location of activities as a consideration. An example is the evaluation of trip generation rates for retail activities in the downtown area in comparison to those of other shopping areas (Rutherford, 1991).

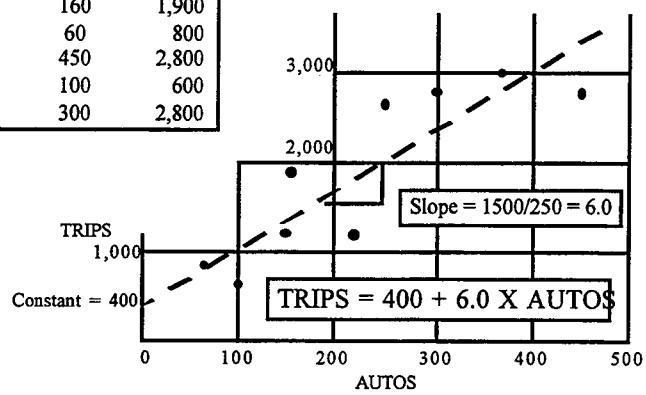
METHODOLOGIES

The two main types of trip generation analysis methodologies are regression and cross-classification. Regression techniques were once the most common methodology for trip generation analyses, but currently, cross-classification is the favored mechanism (DKS Associates, 1994).

Regression Analysis. Regression analysis consists of the development of equations in which a trip rate (i.e., trips per household) is related to independent variables, such as household income, vehicle availability, and total employment. These equations describe how the number of trips, or trip rate, varies because of factors such as those listed above (National Highway Institute, 1994). Of the regression techniques in use today, linear regression models are the most common. They are simple to construct and inexpensive to estimate from data typically available to MPOs. However, the imposition of linearity introduces a number of problems in modeling (DKS Associates, 1994), such as misspecification of variables that may not have a linear relationship. Nonlinear regression techniques allow more modeling flexibility. Some agencies currently use nonlinear regression techniques, primarily because nonlinear models allow both a high degree of flexibility in functional form and a large number of explanatory variables (Harvey and Deakin, 1993). However, they are less frequently available in basic statistical software packages and hence are used less often than linear techniques (DKS Associates, 1994). Overall, regression models (particularly linear regression models) are used less frequently

in basic practice, chiefly because their simple functional forms are more likely than cross-classification to allow the introduction of errors into forecasts (DKS Associates, 1994). An example regression model, using the number of automobiles as an independent variable, is shown in Figure 1.

ZONE	AUTOS	TRIPS
1	230	1,200
2	150	1,130
3	250	2,700
4	380	3,000
5	160	1,900
6	60	800
7	450	2,800
8	100	600
9	300	2,800

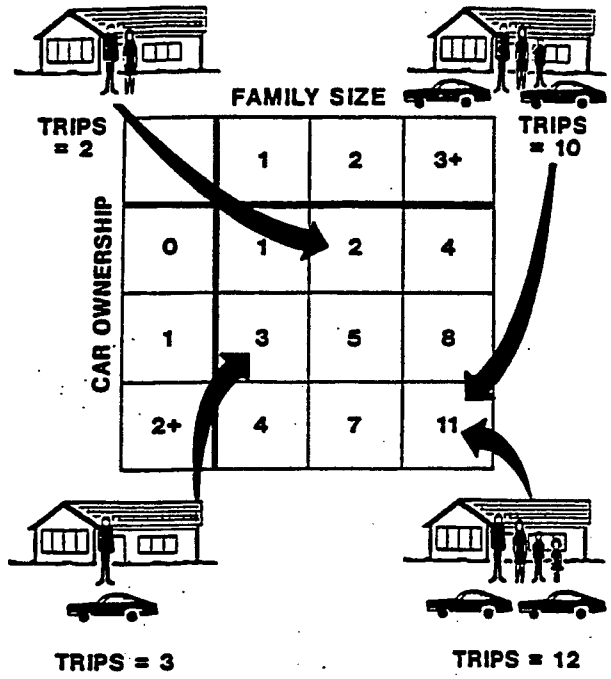


Source: National Highway Institute, 1994

Figure 1: Example Linear Regression Model

Cross-Classification. Cross-classification models group individual households together according to common socioeconomic and demographic characteristics (auto ownership level, income, household size) to create relatively homogenous groups (DKS Associates, 1994). Travel surveys by telephone interviews with members of sampled dwelling units are conducted to gather information used in cross-classification. The household members are asked to keep a trip diary (or log) of all trips taken during a specified period. The surveys are designed to obtain enough data to meet the required statistical analysis for sampling (National Highway Institute, 1994). An example of a

cross-classification model using *car ownership* and *family size* variables is shown in Figure 2.



Source: National Highway Institute, 1994

Figure 2: Example Cross-Classification Model

There are several notable advantages to using cross-classification models:

- The models are simple to use and understand.
- Cross-classification can be employed for both trip generation and mode split.
- Non-linear relationships can be easily accommodated (National Highway Institute, 1994).
- The model can be readily updated (Rutherford, 1991).

The main disadvantages related to cross-classification are that it does not have a well-developed theory for goodness-of-fit indices (in other words, how well the data

support the model structure) (National Highway Institute, 1994), and its predictions are sensitive to the grouping applied in defining ranges for each variable (that is, the model will produce different estimates depending on how the data are aggregated) (DKS Associates, 1994). In addition, as the number of categories or dimensions increases, the necessary sample size increases as well. Because of this sample size problem, the number of cells typically is minimized either by limiting the number of variables or by aggregating the values for each variable into a few ranges (DKS Associates, 1994). Nevertheless, cross-classification is currently the most common method in practice and is a reliable method when a small number of variables is thought to be sufficient for a good trip generation model (Harvey and Deakin, 1993).

A trip generation model is actually made up of two separate submodels— one for trip productions and one for trip attractions (DKS Associates, 1994). Each one is addressed individually below.

Trip Production Model. "Trip production forecasting is based on the relationship between trip making and various household characteristics such as income, auto availability, or household size." (Rutherford, 1991) Figure 3 shows a trip production model structure with household trip rates cross-classified by income and auto availability.

In actual use, Figure 3 might have additional income categories or additional variables, depending on data availability and results obtained when the relationship was used (Rutherford, 1991). As discussed earlier, land-use factors such as residential density and accessibility indicators such as distance of the zone from the CBD sometimes are included (DKS Associates, 1994).

Generally, transportation planners are interested in trip-making characteristics associated with specific purposes, and therefore, the total trip productions are modeled by trip purpose (Rutherford, 1991).

	Auto Availability		
	0	1	2+
1			
2	(Trip productions per household)		
3			
4			
5			

Household Income Level

Source: Rutherford, 1991

Figure 3: Example Trip Production Model (Cross-Classification)

Trip Attraction Model. In contrast to trip production modeling, which focuses on household characteristics, the structure of trip attraction models is based on the activities that might attract the trip productions. These activities can include households, stores, offices, or factories (Rutherford, 1991).

To analyze trip attractions, the number of trips attracted to certain activities is related to a measure of the amount of that activity. For example, the number of trips attracted could be related to the number of employees in a factory or the number of employees in a store (Rutherford, 1991).

The structure of trip attraction models relates the number of trip ends for each purpose to the amount, character, and in some cases, location of the activities, as shown in Figure 4 (Rutherford, 1991).

	Household	Non-Retail Employment	Downtown Retail Employment	Other Retail Employment
Home-based work				
Home-based other	(Trip attractions per unit of activity)			
Non-home-based				

Source: Rutherford, 1991

Figure 4: Example Trip Attraction Model

TRIP DISTRIBUTION

The trip distribution stage determines the destinations of all the trips generated in the trip generation phase. The distribution of trips is based on the relative attractiveness and accessibility of each zone. In other words, trips are more likely to be made to a nearby zone with a high level of activity than to a distant zone with less activity. The output of this phase is a set of tables showing the number of trips between each pair of zones (Rutherford, 1991).

MODE CHOICE

The mode choice stage determines which mode travelers will use to get to their destination. Modes considered in mode choice models generally include automobile and transit; however, some advanced applications also consider non-motorized modes such as walking and bicycling. Mode choice analyses examine the factors that influence the travelers' decision-making process. Three broad categories of factors are considered (Rutherford, 1991):

- the characteristics of the tripmaker
- the characteristics of the trip

- the characteristics of the transportation system.

Analysis of these characteristics results in probabilities for travelers' use of each mode.

Trip Assignment

The trip assignment stage predicts the routes each trip will take. This analysis is usually based on factors such as the minimum travel time or distance between the origin and destination. Advanced applications also include consideration of the impacts of congestion. The output of this analysis is a set of traffic forecasts for the highway system and ridership forecasts for the transit system (Rutherford, 1991).

TDM Strategies in Each Step of the Four-Step Process

Rutherford (1991) prepared an outline of the traditional four-step modeling procedure that indicates where each major TDM strategy should be incorporated into the process. In the trip generation step, TDM strategies should be included that directly reduce the number of trips made or shift trips to other times of the day. These strategies include the following:

- telecommunications
- alternative work schedules (compressed work week, flextime)
- on-site amenities
- non-motorized modes.

In addition, the "cost" of the trip (in terms of fees and charges, value of time) has a direct impact on the number of trips made. Strategies such as congestion pricing, parking charges, and the level of service of the transportation system may affect the number of trips made, the destination of the trip, and the mode and route used. These effects should be taken into account in each step of the four-step process, including trip generation.

Strategies that discourage SOV travel and encourage the use of alternative modes should be incorporated in the Mode Choice step. These strategies include the following:

- fares
- parking fees
- travel allowances
- taxes
- pricing
- park and ride facilities
- vanpools.

In the Trip Assignment step, TDM strategies that affect the routes travelers use are considered. These strategies include the following:

- HOV facilities
- transit services
- non-motorized modes
- toll facilities.

THE REASON FOR EVALUATING TDM STRATEGIES IN A NETWORK-BASED APPROACH

Although techniques for modeling TDM strategies are still somewhat limited at this point, it is widely agreed that the most promising solution is to incorporate the strategies into a regional travel demand model. Numerous case studies have investigated the effectiveness of TDM strategies; however, the direct applicability of these data is limited. Pehlke (1993) noted that "these findings must nonetheless be utilized with extreme caution and thoughtfulness in that they are location and circumstance specific, and therefore do not necessarily transfer easily to other areas." However, she also discussed the importance of

case study data in the modeling process, because these data are "used to develop the effectiveness assumptions which are often necessary as inputs into travel demand modeling assessments" (Pehlke, 1993).

Although case study data are certainly significant, Pehlke cited five major advantages of using a network-based modeling technique for TDM evaluation as opposed to other methods:

- A network-based model affords "more detailed locational and mode accessibility representation."
- "Impacts on congestion and travel path changes are simulated."
- The applicability of TDM strategies can be determined "under a variety of circumstances."
- "Future year conditions" can be modeled.
- The model provides the "ability to design and test very specific program parameters." (Pehlke, 1993)

Taylor and D'Este (1994) also noted the importance of a network-based modeling technique for evaluating TDM strategies: "It is only through the development of a network modeling capability sensitivity to TDM measures that the congestion aspects of TDM policies can be examined. Congestion results from the collective decisions of many travelers with the delays experienced by one traveler dependent on the actions of fellow travelers. By using the network-based model it is possible to predict the equilibrium between travel demand and the service performance of the transport system." (Taylor and D'Este, 1994)

URBAN CENTERS IN THE CENTRAL PUGET SOUND REGION

The Puget Sound Regional Council (PSRC) describes "centers" as follows: "Centers are places of relatively compact development where housing, employment, shopping and other activities are in close proximity. They come in a variety of sizes and types, ranging from large, established downtowns that serve the whole region to emerging suburban crossroads with more of a neighborhood orientation. The centers strategy involves strengthening and revitalizing existing centers as well as encouraging development in suburban places that are emerging as new community and regional hubs" (PSRC, 1996-1997).

"Centers" have become a prominent issue because of the passage of the Washington State Growth Management Act (GMA). The GMA encourages new growth in existing urban areas "to help slow suburban sprawl, conserve farmlands and forests, keep existing city and town centers vital, and allow transportation and other services to be provided more efficiently" (PSRC, 1996-1997).

The largest and most regionally significant centers are called "urban centers." In the four-county central Puget Sound region, 21 urban centers have been designated by the various counties and cities. Collectively, these urban centers represent just over 2.0 percent of the land within the region's urban growth area, but contain approximately 4.7 percent of this area's population and 29.7 percent of its jobs. By the year 2020, the centers could accommodate about 8.0 percent of the urban growth area's projected population and 31.8 percent of its jobs (PSRC, 1996-1997). The locations of each urban center are shown in Figure 5. The heavy lines indicate county boundaries, and the lighter lines denote the boundary of the urban growth area.

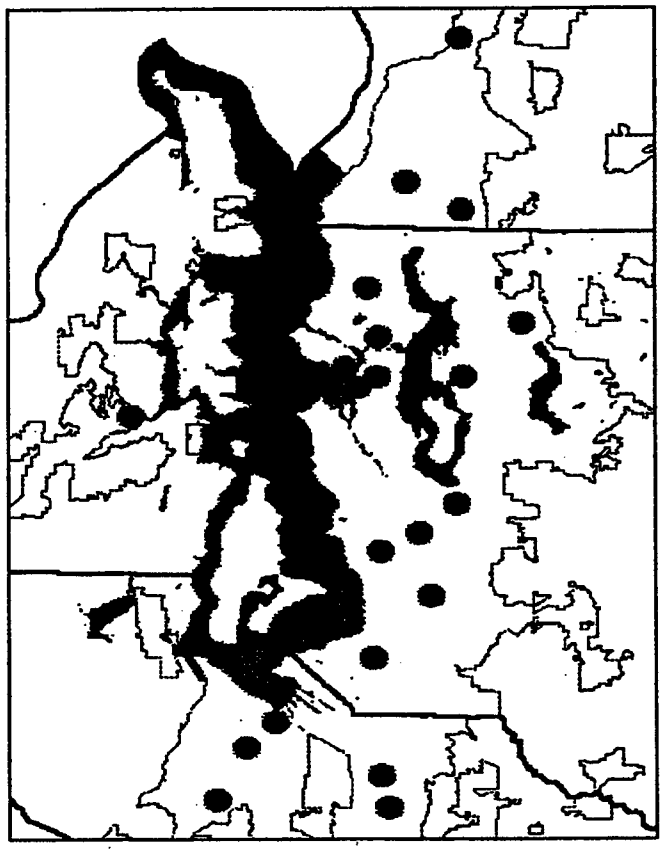


Figure 5: Map of Centers in Puget Sound Region

DEFINITION OF "URBAN CENTER"

VISION 2020 (the growth and transportation strategy for the four-county central Puget Sound region) describes urban centers as places that "include a dense mix of business, commercial, residential, and cultural activity within a compact area of up to 1.5 square miles." Urban centers are also places in which both cars and alternative modes of transportation, such as transit, bicycling, and walking, are viable travel options for residents, employees, shoppers, and visitors. (PSRC, 1995)

Within the region's growth management strategy, urban centers are places designed to handle a substantial portion of regional population and job growth in the coming years.

VISION 2020 suggests that urban centers should work toward the following size and density thresholds (PSRC, 1995):

- 25 to 80 employees per acre
- 10 to 20 households per acre
- 15,000 to 300,000 employees

Characteristics of Urban Centers

Population

The 21 urban centers collectively contain approximately 119,000 people, representing 3.9 percent of the region's population and 4.7 percent of the UGA's population. According to projections for 19 urban centers, 135,000 new residents are expected to move into the centers over the next 20 years, representing 16 percent of the expected regional population growth through 2020. The population density of the urban centers currently averages about 5,313 people per square mile, compared to 2,463 people per square mile for the entire urban growth area. By 2015, the population density for the 19 urban centers with population forecasts is expected to increase dramatically to 11,329 people per square mile. (PSRC, 1996-97)

Employment

The 18 urban centers reporting employment data contain approximately 428,190 jobs, representing 29.7 percent of the jobs in the urban growth area. Over the next 20 years, the centers project a 55 percent increase in the number of jobs, resulting in a 31.8 percent share of urban growth area employment. The density of jobs in urban centers is expected to increase over the next 20 years from the current level of 29.8 jobs per gross acre to 46.1 jobs per gross acre. (PSRC, 1996-97)

Housing

The 19 urban centers reporting housing data contain 76,385 housing units. These 19 centers expect 75,400 new housing units over the next 20 years. Nine urban centers subdivide their housing data by type, and these nine centers indicate that 54 percent of current housing is multi-family, compared with 32 percent regionwide. The average housing density in centers is about 5 dwellings per acre, and over the next two decades, this figure is expected to increase to 12 dwellings per acre. (PSRC, 1996-97)

Land Use, Center Features, and Character

Even among the 21 urban centers, the nature of the land use varies widely from center to center. PSRC states, "Some are more commercial in nature, while others have more of a residential or mixed character. Some have civic attractions such as city halls, state and federal offices, schools and libraries, while others are predominantly places for entertainment and shopping. Some centers are dense, urban places, while others are currently suburban places dominated by parking lots. Ideally, all of the urban centers will grow to have a mix of housing, commerce, entertainment, and services that make them lively, fully functioning centers for their communities." (PSRC, 1996-97)

Urban Form

According to PSRC, "The layout of an urban place— its street and sidewalk network, block configuration, and building placement— is perhaps the most crucial factor for pedestrian and transit access." (PSRC, 1996-97) Two of the measures used to determine pedestrian and transit accessibility are average block size and street network density. Smaller block sizes enable pedestrians to travel from place to place more easily. Older centers have average block sizes of about three acres, whereas newer, more suburban centers have block sizes ranging from 5 to more than 60 acres. In addition, older centers have an average of 25.6 miles of streets per square mile, but new suburban centers average only 9.7 miles per square mile. (PSRC, 1996-97)

PUGET SOUND TRANSPORTATION PANEL

The Puget Sound Transportation Panel (PSTP) is an innovative travel survey designed to gain a better understanding of how people make travel decisions. (PSRC, 1997) The PSTP "is the first application of a general-purpose urban travel panel survey in the United States." (Murakami and Watterson, 1990) The panel comprised about 1700 households in the central Puget Sound region, which consists of King, Kitsap, Pierce, and Snohomish counties. "It specifically include[d] households with at least one regular bus rider, and households with at least one regular carpooler. Other households, whose members drive alone for most of their trips, [were] also included." (PSRC, 1997)

Members of each household recorded their trips for a two-day period in each of the following years: 1989, 1990, 1992, 1993, 1994, and 1996. In addition to providing information on each trip taken, a number of panel members completed a questionnaire regarding their attitudes about different aspects of transportation. (PSRC, 1997)

This project utilized data from the 1990 "wave." This wave was chosen because the demographic data for the urban centers were taken from the 1990 census. This wave consisted of approximately 32,000 valid trips taken from travel diaries given to each household member who as at least 15 years old. Each trip was indexed to a specific household, person, and day. Trip characteristics such as starting time, ending time, purpose, origin location, and destination location were recorded for each trip taken. In addition, socioeconomic and demographic information about survey respondents was indexed by person and household. This information allowed the connections between trip making characteristics and certain household or person characteristics to be studied.

CHAPTER 3: LITERATURE REVIEW

TRAVEL DEMAND MANAGEMENT EFFECTIVENESS EVALUATION METHODOLOGIES

CASE STUDIES

A number of case studies of TDM measures have been documented, and nearly all of them have been based on measures implemented by employers.

REGULATION XV/RULE 1501

Many case studies have been performed in Southern California as a result of Regulation XV legislation in that state, which required all sites employing 100 or more workers to develop trip reduction plans that encourage employees to use modes other than driving alone to get to work.

Regulation XV, a mandatory measure enacted in 1988, was revamped into a voluntary measure known as Rule 1501 in January 1994, which in turn was revamped as an even less-restrictive Rule 2202 in December 1995. Recently, the California legislature enacted SB 836, a bill that will eventually eliminate Rule 2202 by raising the affected employer threshold in several stages. (Wasikowski, 1997) The data described below primarily relate to studies completed for the original legislation, Regulation XV.

These results were summarized in an Institute of Transportation Engineers (ITE) publication entitled "Evaluation of Employee Trip Reduction Programs Based on California's Experience with Regulation XV" (ITE, 1994). This report documents changes in the average vehicle ridership (AVR) and proportion of workers driving alone as a result of the implementation of employer-based trip reduction plans. AVR is calculated by dividing the total number of employees arriving at work between 6:00 and 10:00 AM

(which has since been changed to the four-hour period between 5:00 and 11:00 AM in which the majority of employees arrive at work) by the total number of vehicles driven by these employees, and then averaging these numbers over a period of one week. This report indicated an increase in AVR of 4.5 percent in the "Central City" sub-region, an increase of 2.5 percent in the "Metro Central" sub-region, and an increase of 3.4 percent in the "Metro Suburbs" sub-region. These values corresponded to changes from pre-Regulation XV levels to levels two years after the implementation of this legislation. The results documented in this report were based on a sample of 1,110 trip reduction plans, representing 77 percent of all sites with approved plans.

Although the results at the employer level were encouraging, ITE stated that this legislation still had relatively little effect at an area-wide level. The report stated, "A full 25 percent increase in average vehicle ridership (assuming such an increase is realizable) would produce a 2 to 3 percent decrease in area-wide trips and a 3 to 4 percent decrease in daily VMTs— reductions that would quickly be canceled out by long-term growth in travel." Similarly, ITE refered to studies conducted in the San Francisco Bay area which stated that full implementation of Regulation 13 (the Bay Area's version of Regulation XV) would only lower the region-wide number of work trips by about 3.5 percent. (ITE, 1994)

A more recent document addressing the composite effectiveness of Regulation XV legislation is "Five-Year Results of Employee Commute Options in Southern California" (Young and Luo, 1995). This report expanded on the ITE report by evaluating 4,999 sites with two or more trip reduction plans (more sites developed approved plans over time, accounting for the vast difference in the number of sites on which the studies were based). For these 4,999 sites, the aggregate AVR increased 4.3 percent, from an initial index of 1.205 to an index of 1.257 in November 1993. Also, the drive-alone share decreased from 73.5 percent to 67.2 percent, a reduction of 6.3 percent. The report indicated that this reduction was almost entirely due to increased carpooling.

This report made several conclusions regarding program effectiveness over time. First, it noted that the progress made toward achieving a higher AVR and lower drive-alone share had been "significant, but short of targets." Regulated sites achieved an increase of 4.3 percent in AVR, corresponding to a decline of 4.8 percent in daily vehicle trips per 100 employee trips. Next, AVR progress levels were directly related to the nature of the programs implemented by the individual employers, as well as the standards set by the South Coast Air Quality Management District, which implemented Rule 1501. For example, carpool formation accounted for most of the progress because it was the least disruptive to existing organizations (as opposed to parking charges, telecommuting, and compressed work week schedules). Finally, employers seeking to minimize the costs needed to comply with Rule 1501 had reduced the use of direct financial incentives to encourage ridesharing, and had emphasized strategies such as marketing and rideshare matching. Over five years of Regulation XV implementation, the share of employers offering direct financial subsidies declined from 69.1 percent to 53.4 percent. This report also noted that the AVR progress achieved by individual employers could be approximated by a bell curve, with most employers achieving only very modest gains, and a few employers reporting large decreases or increases in AVR. The employers with the lowest initial AVRs appeared to have made the most progress. (Young and Luo, 1995)

COMSIS DATA

Another significant source of case study data is "Evaluation of Transportation Demand Management Measures to Relieve Congestion" (COMSIS Corporation, 1990). This report addressed the effectiveness of TDM measures at a number of sites in various settings from across the country, such as a regional CBD, a radial corridor, a suburban activity center, and a suburban business park. This report used employee modal split as a measure of effectiveness. COMSIS noted that employee mode split was the most universally available information from TDM programs, and it was measured through

employee surveys. To estimate vehicle trip reduction impact from modal split, a special index was developed entitled *Number of Vehicle Trips per 100 Travelers*. This index represents the rate at which a particular travel population generates vehicle trips. This was done by assuming an occupancy level for each mode:

- Drive Alone - 1 vehicle trip for every person trip
- Carpool - 0.4 vehicle trips for every person trip (assumes 2.5 persons per carpool)
- Vanpool - 0.083 vehicle trips for every person trip (assumes 12 persons per vanpool)
- Transit - 0.033 vehicle trips for every person trip (assumes 30 persons per vehicle)
- Bicycle/Walking - no vehicle trips per person trip

Using this index, the number of vehicle trips made by the TDM population under the TDM program was estimated and then compared to the number of trips that would have been made without the TDM program in place (represented by a control site where no TDM program was in place). This difference is defined as the *net trip reduction* accomplished by the TDM program.

In this report, the effectiveness of the TDM programs was addressed at both an area-wide level and at the individual program level. COMSIS stated that "the area-wide approach to TDM is where the measured effects are currently the most modest, but where the greatest potential lies. TDM should be implemented at an area-wide level to be most effective." The areas studied in this report had an area-wide trip reduction rate ranging from 2.4 percent to 17.8 percent, while trip reduction rates at individual employment sites ranged from 5.5 percent to 47.6 percent. These projections were more optimistic than those posited by ITE regarding Regulation XV, as stated earlier: "A full 25 percent increase in average vehicle ridership (assuming such an increase is realizable) would produce a 2 to 3

percent decrease in area-wide trips and a 3 to 4 percent decrease in daily VMTs—reductions that would quickly be canceled out by long-term growth in travel." (ITE, 1994)

EMPIRICAL MODELS

Several computer-based mathematical models also account for effects of TDM strategies at the network-wide level. Most notably among these are models produced by the COMSIS Corporation and JHK & Associates.

COMSIS MODEL

The COMSIS model is integrated with the traditional four-step modeling process and uses trip tables from these steps as inputs to calculate what changes in travel characteristics can be expected from the implementation of specific TDM strategies. These changes, in the form of mode split, vehicle occupancy, vehicle miles traveled, number of person trips, and number of vehicle trips, are computed relative to existing (before TDM) conditions. As additional inputs, the user defines such parameters as the level of participation in carpool programs, the time savings of an HOV facility, and others. Although this provides flexibility in determining the overall effectiveness that a certain level of participation will produce, it still relies on a number of inputs about each strategy from the user, forcing the user to have an idea of the anticipated effectiveness of each measure. If more data regarding the effectiveness of each strategy were included in the model, some of these inputs would not be necessary.

The COMSIS model is based on a *disaggregate logit choice model*, which predicts the likelihood of changes in mode choice due to changes in the characteristics of particular modes. Analytic mode choice models do not accurately simulate the effects of some TDM strategies; in these cases, empirical data from "look-up tables" are used. This model has potential for further development because it is network-based and can utilize specific trip tables from specific areas. As stated earlier, if further information were included about the

actual effectiveness of individual strategies (particularly area-wide strategies), thus requiring less user input of parameters such as travel time savings or transit wait time, this would be a more powerful application. However, for employer-based strategies, this goal may be difficult to achieve because of the variable nature of these measures.

JHK & ASSOCIATES

The model produced by JHK & Associates also evaluates a number of TDM strategies. However, this is strictly an employer-based model, and the impacts of TDM strategies on an area-wide level are not analyzed. This model requires even more user input regarding the effectiveness of each strategy than the COMSIS model, in terms of parameters such as average daily reduction in vehicle commute trips and reduction in leased parking spaces. In addition, the user most also input the capital and operating costs of each strategy.

Basically, this model is just a spreadsheet that makes calculations of cost-effectiveness based entirely on user inputs. For some strategies, such as telecommuting, the model will produce an estimate of the reduction in vehicle commute trips. However, this is merely a simple calculation based on user inputs of the number of telecommuting employees and the average percentage of workdays spent telecommuting. In short, this model does not present a viable technique for analyzing the *potential* effectiveness of proposed TDM projects because the costs and effectiveness level of each strategy must already be known by the user.

WEAKNESSES OF CURRENT EVALUATION METHODS

Thus far, we have focused on the existence of effectiveness data. However, a review of the literature identified a number of issues associated with the quality and usefulness of these data, such as the following:

- the transferability of effectiveness data between particular areas and applications

- the existence of synergistic or multiplier effects of multiple TDM strategies applied in combination
- the long-term impacts of TDM strategies
- the lack of standard measures of effectiveness.

Each of these issues is addressed below.

TRANSFERABILITY OF DATA

One major concern with TDM data is that the effectiveness of a particular strategy is dependent upon the situation in which the strategy is implemented. The specific location and application of the strategy has a great deal of bearing on its potential effectiveness. As stated earlier, Apogee Research (1994) noted that "readers should not rely on individual estimates of TCMs (Transportation Control Measures) as definitive for individual regions or particular applications." In addition, "further work is clearly needed to establish more definitive numbers for particular TCMs in particular settings and to provide guidance on how to obtain the maximum potential of each TCM." (Apogee Research, 1994)

In "The Effects of Land Use and Travel Demand Management Strategies on Commuting Behavior," Cambridge Systematics (1994) also encouraged caution when effectiveness data are used in different applications. Cambridge note that areas where the land use encourages the use of alternative modes could have a higher level of TDM strategy effectiveness. (Cambridge Systematics, 1994)

SYNERGISTIC AND MULTIPLIER EFFECTS

Another concern with current TDM effectiveness data is that there has been little effort to account for the synergistic effects that may occur when several TDM strategies are applied in combination. That these effects can occur is widely agreed, but current research reveals very little in terms of how to account for them. Apogee Research refered to this

effect when noting, "Knowledge of the potential of additional gains from packages of TCMs is limited..." (Apogee Research, 1994)

The Greater Vancouver Regional District (GVRD) also discussed these effects. GVRD noted that it would be "advantageous" to evaluate packages of TDM strategies, rather than individual tactics. It offered an example of this hypothesis by theorizing that the effectiveness of a ridesharing program would be enhanced if preferential carpool facilities, such as HOV lanes, were implemented concurrently. "The benefits of each TDM measure in isolation may not be linearly additive when more than one measure is applied because of synergism and competition between measures, and because travel markets and trip types affected overlap." In its model, the GVRD applied reduction factors to account for the possibility of double-counting using different strategies, but it did not offer any methodology to account for synergistic effects. (TRANSPORT 2021, 1993)

Cambridge Systematics was slightly more specific in concluding that there is a positive interactive effect between land-use characteristics and financial incentives. Cambridge stated that there is "a positive cumulative impact on increasing average vehicle ridership and reducing drive-alone mode share when both financial incentives and one of the five land use characteristics analyzed (mix of land uses, accessibility to services, preponderance of convenient services, perception of safety, and aesthetic urban setting) are present." However, the report noted that as further TDM strategies are added, the impacts on mode share are not linearly additive. In this case, the cumulative effect is less than the sum of the effects of the individual strategies. These findings were based on a study of the work sites affected by Regulation XV. (Cambridge Systematics, 1994)

LONG-TERM IMPACTS

Because large-scale implementation of TDM strategies is a relatively new phenomenon, there is obviously a dearth of data regarding the long-term impacts and effectiveness of TDM strategies. Apogee Research confirmed this issue by statingthat "the

longer-term effects of TCMs have yet to be analyzed." However, it also noted that some strategies "have inherently limited effectiveness over time; the impacts of others may persist or strengthen." (Apogee Research, 1994)

STANDARDIZED MEASURES OF EFFECTIVENESS

Another major issue that merits consideration is that the current effectiveness data exist in a number of different units of measure. If a standard unit(s) were used, the data would be much more useful. In "Evaluating the Effectiveness of Travel Demand Management," C. Kenneth Orski addressed this problem. He stated that TDM impacts and effectiveness were being assessed through many different measures, making it extremely difficult to compare results or to develop common standards. Some of these measures of effectiveness are as follows:

- effect on travel congestion (level of service)
- effect on average daily traffic
- effect on peak-period traffic
- effect on drive-alone rate (modal split)—peak period
- effect on drive-alone rate (modal split)—daily average
- effect on vehicle-miles of travel
- effect on vehicle trip generation (peak period)
- effect on vehicle trip generation (daily average)
- effect on average vehicle ridership (morning peak period)
- effect on V/E ratio (vehicles per 100 employees)
- effect on vehicle emissions (ozone, carbon monoxide).

The use of so many different performance measures makes it difficult to compare results in different areas or to develop a common "standard." Orski also noted that several

issues must be addressed when a "standard" is being defined. For instance, the degree of participation in commute alternatives, which can be measured through surveys, is the most easily measured effect of TDM programs. However, there is no direct connection between this effect and other measures such as VMT reduction and level of service. Furthermore, Orski raised the question of whether TDM effectiveness should be measured in absolute or relative terms; that is, should the focus be on obtaining a certain degree of change from a baseline, or should measures strive to reach a predetermined standard? (Orski, 1991)

CURRENT TRAVEL DEMAND MANAGEMENT MODELING APPLICATIONS

A number of regional MPOs have attempted to incorporate TDM strategies into their regional travel demand models. The practices of four representative regions—Vancouver, B.C.; Portland, Oregon; Washington, D.C.; and the San Francisco Bay Area, California—are examined.

VANCOUVER, B.C.

The Greater Vancouver Regional District has taken steps to analyze a number of TDM strategies in its regional travel demand model. The strategies modeled are as follows:

- telecommuting
- employer-based trip reduction program
- bus priority facilities
- HOV lanes
- parking charges
- motive fuel tax
- CBD licensing fee

- bridge tolls.

A helpful summary of the modeling approach for each of these strategies is contained in the report "Transportation Demand Management: A Forecast Modelling Approach," produced by TRANSPORT 2021. The methods used to model each of these strategies are examined below.

TELECOMMUTING

To model the effects of telecommuting, GVRD ran its trip generation and trip distribution models without any modifications. Because telecommuting primarily affects work trips, the work trip matrix generated after the trip distribution step was reduced by a specified percentage on the basis of assumptions regarding the number of people that would telecommute. After the work trip matrix was modified, the mode choice and trip assignment models were executed.

EMPLOYER-BASED TRIP REDUCTION PROGRAM

Like telecommuting, employer-based trip reduction programs were modeled by adjusting the trip tables generated for the work trip purpose. GVRD assumed a certain-percentage reduction in the number of vehicle trips and then assumed that the number of SOV trips reduced would be redistributed to carpools and transit. The trip generation and trip distribution components were run without any modifications. After the mode choice model had been executed, the auto driver, auto person, and transit passenger matrices for the work trip purpose were modified. First, the auto driver work trip matrix was multiplied by the assumed reduction in vehicle trips. Next, the auto person work trip matrix was multiplied by the same factor, but the mode split ratio matrix was used to reallocate a certain percentage of trips back to the auto person matrix to account for a number of drivers becoming passengers. The remaining trips were then assumed to be taken by transit and

were added to the transit work trip matrix. Following these modifications, the trip assignment model was executed without any changes.

Bus Priority Facilities

To evaluate bus priority facilities (e.g., bus lanes, queue jumps), the transit travel time in the mode split model was modified. GVRD made assumptions about which corridors these facilities would be implemented on and then assumed a given amount of travel time savings. In the mode split step, a new transit travel time matrix was created for the work-purpose trip tables by subtracting the assumed amount of time savings for all of the origin/destination pairs between the new facilities. The mode split model was then re-executed on the basis of the new transit travel time matrices.

HOV Lanes

To model HOV lanes, modifications were made to the auto occupancy sub-model, which is used as an input to the trip distribution and mode choice models. The original auto occupancy sub-model was based on distance and parking charges, and to include the effects of HOV lanes, a ratio of the automobile travel time between two zones divided by the HOV travel time between two zones was incorporated into this sub-model. The newly calculated auto occupancy matrix was then used in the mode choice calculations.

Parking Charges

Parking charges were modeled by making the auto occupancy sub-model and mode choice model sensitive to these charges. Because the models used by GVRD already included a parking charge variable, no modifications were necessary. Additional increases in parking charges can be easily modeled by adjusting the variables in the auto occupancy and mode choice models and then re-calculating these matrices.

Motive Fuel Tax

The modeling of a motive fuel tax was similar to the procedure for modeling parking charges. Basically, the auto occupancy sub-model was reformulated to include a

variable depicting the "real increase in operating costs as a result of the higher motive fuel tax." (TRANSPORT 2021, 1993) After some experimentation, GVRD found a formulation that produced "reasonable results." The new auto occupancy matrix for each trip purpose was then evaluated in the mode choice model.

CBD LICENSING FEE

The modeling of this strategy was quite simple. CBD licensing fees were evaluated by adding the new fee to the parking charges that were already represented in the auto occupancy and mode choice models (as discussed earlier). The new fee was added for all trips destined for the CBD, as depicted in the trip distribution step. After the new fee had been incorporated into the existing parking charge matrix, the auto occupancy and mode choice models were simply recalculated for each trip purpose.

BRIDGE TOLLS

Bridge tolls were modeled in a fashion similar to the CBD licensing fee. A new variable was added to the auto occupancy sub-model, but instead of applying the new formulation to all trips destined for a certain area, the new model was applied only between certain origin/destination pairs (indicating where a bridge was located). After the adjusted formulation had been incorporated into the auto occupancy sub-model, the mode choice model was recalculated for each trip purpose.

TDM PACKAGES

GVRD attempted to model a package of strategies, and several adjustments were made to account for the effects of double-counting. However, no mention was made of synergistic effects. The Vancouver TDM package consisted of each of the strategies discussed earlier in this section, with the exception of the CBD licensing fee. It was excluded because "it would be impractical to impose concurrent higher parking charges and licensing fees on downtown Vancouver." (TRANSPORT 2021, 1993) To account for double-counting, the following assumptions were made:

- "The telecommuting trip-reduction target was subtracted from the employer-based trip-reduction targets, on the basis that telecommuting would be included in such a program." (TRANSPORT 2021, 1993)
- "The employer-based trip-reduction program was not applied to work trips destined to the CBD and regional town centres because the increased parking charges in these areas would duplicate the effect of the trip-reduction program. A trip-reduction program would likely include higher employee parking charges as a critical element." (TRANSPORT 2021, 1993).

To model this package of strategies, no adjustments were made to the trip generation or trip distribution models. In the auto-occupancy sub-model, the original equation was reformulated to include increased operating costs due to a higher fuel tax, the cost of the bridge toll between two zones, and a ratio of the auto travel time between two zones divided by the HOV travel time between two zones. These adjustments were then incorporated into the mode split model. In the mode split model, the transit impedance equation was modified slightly to reflect the use of the new in-vehicle transit time (due to the bus priority facilities), and the auto impedance equation was adjusted to include the higher operating costs due to the increased fuel tax, parking charges, and bridge tolls. After these changes had been made, the mode split model was recalculated for each trip purpose.

PORTLAND, OREGON

The Portland Metropolitan Service District (Metro) uses a comparatively advanced regional travel model, especially with regard to the inclusion of land-use factors in the model. The incorporation of development density by zone, transit level-of-service, and pedestrian environment factors (PEF) has led to improved predictions of transit, walk, and bicycle trips and can help explain travel behavior affected by land-use considerations.

Metro has expanded the traditional four-step process to six steps with the development of "pre-generation" and "pre-mode choice" steps. Land-use factors such as the PEF, the number of retail employees located within 1 mile, and the number of employees within 30 minutes by transit are input into the auto ownership model, which in turn is input into the actual trip generation model. Inclusion of these land-use variables in this stage is designed to more accurately represent trips taken by alternative modes.

The use of alternative modes is also taken into account in the "pre-mode choice" model. This model is actually a set of algorithms designed to separate person trips taken by non-motorized modes (foot or bicycle) from motorized modes (auto or transit). The number of trips taken by non-motorized modes is based partially on "maximum allowable distances" for usage of these modes. These "maximum allowable distances" were developed by trip purpose for foot and bicycle modes from 1985 survey data. The mode choice model then splits the remaining person trips into auto and transit modes.

The PEF, which is used in the pre-generation, pre-mode choice, and mode choice steps, is designed to reflect the character of the pedestrian environment, including ease of street crossings, sidewalk continuity, local street characteristics, and topography. The PEF score is obtained by adding ratings of 1, 2, or 3 (corresponding to "bad," "average," and "good") in each of these categories. Use of the PEF has been somewhat controversial, and Metro intends to develop more objective environmental estimators. Nevertheless, Metro's model structure is quite advanced in its treatment of land use considerations. (Cambridge Systematics, 1996)

WASHINGTON, D.C.

Through work with COMSIS Corporation, both the Metropolitan Washington Council of Governments (MWCOG) and the Delaware Valley Regional Planning Commission (DVPRC) have conducted analyses of the potential effectiveness of numerous

TDM strategies and other transportation control measures in the Washington, D.C., and Philadelphia, Pennsylvania, metropolitan regions, respectively. The TDM evaluations were accomplished through three mechanisms: the respective regional travel demand models, the *COMSIS TDM Evaluation Model*, and various sketch planning tools. This project focused on the strategies evaluated with the regional travel demand models. For further information regarding the use of the *COMSIS TDM Evaluation Model* or the sketch planning techniques, the reader is referred to the documents published by the Metropolitan Washington Council of Governments and the Delaware Valley Regional Planning Commission.

The TDM strategies evaluated in the regional travel demand models for Washington and Philadelphia were assessed exclusively within the mode choice models. Pricing strategies (such as congestion pricing, parking pricing, taxes, and fees) and transit improvement strategies (such as increased service frequency and increased bus speeds in high-volume bus corridors) were the main types of strategies evaluated within the mode choice models. These strategies were modeled by adjusting the vehicle operating costs and the in-vehicle travel times, which are explicit variables in the mode choice models. One land-use strategy (shorter distances from bus stops to buildings) was also evaluated in the MWCOG mode choice model. This tactic was modeled by adjusting the transit access time downward.

One of the main weaknesses associated with this scheme is that only mode shifts are taken into account. TDM strategies can also affect the generation, distribution, and assignment of trips, but these effects are not considered in the current modeling scheme. MWCOG acknowledges this weakness and is currently updating its models to address this issue. (Metropolitan Washington Council of Governments, 1994)

San Francisco Bay Area, California

In the San Francisco Bay area, the TRIPS model is the primary travel model used to evaluate demand management strategies. The TRIPS model was used to study strategies related to pricing (such as tolls, taxes, and parking charges) and to travel time (such as HOV facilities). Several of the strategies related to expanded transit options, travel time, land-use changes, activity constraints, and promotion of alternative modes were modeled with "local data, empirical studies reported in the literature, and interviews with experts." Furthermore, strategies involving pedestrian and bicycle improvements were evaluated with a regional mode choice model developed by Deakin in the mid 1980s. This mode choice model uses bicycle and foot as explicit modes. (Johnston and Rodier, 1994)

The TRIPS model was developed from models produced in the 1970s. Transit and highway travel times and costs are taken into account in all of the model steps, and iteration between the steps takes place. The model is based on a sample of households from the most recent travel survey conducted in the Bay Area. One significant shortcoming of this model is that it does not include a detailed network representation and trip assignment algorithm. Instead, "as an approximation, a simple routing for estimating changes in level of service has been incorporated in the model." (Johnston and Rodier, 1994)

LIMITATIONS OF CURRENT MODELING METHODOLOGIES

Much research is still needed to find a way to effectively integrate TDM strategies into a network-based modeling approach. Several authors have commented on the deficiencies of current models in incorporating TDM strategies. Stopher, Hartgen, and Li noted that the current four-step process "continues to exhibit a lack of behavioral content that prevents the analyst from evaluating alternative policies that are unrelated to investment proposals for major facilities." (Stopher, Hartgen, and Li, 1996)

Kitamura et al. (1996) offered more specific limitations of the current modeling approach. According to the authors, two major shortcomings of the current approach are that the models are trip-based, which does not "appropriately reflect the fact that the decisions associated with a particular trip are integrally related with the decisions for other trips," and that the models lack a time-of-day dimension, which "implies that these model systems are unable to predict changes in when trips will be made." This second shortcoming especially limits the evaluation of congestion pricing schemes. The authors noted several other limitations, including "the use of static models based on cross-sectional data, an inability to address the evolution of the vehicle fleet mix, and the use of exogenous land-use and socio-demographic inputs." These shortcomings "severely limit the usefulness of the four-step procedures in much needed applications such as the evaluation of TDM effectiveness." (Kitamura et al., 1996)

Ferguson (1991) also noted specific deficiencies of the current four-step modeling technique. He stated that the models "may be faulted for their failure to include nontechnological modes of travel such as walking and bicycling explicitly, for treating ridesharing as being entirely subsumed within the automobile mode of travel, and for treating regional travel demand as more or less permanently fixed, once the trip generation stage of modeling has been completed. Unless these limitations are lifted, aggregate models will serve TDM evaluation needs only poorly." (Ferguson, 1991)

NEW DEVELOPMENTS IN NETWORK-BASED MODELING

Several new approaches to network-based modeling are currently receiving notable research attention. Each of these schemes is designed to address the general deficiencies of the traditional four-step modeling process, and these approaches are also likely to offer enhanced TDM modeling capabilities. Two of the more promising methodologies, activity-based modeling and TRANSIMS, are introduced below.

ACTIVITY-BASED MODELING

RDC, Inc., defined activity-based approaches as approaches that "explicitly recognize that travel demand is derived from the need to pursue activities that are dispersed in time and space. Moreover, these approaches recognize the inter-dependence among decisions for a series of trips made by an individual." (RDC, Inc., 1995) The concept of activity-based analysis was introduced in the 1970s; however, because behavioral aspects of transportation were not major considerations until recently, activity-based modeling has not garnered much research attention until now. Because the effectiveness of TDM strategies is rooted in behavioral decisions, the consideration of behavioral factors in transportation decisions is what makes this approach so attractive in modeling TDM strategies. RDC noted, "Relationships among human travel behavior patterns and the attitudes, values, and constraints that determine these patterns are extremely complex in nature, and traditional forecasting methods do not explicitly model these relationships in a theoretically sound framework." (RDC Inc., 1995)

Because activity-based modeling has been receiving research attention only recently, no MPOs currently use this methodology for TDM evaluation or for general modeling. The most significant effort to date is a study completed by RDC, Inc., for the Metropolitan Washington Council of Governments in 1995. The goal of this study was to determine the feasibility and practicality of implementing an activity-based modeling scheme in a large urban area. A small data set consisting of revealed preference and stated preference information was tested using RDC's prototype Activity-Mobility Simulator (AMOS), which is "a dynamic microsimulator that replicates responses to TDM measures." (RDC, Inc., 1995)

The results of this study were very encouraging. The most notable conclusions are outlined below.

- The study showed that an activity-based modeling scheme can be implemented with existing MPO data, such as trip diary data, network data, and land-use data. Additional necessary information consists of stated-preference survey data, which are used to model the area residents' responsiveness to TDM strategies
- The project demonstrated that travel forecasting can be accomplished by considering the entire daily travel pattern, rather than a series of disconnected trips.
- The study concluded that stated-preference surveys are a valid method for assessing the potential impacts of TDM measures.
- The AMOS prototype can generate aggregate travel demand statistics at levels comparable to traditional four-step models. (RDC, Inc., 1995)

Although no MPOs currently use this approach, the advantages of using an activity-based approach are significant, and it is likely that this scheme will receive being to more attention, especially for modeling TDM strategies.

TRANSIMS

The development of the TRansportation ANalysis and SIMulation System (TRANSIMS) is a long-term effort designed to significantly improve travel forecasting and impact assessment. (Weiner and Ducca, 1996) TRANSIMS forecasts travel behavior for individual households, residents, and vehicles rather than for zonal aggregations of households, as is the case with the current four-step scheme. TRANSIMS performs the same functions as the current four-step approach, but it expands the capabilities of the existing process and performs the tasks in a different fashion. (Shunk, 1994) As stated by Shunk, "The TRANSIMS process forecasts information related to trip generation and trip distribution in an 'activity planner' and for mode and route assignment in a 'trip planner.' The trip planner is then iterated to modify trip destinations and/or mode choice in response

to congestion on chosen modes or routes." (Shunk, 1994) After the individual trip characteristics have been developed in the activity planner and trip planner, the trips are loaded on the transportation network with a microsimulator to evaluate the performance of individual vehicles and the transportation system. (Shunk, 1994)

The activity planner and trip planner modules will allow major advances in modeling the generation of trips. TRANSIMS attempts to minimize the "effective cost" of satisfying the traveler's requirements and preferences for activities and travel. The cost can be measured in terms of money, time, or other considerations important for the traveler. TRANSIMS iterates until the "best" (least-cost) combination of mode and route is obtained. If TRANSIMS determines that the requirements of a certain activity can not be met under the given conditions, adjustments are made to make the trip feasible. This is done by adjusting the traveler's preferences; for example, the departure time for a trip may be adjusted if the trip plan indicates that a traveler will be late for work. (Shunk, 1994)

The determination of trips based on "effective cost" will allow major improvements in modeling TDM strategies. One of the major deficiencies of the current trip generation scheme is that the cost of travel is not a consideration.

CONCLUSIONS

In conclusion, there is much room for improvement in modeling TDM strategies. Although it seems obvious that these strategies should be included in the regional modeling process, the few MPOs that currently attempt to include these strategies do so only in a fairly rudimentary fashion. Despite the definite deficiencies in the current scheme, further research may offer substantial improvements in the modeling process.

CHAPTER 4: OBJECTIVES AND METHODOLOGY OF STUDY

The purpose of this project was to examine the effects of TDM strategies on trip generation rates. Five TDM strategies that may affect trip generation rates were identified:

- *Telecommunications Strategies*, including telecommuting and other advanced telecommunications activities such as teleshopping
- *Alternative Work Schedules*, such as a compressed work week schedule in which employees work a normal 40-hour week in less than five days
- *On-site Amenities*, which are facilities such as cafeterias, post offices, automated teller machines, and child care centers located directly at large employment sites, encouraging employees to take care of personal business at the worksite instead of going off-site to run errands
- *Pricing Strategies*, such as highway tolls, gas tax increases, VMT taxes, and regionwide parking charges
- *Land Use Strategies*, such as encouraging the development of higher density levels and a more diverse mixture of land uses.

The treatment of these strategies in this study is discussed below.

TRIP GENERATION MODEL DEVELOPMENT

The first objective of this study was to develop a series of trip generation models that predict the number of trips made by a household for a specific purpose. In addition to the traditional socioeconomic and demographic variables used to predict number of trips taken, a series of variables describing various TDM strategies was also tested. The purpose

of this phase of the study was to determine which variables describing TDM measures are significant in the various trip generation models.

DATA PREPARATION

The main source of data for this study was the Puget Sound Transportation Panel (see Chapter 2). The models were developed with Wave 2 data from 1990. Wave 2 data were selected because the demographic information regarding the urban centers was also collected in 1990.

The data set used in this study was "Version 3" of the 1990 wave. Version 1 was the raw data with no cleaning or organizational improvements. In Version 2, the data were cleaned up and reorganized by the Pennsylvania Transportation Institute at Penn State University under contract with PSRC. Corrections were made where necessary, and the data files were standardized and reorganized. In Version 3, PSRC made further revisions to the data set. PSRC established a uniform file structure across all waves, removed unnecessary or redundant fields, and simplified the range of values in several computed fields. (PSRC, *Readme* file)

Four different surveys from the PSTP were used:

- trip survey, which included information about each trip recorded by the survey respondents
- person survey, which included demographic and socioeconomic information about the survey respondents
- household survey, which included demographic and socioeconomic data at the household level
- attitude survey, which measured respondents' feelings about key transportation issues.

To manipulate the PSTP data, the statistical software package SPSS was used. The trip survey data file was imported into SPSS, and then a number of variables from each of the other three surveys were incorporated into the same working file by matching the household and person identification variables that are common to all four surveys.

From the person survey, variables such as "the distance from home to workplace," "number of days/week respondent works," and "parking costs" were imported into the working data file. Key variables from the household survey included "household income," "number of household vehicles," "household size," and the number of household members in various age ranges. From the attitude survey, variables such as "frequency needing car for personal trips during day" and whether the employer provided free or reduced-fee parking were imported into the working data file for further study.

After the initial working data file had been established with the trip data and selected variables from each of the other three surveys, several modifications were made to the data. First, the PSTP trip data were divided into three trip purposes: home-based work, home-based other, and non-home-based. For this study, several additional purposes were defined, so that each of the following purposes were analyzed:

- home-based work
- home-based shopping
- home-based school
- home-based college
- home-based other
- work-other
- other-other.

These are the same trip purposes that DKS Associates examined in its recent study of PSRC's trip generation models. (DKS Associates, 1994)

To redefine the original three purposes into these seven purposes, the activity codes for each trip in the PSTP data set were used to define the appropriate productions and attractions for each new trip purpose. The activity codes are given in Table 2.

Table 2: Activity Codes in PSTP Surveys

Activity code (**purpose** variable)	Activity
1	Work
2	Shopping
3	School
4	Visiting
5	Free-time
6	Personal
7	Appointments
8	Home
9	College

Source: DKS Associates, 1994

The activity codes corresponding to specific productions and attractions were then used to define the new set of trip purposes. The specific production and attraction codes, along with their corresponding trip purpose, are shown in Table 3.

As stated earlier, one of the TDM strategies that was identified as potentially affecting trip generation rates is land use changes. The initial intention of this study with regard to this strategy was to develop several different trip generation models for areas with differing land use patterns, using the urban centers defined by PSRC (see Chapter 2 for a discussion of urban centers) to differentiate between areas with distinct land use patterns. In order to accomplish this objective, we would have to know which trip ends are located in which urban centers. Using ArcView GIS software, the geocoded urban center areas were linked with the working trip data file, producing a new "identifier" variable that indicated whether or not each trip end was located in an urban center, and if so, which

Table 3: Conversion of Activity Codes to Trip Purposes

Production Code	Attraction Code	Trip Purpose
8	1	Home-Based Work
8	2	Home-Based Shopping
8	3	Home-Based School
8	9	Home-Based College
8	4 -7	Home-Based Other
1	1 -7, 9	Work - Other
2 - 7, 9	2 - 7, 9	Other - Other

Source: DKS Associates, 1994.

urban center. Each of the 21 urban centers was assigned a numerical identifier ranging from 1 to 21. The trip ends located within center boundaries were identified by the appropriate numerical identifier, and if a trip end was not located in a center, a value of "0" was assigned.

Because the trip data were organized by origins and destinations, these data had to be converted into productions and attractions; and for those trips beginning or ending in an urban center, identifiers had to be added indicating which urban center(s) served as the production and/or attraction. Using the variables from the travel survey indicating trip type and purpose, two new variables called "prodflag" and "attrflag" were defined to signify the urban centers that served as the production and attraction, respectively, for each trip. The codes used for **prodflag** and **attrflag** were the same as those used for the original identifier described above. If the production or attraction end was not located in an urban center, a value of "0" was assigned.

After all variables had been defined in the working data file, the data were selected by trip purpose and segregated into seven different files, each of which contained trip data for one of the seven trip purposes examined in this study.

Next, data from each trip purpose were aggregated by household, resulting in a new data file for each trip purpose that contained the total number of productions (by household), along with the selected variables from the person, household, and attitude surveys. For the data that were collected at the person level (from the person and attitude surveys), the mean values of the responses from each household member were aggregated. For example, a two-worker household whose members indicated travel times to work of 10 minutes and 20 minutes, respectively, was assigned an average household travel time of 15 minutes.

In addition to the aggregation by household, the trip productions for each household were organized by centers to enable the selection of trips produced in centers (or a specific center).

The trip productions by household were aggregated on the basis of two consecutive days, which is the same period of time used for the PSTP travel diaries. Therefore, all trip production rates in this study were based on a period of two days.

Potential Travel Demand Management Variables

As noted at the beginning of this section, five TDM strategies were examined in this study: telecommunications strategies, alternative work schedules, on-site amenities, pricing strategies, and land-use strategies. Several variables in the PSTP describe some of the effects of each of these strategies. In addition to traditional socioeconomic and demographic variables, which address such characteristics as household size, household income, and vehicle availability, each of the variables described below was tested for relevance in the appropriate models.

Telecommunications Strategies

Of all the telecommunications strategies, telecommuting has received the most research attention and has the greatest potential for affecting travel behavior. For this

reason, incorporating telecommuting impacts into trip generation models was the focus for this category of TDM strategies.

Three variables from the PSTP Person survey and Attitude survey describe some of the travel characteristics potentially related to telecommuting:

- **home**— "Worked at home (Y/N)" (from the Person survey)
- **wk_freq**— "Number of days/week respondent works" (from the Person survey)
- **days**— "How many days a week do you work?" (from the Attitude survey)

  (**wk_freq** and **days** are basically the same variable but are found in different surveys.)

Current research indicates that telecommuting may affect not only home-based work trip generation but also other home-based and non-home-based trips (see Chapter 6). Therefore, the variables described above were evaluated in trip production models for every purpose.

ALTERNATIVE WORK SCHEDULES

The two most prominent types of "alternative work schedules" are flextime and compressed work week schedules. Of these two, compressed work weeks affect the number of work trips generated. The following variables from the PSTP Person and Attitude surveys account for compressed work weeks:

- **wk_freq**— "Number of days/week respondent works" (from the Person survey)
- **days**— "How many days a week do you work?" (from the Attitude survey)

These variables seem especially promising because they can account for the impacts of both telecommuting and compressed work weeks. Case study data regarding compressed work week schedules are limited, but Ho and Stewart found that in addition to the obvious effects on home-based work travel, non-work travel behavior may also be

affected by these schedules (see Chapter 6). (Ho and Stewart, 1992) For this reason, these variables were analyzed in trip production models for every purpose.

ON-SITE AMENITIES

Post office, dry cleaning, child care, and other services located at employment sites are designed to reduce the need for workers to travel off-site to run errands. Therefore, this TDM strategy was tested in the Work-Other trip generation model. A couple of variables in the PSTP surveys that may help describe the trip generation impacts of on-site amenities are outlined below:

- **freqpers**—"Frequency needing car for personal trips during day" (from the Attitude survey)
- **freqerrd**—"Frequency needing car for other personal errands before or after work" (from the Attitude survey)

From these two variables, another variable was defined as the average value of **freqpers** and **freqerrd** for each household. This variable, **needcar**, received the most attention of these three variables in this study.

PRICING STRATEGIES

As noted earlier, pricing strategies can take on many forms. Regionwide pricing policies such as an increased gas tax, VMT tax, or regional congestion pricing are likely to affect trip generation rates, whereas site-specific strategies such as parking charges and bridge tolls seem more likely to affect the choice of destination, mode, or route taken. No regionwide pricing variables are specified in the PSTP surveys, but several parking charge variables may give some evidence regarding trip generation impacts of pricing:

- **parking**—"Parking costs" (from the Person survey)
- **paypark**—"If driving, do you personally pay for parking?" (from the Attitude survey)

- **freepark**—"Does employer provide free or reduced fee parking?" (from the Attitude survey)

Because pricing strategies could potentially affect trip generation rates for all trip purposes, these variables were tested in each trip production model.

LAND-USE STRATEGIES

Initially, the intention of this study was to produce a series of trip generation models by purpose based on several areas with differing land-use patterns. Ideally, the urban centers could be subdivided into true "urban centers," which contain high densities and a mixture of uses, and "suburban centers," which contain more low-density development and a less diverse land-use pattern. Trip generation rates from these "centers" could then be compared to rates produced in "non-centers." However, the PSTP data did not provide enough data from the centers to derive any useful models for "urban" or "suburban" centers (or even all centers as a whole).

As a result, the focus of this study turned to developing one series of models applicable to all land-use patterns but containing some type of land-use variable that would distinguish between trip productions in a center and trip productions in a non-center. A "center flag" variable (**cflag**) was defined so that if any of each particular household's trips were produced in an urban center, a value of "1" was assigned. If no trips from a household were produced in a center, a value of "0" was assigned. The hypothesis behind this variable was that the land-use nature of a center will produce more (albeit shorter distance) trips than a non-center.

In addition to the **cflag** variable, the distance from home to the workplace variable (**mile**) may also indirectly address land-use issues. Work by the Metropolitan Planning Commission in the San Francisco Bay Area of California (Purvis, Iglesias, and Eisen, 1996) indicated that work trip accessibility does affect non-work travel behavior.

According to their research, "a 10 percent decrease in the regional work trip duration yields a 1.2 percent increase in regional home-based shop/other trips and a 0.9 percent increase in regional home-based social/recreation trips." (Purvis, Iglesias, and Eisen, 1996) Land-use strategies such as encouraging more mixed-use development might enable more people to live nearer to their workplace, thus reducing the distance (or time) they need to travel to work. This, in turn, could affect the number of non-work trips generated. The **mile** variable in the PSTP survey addressed the issues of travel induced by work trip accessibility, and indirectly, the potential changes in travel behavior that would result if land-use strategies were enacted to reduce the average distance from home to work.

Both **mile** and **cflag** were tested for significance in the models for each trip purpose.

METHODOLOGY FOR MODEL ESTIMATION

Although cross-classification is currently the favored technique in practice, one of its main disadvantages is that there are no well-developed goodness-of-fit indices associated with this methodology. In this study, the most important considerations in specifying the model were the relative significance of variables and the goodness-of-fit of each model. These model attributes are much easier to evaluate with regression techniques; as a result, regression techniques were used in this study. In practice, however, a cross-classification model employing TDM strategies might be considered.

Traditionally, the trip generation models that have been estimated with linear regression methods. Obviously, the use of linear regression analysis imposes certain limitations on the model, particularly the fact that certain trip-making characteristics may be nonlinear in nature but can not be modeled as such. Some MPOs are experimenting with nonlinear regression analysis and are reporting improvements in the quality of their models.

The main drawback associated with nonlinear regression is the increase in complexity in comparison to traditional linear regression.

Poisson regression is rarely mentioned as a trip generation modeling technique. However, the nature of this type of analysis seems to lend itself to the type of data often used for trip generation analysis. Poisson regression techniques are used to model count data, which require that the dependent variable consist of non-negative integers. In the case of trip generation modeling, households can not make a fraction of a trip, so the number of trips per household can be represented by count data.

Count data are found in many aspects of transportation, such as the number of driver route changes per week and the number of driver departure time changes per week; however, the use of an appropriate statistical methodology to model these data is relatively limited. Most often, count data are modeled as continuous variables rather than discrete variables with traditional least squares regression methods. The use of these methods is not entirely correct for the following reasons.

1. Least-squares regression models can predict values that are not integers.
2. Least-squares regression models can predict values that, in some cases, are negative (Mannering, 1997).

When applied to trip generation, Poisson regression may be able to better predict travel behavior relationships that are nonlinear. For these reasons, Poisson regression was selected as the methodology for estimating the trip generation models in this study.

POISSON REGRESSION

The Poisson model is specified as follows:

$$P(n_i) = \frac{\exp(-\lambda_i)\lambda_i^{n_i}}{n_i!} \qquad (1)$$

where in this study, $P(n_i)$ was the probability of household i making n trips every two days, and λ_i was the Poisson parameter for household i. The Poisson parameter is equal to the expected number of trips made by household i (i.e., $E(n_i)$). This parameter is a function of explanatory variables, which in this case included socioeconomic and demographic variables as well as the TDM variables described earlier. The Poisson parameter is specified as,

$$\lambda_i = \exp(\beta \mathbf{X}_i) \tag{2}$$

where $\mathbf{X}_i$ is a vector of explanatory variables and β is a variable of estimable coefficients. Thus, the Poisson regression described in equations 1 and 2 is estimable by using standard maximum likelihood methods with the likelihood function,

$$L(\beta) = \prod_i \frac{\exp\left[-\exp(\beta \mathbf{X}_i)\right]\left[\exp(\beta \mathbf{X}_i)\right]^{n_i}}{n_i!} \tag{3}$$

(Mannering, 1997). For this study, the Poisson parameter (λ_i), which indicates the expected number of trips made by each household, was of primary interest.

Mannering noted that "Poisson regression is a powerful analysis tool, but it can be used inappropriately if its limitations are not fully understood." (Mannering, 1997) One of the main restrictions of the Poisson formulation is that the mean and the variance of the distribution must be approximately equal (i.e., $E[n_i] = var[n_i]$). If this relationship does not hold, the data are said to be overdispersed, and the coefficient vector β will be biased if corrective measures are not taken. Because some of the data used in this study were overdispersed (see Chapter 5), this limitation was a definite consideration. To account for this restriction, the negative binomial model, which is an extension of the Poisson model, can be used.

NEGATIVE BINOMIAL REGRESSION

The negative binomial formulation allows the mean of the distribution to differ from the variance by adding an independently distributed error term, ε, to equation (2) such that,

$$\ln \lambda_i = \beta \mathbf{X}_i + \varepsilon_i \tag{4}$$

or

$$\lambda_i = \exp(\beta \mathbf{X}_i + \varepsilon_i) \tag{5}$$

where $\exp(\varepsilon_i)$ is a gamma-distributed error term with a mean of 1 and a variance of α. This results in the following conditional probability,

$$P(n_i|\varepsilon) = \frac{\exp[-\lambda_i \exp(\varepsilon_i)][\lambda_i \exp(\varepsilon_i)]^{n_i}}{n_i!} \tag{6}$$

Next, ε is integrated out of this expression, resulting in the unconditional distribution of n_i. The formulation of this distribution, used in maximum likelihood estimation, is

$$P(n_i) = \frac{\Gamma(\theta + n_i)}{[\Gamma(\theta) \cdot n_i!]} \cdot u_i^{\theta}(1-u_i)^{n_i} \tag{7}$$

where $u_i = \theta\ (\theta + \lambda_i)$ and $\theta = 1/\alpha$. This formulation produces a negative binomial model that enables the mean of the distribution to differ from the variance as follows:

$$\mathrm{var}[n_i] = E[n_i][1+\alpha E[n_i]] \tag{8}$$

where α is an additional estimable parameter. (Poch and Mannering, 1996) The appropriateness of the negative binomial model in comparison to the Poisson model is determined by examining the statistical significance of the parameter α. If α is not significantly different from zero, the negative binomial formulation simply reduces to a Poisson formulation. If α is significantly different from zero, we know that the negative

binomial model should be used. The statistical significance of α is determined by examining its t-statistic (Poch and Mannering, 1996).

An additional constraint was necessary when the Poisson and negative binomial models were developed for this project. The data used for each trip purpose did not include data from households indicating zero trips of that particular type. Thus, the models were left-truncated at zero, so that the model could not predict the probability of a household making zero trips.

In each of the trip generation models estimated for this project, both Poisson and negative binomial regressions were used. After the t-statistic of α had been examined, the appropriate model formulation was determined.

Production versus Attraction Modeling

For this project, only trip production rates were studied. TDM strategies are intended to affect the number of trips produced in a household or zone, whereas trip attraction rates are developed on the basis of the amount and character of activity in a zone. For this reason, it is much more sensible to evaluate TDM strategies in trip production models rather than in trip attraction models. Also, the development of trip attraction rates has received much less research attention than trip production models, and as a result, many MPOs have based their trip attraction rates on those developed by other MPOs.

Initial Modeling Efforts

Before TDM strategies could be incorporated into the trip generation models, a "base" model was derived for each trip purpose. These models included common independent variables such as household income, number of vehicles in each household, and household size. The dependent variable for each model was the number of trips by household. PSRC models (DKS Associates, 1994) as well as models from the Metropolitan Transportation Commission in the San Francisco Bay Area (Purvis, 1997) were used as starting references.

After a reasonable "base" model had been established for each trip purpose, the TDM variables described earlier were tested for relevance.

STATISTICAL MEASURES USED FOR MODEL ANALYSIS

To estimate the trip generation models, the software package LIMDEP was used (SPSS could not be used because it does not have the capability to execute a Poisson or negative binomial regression analysis). The model results were analyzed as described below.

SIGNIFICANCE OF INDIVIDUAL VARIABLES

According to Ben-Akiva and Lerman, "The first model estimation outputs to be examined are the signs and relative values of the coefficient estimates and the significance of individual coefficients." (Ben-Akiva and Lerman, 1985) For each model, the relative magnitude and sign of each coefficient was examined to determine whether the values were sensible.

To examine the significance of individual variables, the t-statistic was used. This is a measure of how confident we can be that the coefficient is significantly different from zero. Variables with low t-statistics are more likely to be statistically insignificant and were thus excluded from the final model specification. Along with the t-statistic itself, the computed probability that each coefficient is significantly different from zero was used to determine whether a variable was "significant."

OVERALL MODEL FIT

In least squares regression modeling, R^2 is the most commonly-used statistic for the overall "goodness-of-fit" of the estimated model. R^2 is the ratio of data variance explained by the model to total data variance. (Mannering, course notes) A similar statistic for discrete choice models such as Poisson and negative binomial regressions is the likelihood ratio index (ρ^2). The ρ^2 statistic is formulated as follows:

$$\rho^2 = 1 - \frac{L(\beta)}{L(0)} \tag{9}$$

where L(β) is the log-likelihood at convergence and L(0) is the log-likelihood at zero. Unfortunately, there are no standard guidelines to determine if a value of ρ^2 is significantly high (Ben-Akiva and Lerman, 1985). However, ρ^2 values tend to be lower than R^2 values (Mannering, course notes).

The ρ^2 statistic will always increase if additional variables are modeled, so that even if a insignificant variable is added, the statistic will still that the variable improved the model fit. To account for this shortcoming, an adjusted ρ^2 statistic was used. This formulation accounts for the number of variables in a model as follows:

$$adjusted\rho^2 = 1 - \frac{L(\beta) - \left(\frac{K}{2}\right)}{L(0)} \tag{10}$$

where K is the number of coefficients in the model. (Mannering, course notes) In this study, assessments of overall model fit were based on the adjusted ρ^2 statistic.

JUSTIFICATION OF VARIABLES

One of the most important objectives of this study as to determine which of the variables that might describe TDM strategies are significant in the trip generation models for each purpose. However, we had to be certain that the significance of individual variables was in fact caused by the effects of TDM strategies, rather than something else. Detailed explanations are offered regarding the reasoning for the significance of each variable that was indeed found to be significant.

ELASTICITY ANALYSIS OF TRAVEL DEMAND MANAGEMENT VARIABLES

To better understand the relationships between individual variables and trip-making characteristics, elasticities were computed for several of the "TDM" variables. This analysis helpd us to see the potential travel impacts that specific TDM strategies may have on trip generation. Elasticity is defined as:

$$E_{x_{ik}}^{\lambda_i} = \frac{\partial \lambda_i}{\partial x_{ik}} \cdot \frac{x_{ik}}{\lambda_i} \qquad (11)$$

where λ_i is the average number of trip productions (for a specific purpose) for household i, and x_{ik} is the value of the explanatory variable k for household i. Differentiating equation 4 and applying equation 11 gives the following:

$$E_{x_{ik}}^{\lambda_i} = \beta_k x_{ik} \qquad (12)$$

where β_k is the coefficient estimate of explanatory variable k. (Poch and Mannering, 1996)

The average elasticity for several of the variables describing TDM strategies in each particular model was computed with equation 12. Chapter 6 contains an interpretation of the elasticity of each variable.

CHAPTER 5: SPECIFICATION OF TRIP GENERATION MODELS

The recommended trip generation model specifications are discussed below. Estimations for five of the seven trip purposes defined for this study are included. Two of the trips purposes, home-based school and home-based college, suffered from a low number of observations, particularly for trying to test variables describing TDM strategies. Therefore, estimations for these two trip purposes are not included here. For each model, the following information is addressed:

- the distribution of the number of trips reported by PSTP survey households (the dependent variable)
- definitions of each variable included in the model specification (the independent variables)
- values of the coefficient for each variable, along with the standard error, mean, and standard deviation
- justification for the significance of each variable
- values of the t-statistic and significance level for each coefficient, showing the relative significance of variables
- assessment of overall model fit.

In the discussion of significance of variables, each variable is labeled as either a "traditional variable" or a "TDM variable." Traditional variables are those used to estimate most current trip generation models and include characteristics such as household size, the total number of adults in the household, household income, and vehicle availability. TDM variables are those that help describe the impacts of TDM strategies. A full description of the TDM variables tested is in Chapter 4.

HOME-BASED WORK MODEL

MODEL SPECIFICATION

After the PSTP data had been aggregated to the household level and cases that contained no missing data for the specified variables had been selected, 736 households remained that reported making one or more home-based work trips during the two-day period in which trips were recorded by each household. The mean number of home-based work trips made by each household was 4.9, with a variance of 6.3. A histogram of the number of home-based work trips reported is shown in Figure 6. As can be seen in the graph, a relatively large percentage of the responding households made four work trips over the two-day period, which makes sense.

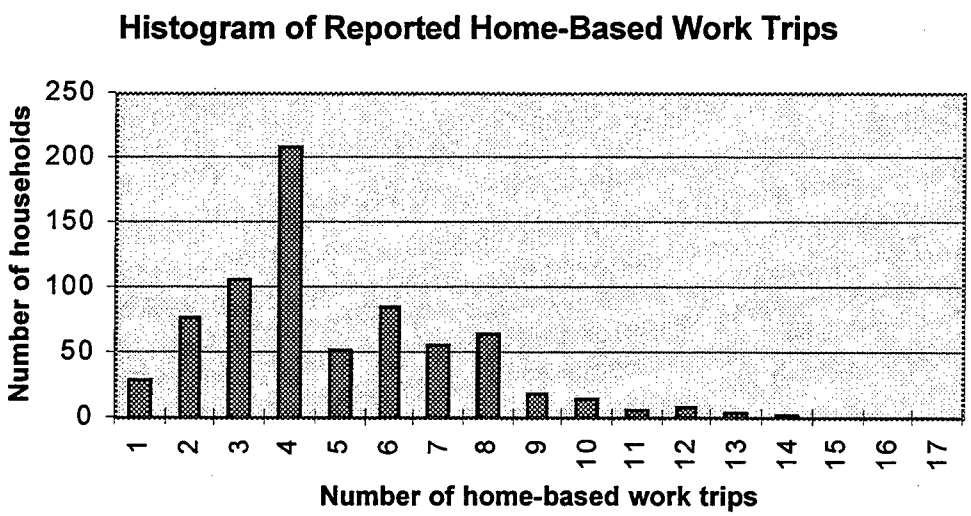


Figure 6: Histogram of Reported Home-Based Work Trips (for two-day period)

The number of trips reported ranged from one to seventeen. Although the number of households reporting more than eight home-based work trips was much lower than the number reporting eight or fewer trips, it is still somewhat surprising that the range was this large. Some respondents might have worked at multiple jobs, thus producing some

responses with a high number of home-based work trips; unfortunately, the PSTP survey did not ask the respondents if they worked more than one job.

The mean and variance of this distribution were relatively close, indicating that a Poisson regression was likely to be the appropriate model formulation. To confirm this hypothesis, the α parameter was examined. The negative binomial analysis resulted in a t-statistic for α of 0.826. This corresponds to a significance level of approximately 0.41, meaning that we can be only about 59 percent certain that α is significantly different from zero. Because of the relative insignificance of α, the Poisson model was chosen to specify the recommended home-based work model.

The recommended home-based work trip production model was specified with the following six significant variables, in addition to a constant term.

- **cflag**: If any of a household's home-based work trips were produced in a center, this variable equals 1. Otherwise, it equals 0.
- **income**: Total household income. The following scale was used:

  1 = < $7,500
  2 = $7,500 - 15,000
  3 = $15,000 - 25,000
  4 = $25,000 - 30,000
  5 = $30,000 - 35,000
  6 = $35,000 - 50,000
  7 = $50,000 - 70,000
  8 = > $70,000
- **mile**: Distance from home to workplace (in miles)
- **numveh**: Number of household vehicles
- **totadult**: The total number of adults (age 18 and older) in the household
- **wk_freq**: Number of days/week respondent works (average for household)

The values of the coefficient, standard error, mean, and standard deviation for each variable are shown in Table 4.

Table 4: Home-Based Work Model Specification

Variable Name	Coefficient	Standard Error	Mean	Standard Deviation
cflag*	0.231	0.064	0.061	0.240
income	0.045	0.013	5.93	1.58
mile*	-0.011	0.002	13.08	8.90
numveh	0.038	0.018	2.28	1.07
totadult	0.270	0.031	1.93	0.562
wk_freq*	0.059	0.031	4.89	0.578
Constant	0.520	0.170		

* "TDM" variable

JUSTIFICATION OF VARIABLES

cflag—This is a binary (0/1) variable, and the positive sign of the coefficient indicates that households where any home-based work trips were produced in a center will make more trips than households where none of the trip productions were located in a center. Simply put, a center encourages more home-based work trips. This effect possibly could be due to several reasons: people living in a center may be more likely to live near their jobs, thus encouraging multiple home-work-home trips during the day; people living in centers may be more apt to work multiple jobs; or the mixed land-use of a center may encourage more work trips without chained stops for shopping or errand-running during the trip to or from work.

There is some evidence that households located in centers make more non-chained (direct) home-work and work-home trips, whereas households not located in centers are more apt to stop along the way to or from work. Although the average number of days working per week is virtually the same for households both within and outside of centers, the households located in centers reported making more direct home-work and work-home trips. Over the two-day test period, the average number of direct home-work and work-home trips made by households within a center was 5.18. However, households located outside of a center made 4.61 direct home-work and work-home trips.

Thus, the positive coefficient of the **cflag** variable does not necessarily mean that people living in centers work more; instead, people living within a center seem less likely to chain their home-based work trips with shopping or other personal trips on the way to or from work. This could be due to the mixed land-use within a center—people living in centers can make shopping and other personal trips outside of their work commute more easily than people living outside of a center. If no chaining takes place between home and work, two home-based work trips are produced. However, if any chaining occurs on the way to or from work, the trip is no longer modeled as a home-based work trip, even though the ultimate destination remains either home or work.

To test this hypothesis, a variable named **chain** was defined. This variable counted the total number of home-work, work-home, and home-home "chains." A chain was defined as the combination of trips between home and work, work and home, and home and home. Thus, individual "trips" were not analyzed, but instead, each trip was organized into a particular chain of trips. The **chain** variable counted the number of trip chains (as defined above) for each household over the two-day study period.

With regard to our hypothesis that households located in a center are less likely to chain trips, the PSTP data revealed that households that indicated at least one production in a center made 1.48 individual trips within each home-work, work-home, and home-home chain, whereas households not reporting any center productions made 1.72 individual trips within each "chain," as defined above (the number of individual trips were based on all trip purposes). This evidence thus lent support to our hypothesis that households not located in centers tend to chain the work trip with other trips, thus producing fewer true "home-based work" trips.

Although this evidence indicated that households located in centers are more apt to chain work trips with other trips, there was also some evidence that households located in centers actually do make more work trips (even if they are not specifically home-based

work trips). A variable called **worktrip**, which denoted the number of trips reported by each household where "work" was listed as the destination (this could include home-based work as well as work-other trip purposes) was developed. Households reporting at least one center production recorded an average of 6.87 true "work trips," whereas households not reporting any center productions had an average of 4.74 true "work trips."

income—This is a traditional variable included in many MPOs' trip generation models, and it was a significant variable here. The positive coefficient indicates that higher average household income correlates to more home-based work trips. This sign makes sense because it indicates that households with higher incomes work more often, which is confirmed by Figure 7. This graph shows the average work frequency for each household income category, for all participating households in the 1990 wave of the PSTP. See the definition of **income** given earlier in this section for the income range of each category.

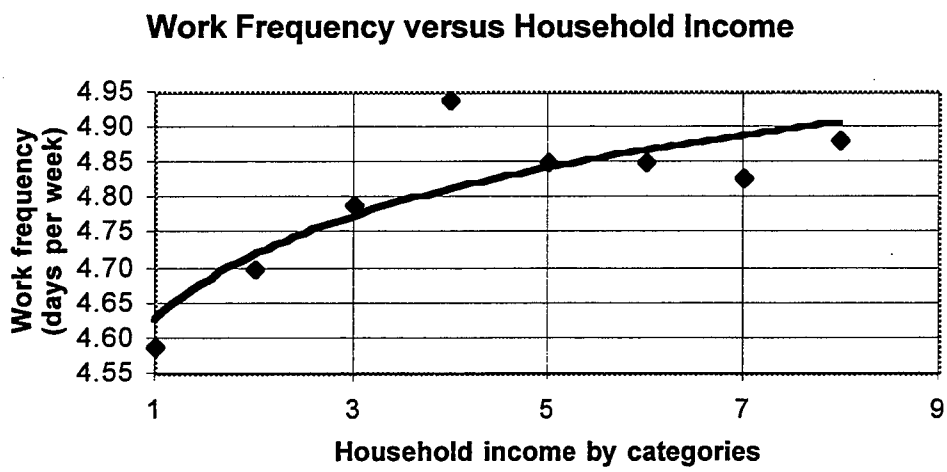


Figure 7: Work Frequency versus Household Income

mile—The negative sign of this coefficient indicates that as people live farther away from their worksite, they are more likely to make fewer home-based work trips. Our first hypothesis was that people living a long distance away from their worksites are more

likely to telecommute or to use a compressed work week schedule. To test this hypothesis, the Attitude survey from the 1996 wave of the PSTP was used (the 1990 wave did not contain a frequency of telecommuting question). The telecommuting frequency was compared to the respondents' travel time to work. As shown in Table 5, there may be some relationship between the two variables, but this hypothesis merits further study.

Table 5: Telecommuting Frequency versus Travel Time to Work

Frequency of working at home instead of workplace	Travel time to work (minutes)	Number of observations (N)
More than once a week	25.00	94
Once a week	25.47	60
1 or 2 times a month	31.44	180
Never	27.99	1707

Another possible explanation for the significance of mile is similar to the one posited for **cflag** earlier. Perhaps people living farther away from work are more likely to chain their work trip with shopping or other personal trips on the way to or from work. Thus, people living farther away do not necessarily go to work less often, but from a modeling standpoint, they make fewer direct home-work and work-home trips. To test this hypothesis, a **worktrip** variable was used. As noted earlier, this variable denoted the number of trips reported by each household where "work" was listed as the destination (this could include home-based work as well as work-other trip purposes). Figure 8 shows the number of work trips (both home-based and non-home based) reported by each household. As can be seen in the graph, there is no apparent trend, indicating that people living farther away from their worksite do not make fewer work trips but may be more apt to chain work trips with other trips, thus producing fewer <u>home-based</u> work trips.

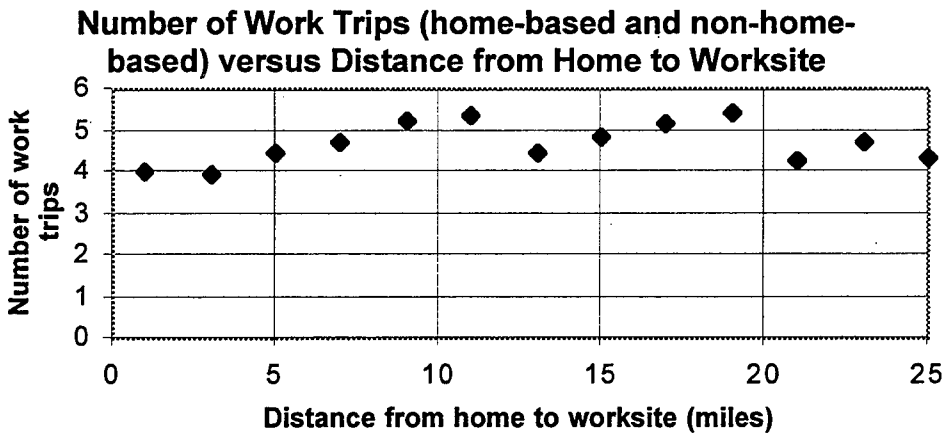


Figure 8: Number of Work Trips (home-based and non-home-based) versus Distance from Home to Worksite

Given the finding that the number of true work trips is not related to distance from home to work, the number of chains (as defined earlier) was compared to the average household distance from home to work, as shown in Figure 9. As shown by the second-degree polynomial trendline, people living the farthest away from their worksite tend to make fewer trip chains, which actually signifies that more individual trip chaining is occurring. The "hump" in the graph is interesting. Perhaps people who live close to their worksite are more apt to walk or bicycle to and from work, and thus may be more likely to chain trips than they would be if they were driving. This hypothesis would require additional research to prove or disprove. Nevertheless, most people live farther away from their worksite than this, and Figure 9 shows a general trend of fewer total trip chains (more intermediate stops in each trip chain) as distance increases. There were few observations with an average home to work distance of more than 25 miles; therefore, these observations were not included in the graph.

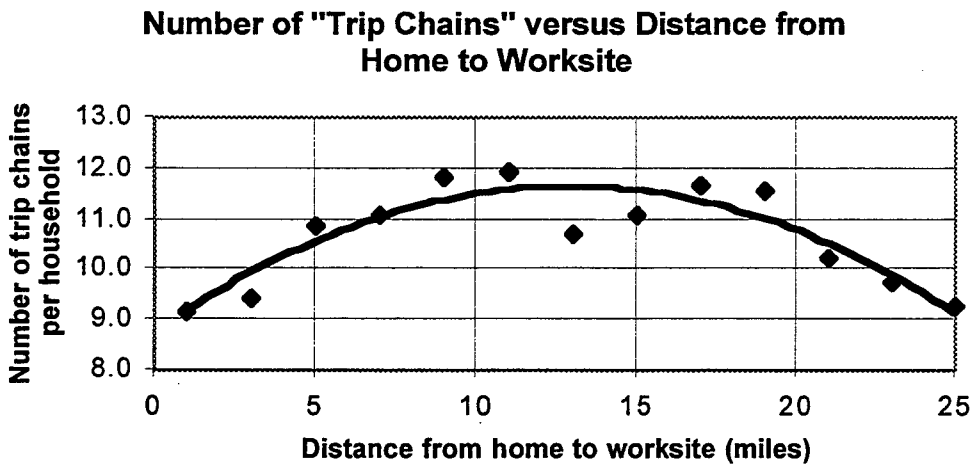


Figure 9: Number of Trip Chains versus Distance from Home to Work

numveh— The vehicle availability for a household is a significant variable in many traditional trip generation models, and it was significant here as well. This variable had a positive coefficient, meaning that households with more vehicles available for use tend to make more home-based work trips. This variable may have captured some of the same effects as **income**, but the t-statistics indicated that both variables should be included in the home-based work model.

totadult—Like **income** and **numveh**, **totadult** is another traditional variable used in a number of trip generation models. Recently, many home-based work models have been specified with *number of workers per household* as a variable rather than the *number of adults*. However, in the PSTP survey, the *number of workers* variable was not readily available. Nevertheless, the number of adults is highly correlated with the number of workers, and for the purposes of this study, the **totadult** variable was sufficient. As expected, the positive sign of this variable indicated that the more adults in the household, the more home-based work trips produced.

wk_freq—At first glance, this variable may seem endogenous. However, the number of work trips produced does not necessarily affect the "number of days per week that the respondent works." This variable allows the model to consider the fact that not everyone works a five-day work week. This could be a key variable with regard to TDM strategies such as telecommuting and compressed work week schedules. If a variable such as this one is included in a work trip generation model, the analysis of the travel behavior effects of these strategies becomes much more straightforward. The positive sign of this variable makes sense—the employees who work more days make more home-based work trips.

SIGNIFICANCE OF VARIABLES

The t-statistics for these variables ranged from a magnitude of 1.929 for **wk_freq** to 8.610 for **totadult**. The relatively high values for each variable indicated that each one was quite significant. Even for the variable with the lowest t-statistic, **wk_freq**, we can be approximately 95 percent certain that the coefficient was significantly different from zero. Of the seven coefficients in this model, three (**cflag**, **mile**, and **wk_freq**) represented variables that might be used to help explain the significance of TDM strategies. The coefficients and t-statistics for each variable are summarized in Table 6.

Table 6: Significance of Variables in Home-Based Work Model

Variable Name	t-statistic	Significance Level
cflag*	3.623	0.00029
income	3.577	0.00035
mile*	-5.523	0.00000
totadult	8.610	0.00000
wk_freq*	1.929	0.05378
Constant	3.057	0.00223

* "TDM" variable

OVERALL MODEL FIT

To judge overall model fit, the values for ρ^2 and adjusted ρ^2 were computed. This model specification resulted in a ρ^2 statistic of

$$\rho^2 = 1 - \frac{-1578.542}{-1677.609} = 0.059$$

and an adjusted ρ^2 statistic of

$$adjusted\rho^2 = 1 - \frac{-1578.542 - \left(\frac{7}{2}\right)}{-1677.609} = 0.057$$

These values seem low, which could be due to some multicollinearity issues in this model. In particular, there could be some correlation issues among the **income**, **numveh**, and **wk_freq** variables. However, examining these issues would require more detailed testing of the model, and for this study, the significance of the variables was most important.

HOME-BASED SHOPPING MODEL

MODEL SPECIFICATION

After the PSTP data had been aggregated to the household level and cases containing no missing data for the specified variables had been selected, 719 households remained that reported making one or more home-based shopping trips during the two-day period in which trips were recorded by each household. The mean number of home-based shopping trips made by each household was 2.7, with a variance of 3.6. A histogram of the number of home-based shopping trips reported is shown in Figure 10. As can be seen in the graph, most households reported relatively few trips of this nature.

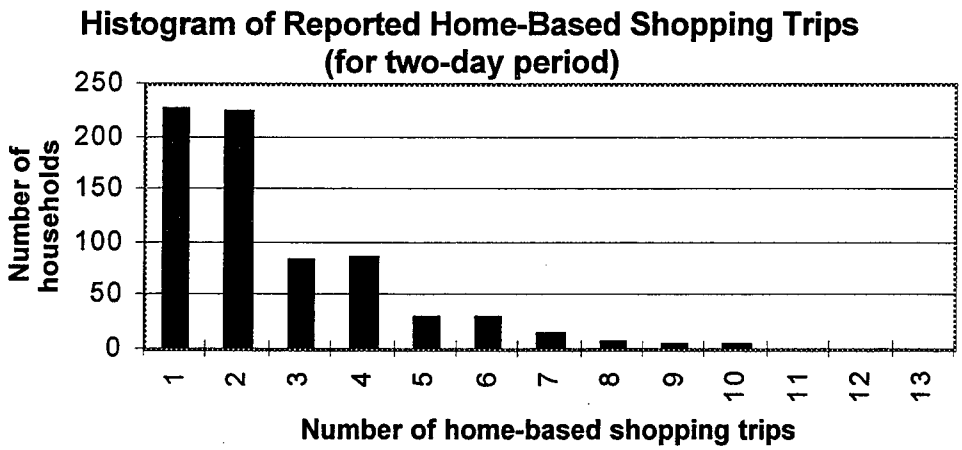


Figure 10: Histogram of Reported Home-Based Shopping Trips (for two-day period)

The number of reported home-based shopping trips over the two-day study period ranged from one to thirteen. Most households reported making one or two trips, but a significant number of households reported making three or four trips. Nearly 87 percent of the households made four or fewer trips.

Because the values of the mean and variance were fairly close, the Poisson regression was originally thought to be the appropriate modeling technique. However, evaluation of the α parameter revealed a t-statistic for this term of 4.912, corresponding to a significance level of 0.00000. Because we could be almost completely certain that α was significantly different from zero, the negative binomial regression was used to specify this model.

The final home-based shopping trip production model was specified with the following four variables, in addition to a constant term.

- **cflag**: If any of a household's home-based shopping trips were produced in a center, this variable equals 1. Otherwise, it equals 0.
- **hhsize**: The total number of household members

- **mile**: Distance from home to workplace (in miles)
- **numveh**: Number of household vehicles

The values of the coefficient, standard error, mean, and standard deviation for each variable are shown in Table 7.

Table 7: Home-Based Shopping Model Specification

Variable Name	Coefficient	Standard Error	Mean	Standard Deviation
cflag*	0.297	0.239	0.042	0.200
hhsize	0.159	0.035	2.74	1.23
mile*	-0.006	0.005	11.28	8.27
numveh	0.068	0.033	2.34	1.16
Constant	0.149	0.144		

* "TDM" variable

JUSTIFICATION OF VARIABLES

cflag—The positive coefficient of **cflag** indicated that households reporting at least one home-based shopping trip production in a center were likely to make more total home-based shopping trips than households that did not record any home-based shopping trip productions in a center. As was discussed with respect to home-based work trips, this could be due to the effects of trip chaining. Perhaps because of the mixed land-use of most centers, households located in centers may be more apt to make shopping trips outside of their commute trip because shopping facilities are more accessible than they are in non-centers. As noted in the discussion of this variable in the home-based work model, households not located in centers may be more likely to chain trips than those located within centers. However, there is also some evidence that households reporting a center production do make more shopping trips (both home-based and non-home-based). The variable **shoptrip** was defined as the total number of trips reported by a household that listed "shopping" as its destination. Those households reporting at least one center production had 1.77 shopping trips (both home-based and non-home-based), whereas

households without any center productions reported 1.68 shopping trips. Although this difference is small, this finding, along with the trip chaining evidence, helped to justify the significance of this variable.

hhsize—This is a "traditional" variable used in many MPOs' trip generation models, and it was significant here as well. The positive coefficient indicated that the larger the household, the more home-based shopping trips made. Because every member of a household has shopping needs, the positive sign of this coefficient makes sense.

mile—The negative coefficient of this variable indicated that as the average distance for a household from home to work increases, the number of home-based shopping trips decreases. This could be due to a couple of different factors. First, as discussed with respect to home-based work trips, the effects of trip chaining could contribute to the significance of this variable (i.e., people who live farther away still make just as many shopping trips as people living close to their workplace, but they chain them with other trips, resulting in fewer "home-based shopping" trips). On the other hand, perhaps the significance of **mile** can be attributed to the effects of induced demand—if people spend less time traveling to and from work, they might be likely to make more shopping trips simply because they have more time available to make shopping trips.

The significance of this variable was likely due to a combination of these factors. As noted earlier, people who live farther away from their workplace seem to be more likely to chain individual trips together, but there is also some compelling evidence that supports the induced demand hypothesis. The **shoptrip** variable was examined to determine whether any relationships could be found between the number of true shopping trips (both home-based and non-home-based) and the distance from home to the workplace. Figure 11 shows that as the distance from home to work increased, the number of total shopping trips per household actually did decline, providing evidence that the significance of this variable can be attributed at least in part to induced demand.

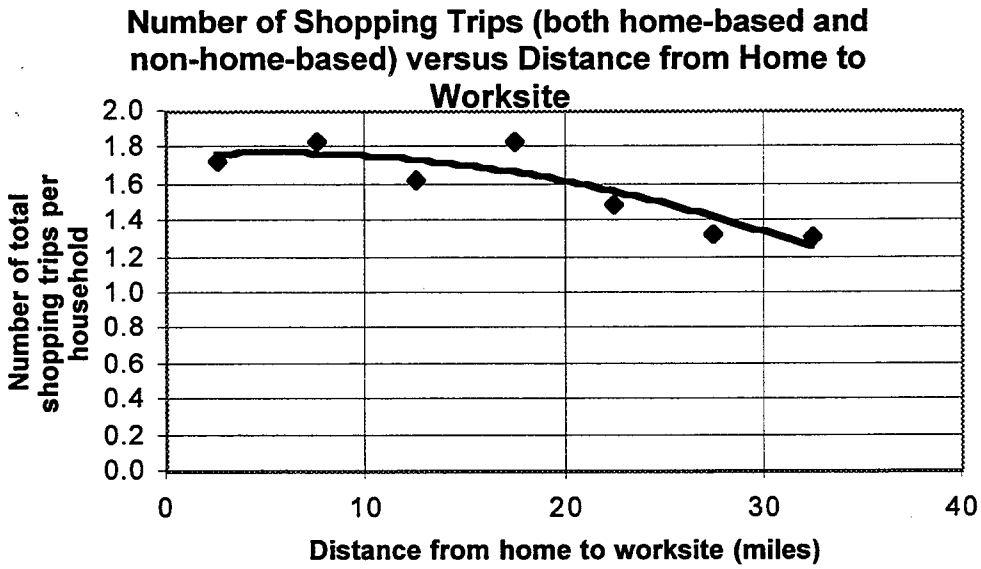


Figure 11: Number of Shopping Trips (both home-based and non-home-based) versus Distance from Home to Worksite

numveh—The positive sign of the coefficient signified that households that have more vehicles are likely to make more shopping trips than households with fewer vehicles, which makes sense. Members of households with several vehicles can make trips more easily because they are more likely to have a car at their disposal than households with one or no vehicles.

SIGNIFICANCE OF VARIABLES

The t-statistics for these variables ranged from a low of 1.04 (**Constant**) to a high of 4.56 (**hhsize**). The two "traditional" variables (**hhsize** and **numveh**) had the highest t-statistics, wheras the "TDM" variables (**cflag** and **mile**) were less significant. The variable **cflag**, in particular, was only marginally significant from a modeling standpoint, and more data would be helpful in confirming the significance of this variable. Although the constant term had a low t-statistic, it was still included in the recommended model for completeness.

The t-statistics and corresponding significance level for each variable in the home-based shopping model are shown in Table 8.

Table 8: Significance of Variables in Home-Based Shopping Model

Variable Name	t-statistic	Significance Level
cflag*	1.242	0.21415
hhsize	4.553	0.00001
mile*	-1.391	0.16438
numveh	2.042	0.04116
Constant	1.037	0.29976

* "TDM" variable

OVERALL MODEL FIT

To judge overall model fit, the values for ρ^2 and adjusted ρ^2 were computed. This model specification gave a ρ^2 statistic of

$$\rho^2 = 1 - \frac{-1241.751}{-1382.662} = 0.102$$

and an adjusted ρ^2 statistic of

$$adjusted\rho^2 = 1 - \frac{-1241.751 - \left(\frac{6}{2}\right)}{-1382.662} = 0.100$$

The ρ^2 statistics for this model also seemed low, but they were not as low as the ρ^2 statistics for the home-based work model. Again, the significance of individual variables was the first consideration in this study.

HOME-BASED OTHER MODEL

MODEL SPECIFICATION

After the PSTP data had been aggregated to the household level and cases containing no missing data for the specified variables had been selected, 1565 households

remained to report making one or more home-based other trips during the two-day period in which trips were recorded by each household. The mean number of home-based other trips made by each household was 6.0, with a variance of 18.1. A histogram of the number of home-based other trips reported is shown in Figure 12. As can be seen in the graph, there was a fairly wide range in the number of trips reported by a significant number of households.

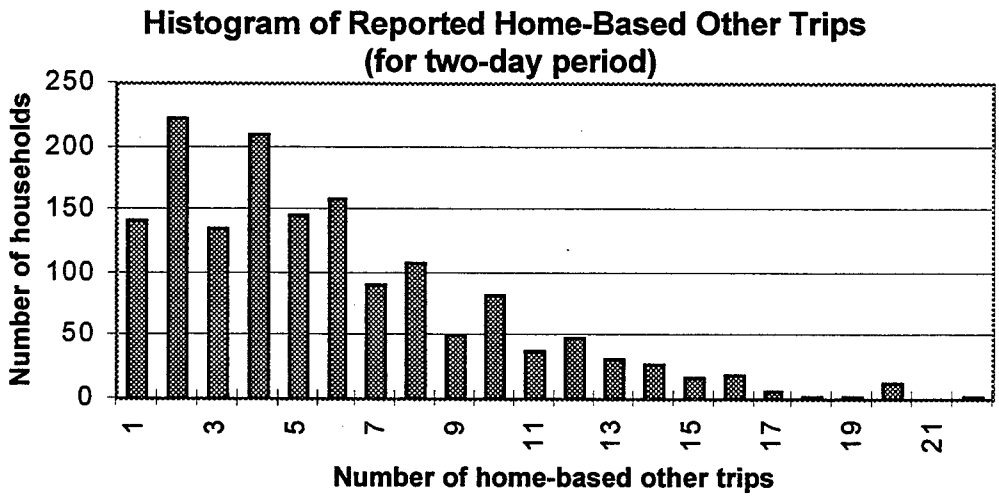


Figure 12: Histogram of Reported Home-Based Other Trips (for two-day period)

The PSTP households made anywhere from one to 28 home-based other trips over the two-day study period (the six households reporting more than 22 trips are not depicted in Figure 12). The extent of this range was somewhat surprising, but approximately 86 percent of the households surveyed made ten or fewer trips.

The mean and variance of this distribution were quite different, indicating that the negative binomial formulation was likely to be the proper method to use in estimating this model. Evaluation of the α parameter proved this hypothesis. The t-statistic of α was calculated as 13.974, corresponding to a significance level of 0.0000. Thus, we could be

almost completely certain that α was significantly different from zero. For this reason, the negative binomial regression technique was used to specify this model.

The recommended home-based other trip production model was specified with the following two variables, in addition to a constant term.

- **hhsize**: The total number of household members
- **numveh**: Number of household vehicles

The values of the coefficient for each variable, its standard error, mean, and standard deviation are shown in Table 9.

Table 9: Home-Based Other Model Specification

Variable Name	Coefficient	Standard Error	Mean	Standard Deviation
hhsize	0.233	0.016	2.67	1.25
numveh	0.049	0.018	2.19	1.09
Constant	0.972	0.055		

* "TDM" variable

JUSTIFICATION OF VARIABLES

hhsize—The positive coefficient indicated that the larger the household, the more home-based other trips made by the household. Every individual makes home-based other trips, and as the household size increases, the number of trips made by the household accumulates.

numveh—This variable can sometimes act as a surrogate for household income, and especially in cases where the trip purpose is likely to be discretionary, the vehicle availability of a household seems to be a better predictor of trips than household income. The positive sign of the coefficient signified that households that had more vehicles were likely to make more home-based other trips than households with fewer vehicles. As is the case with home-based shopping trips, members of households with several vehicles can

make trips more easily because they are more likely to have a car at their disposal than households with one or no vehicles.

SIGNIFICANCE OF VARIABLES

Only three coefficients were found to be significant in the home-based other model. Other than the constant term, the two significant variables were both "traditional variables." No "TDM variables" were found to be significant in this model. However, each of the three coefficients included in the final model estimation was highly significant, as shown by the t-statistics and corresponding significance levels in Table 10.

Table 10: Significance of Variables in Home-Based Other Model

Variable Name	t-statistic	Significance Level
hhsize	14.424	0.00000
numveh	2.773	0.00555
Constant	17.548	0.00000

* "TDM" variable

OVERALL MODEL FIT

To judge overall model fit, the values for ρ^2 and adjusted ρ^2 were computed. This model specification gave a ρ^2 statistic of

$$\rho^2 = 1 - \frac{-4016.013}{-4848.194} = 0.172$$

and an adjusted ρ^2 statistic of

$$adjusted\rho^2 = 1 - \frac{-4016.013 - \left(\frac{3}{2}\right)}{-4848.194} = 0.171$$

In comparison to the home-based work and home-based shopping models, the ρ^2 and adjusted ρ^2 statistics for the home-based other model were relatively high.

WORK-OTHER MODEL

MODEL SPECIFICATION

After the PSTP data had been aggregated to the household level and cases containing no missing data for the specified variables had been selected, 619 households remained that reported making one or more work-other trips during the two-day period in which trips were recorded by each household. The mean number of work-other trips made by each household was 4.9, with a variance of 17.1. A histogram of the number of work-other trips reported is shown in Figure 13. The number of households reporting more than one or two work-other trips per two days was somewhat surprising, but this phenomenon was most likely due to the effects of trip chaining.

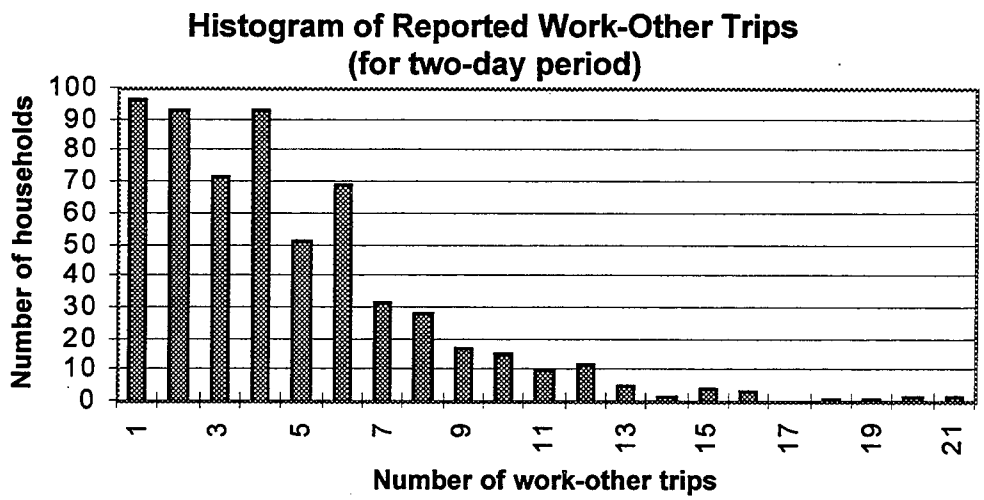


Figure 13: Histogram of Reported Work-Other Trips (for two-day period)

The number of trips recorded in the travel diaries ranged from one to 32 trips per household (seven households reporting more than 21 trips are not shown in Figure 13). This is quite a range, but nearly 90 percent of the households made nine or fewer work-

other trips over the two-day study period. Nevertheless, more work-other trips were reported than had been expected.

The mean and variance for this distribution were quite different, suggesting that the negative binomial regression should be used to specify this model. The t-statistic of the α parameter was calculated as 9.396, corresponding to a significance level of 0.0000. Because we could be virtually completely certain that α was significantly different from zero, the negative binomial formulation was the correct modeling methodology.

The final work-other trip production model was specified with the following seven variables, in addition to a constant term.

- **cflag**: If any of a household's work-other trips were produced in a center, this variable equals 1. Otherwise, it equals 0.
- **hhsize**: The total number of household members
- **income**: Total household income. The following scale was used:

  1 = < $7,500
  2 = $7,500 - 15,000
  3 = $15,000 - 25,000
  4 = $25,000 - 30,000
  5 = $30,000 - 35,000
  6 = $35,000 - 50,000
  7 = $50,000 - 70,000
  8 = > $70,000

- **needcar**: Average value of "frequency needing car for personal trips during the workday" and "frequency needing car for other personal errands before or after work." The following scale was used:

  1 = 3 or more days a week
  2 = 1 or 2 days a week
  3 = 2 or 3 times a month
  4 = Once a month or less
  5 = Never

- **numveh**: Number of household vehicles
- **parking**: Parking costs in dollars
- **wk_freq**: Number of days/week respondent works (average for household)

The values of the coefficient, standard error, mean, and standard deviation for each variable are shown in Table 11.

Table 11: Work-Other Model Specification

Variable Name	Coefficient	Standard Error	Mean	Standard Deviation
cflag*	0.392	0.071	0.477	0.500
hhsize	0.114	0.024	2.68	1.22
income	0.064	0.029	5.97	1.58
needcar*	-0.100	0.027	2.38	1.03
numveh	0.071	0.035	2.32	1.09
parking*	-0.004	0.003	2.88	11.76
wk_freq*	0.092	0.061	4.92	0.616
Constant	0.211	0.352		

* "TDM" variable

JUSTIFICATION OF VARIABLES

cflag—The positive coefficient of **cflag** indicated that households reporting at least one work-other trip production in a center made more trips than households in which no work-other trips were produced in a center. In the case of this trip purpose, **cflag** did not provide any idea of whether the household was located in a center because this is a non-home based trip type, with the origin of each trip serving as the production. Instead, it is likely that the higher-density nature of centers encourages more work-other trips by each household than is the case for non-centers. Furthermore, a significant proportion of employment is located in centers, so the proximity to nearby activities for those working in centers is likely to prompt more work-other trips within the center than would be the case for employees not working in centers.

hhsize—The positive coefficient of **hhsize** indicated that larger households made more work-other trips than smaller households. This makes sense, because members of larger households may be more apt to go from work to other places instead of home, such as going to pick children from school or other functions.

income— This variable also had a positive coefficient, signifying that households with a higher income were likely to make more work-other trips. The reasoning for the significance of this variable is similar to that related to the home-based work trip model. Because households with higher incomes tend to work more often (see Figure 7), these households have greater opportunity to make work-other trips. In addition, other factors are likely to be contributing to the significance of income. For example, those with higher incomes may make more discretionary work-other trips to go shopping or to run errands.

needcar—The negative coefficient of **needcar** indicated that the less often a person needs a car for errand-running or other personal trips before, during, or after work, the fewer work-other trips made. This relationship shows that the automobile is the primary mode for making work-other trips—if other modes were used more often (or were more viable), there might not be a relationship such as this one. However, given that the automobile's mode share is so high, the sign of this variable makes sense.

numveh—This variable had a positive coefficient, meaning that households with more vehicles available for use tended to make more work-other trips. This variable may have captured some of the same effects as **income**, but the t-statistics indicated that both variables should be included in the work-other model.

parking—Parking costs were only marginally significant in this model, but as expected, the higher the parking costs, the lower the number of work-other trips produced. This variable is not the best variable to use in the evaluation of pricing strategies because parking charges are site-specific. If one location has high parking charges, the tripmaker will be more likely to change the destination or mode used to get there, rather than avoiding

the trip altogether. However, the significance of the **parking** variable indicated that improved "pricing variables" may be even more significant in trip generation models.

wk_freq—The positive coefficient of **wk_freq** indicated that the more often a person worked, the more work-other trips taken. This makes sense, because a person who works frequently will have more opportunities to make work-other trips than someone who works less often. If a person does not work, there is no way that a work-other trip can be made.

SIGNIFICANCE OF VARIABLES

For the eight coefficients included in the recommended work-other model specification, the t-statistics ranged from a low of 1.342 (**parking**) to 5.525 (**cflag**). Three "traditional variables" (**hhsize**, **income**, and **numveh**) were found to be significant, in addition to four "TDM variables" (**cflag**, **needcar**, **parking**, and **wk_freq**). Of the four TDM variables, **cflag** and **needcar** were highly significant, whereas **wk_freq** and **parking** were less significant. In addition, although it had a low t-statistic, a constant term was included for completeness. The t-statistics and corresponding significance levels for each variable are shown in Table 12.

Table 12: Significance of Variables in Work-Other Model

Variable Name	t-statistic	Significance Level
cflag*	5.525	0.00000
hhsize	4.746	0.00000
income	2.212	0.02696
needcar*	-3.688	0.00023
numveh	2.001	0.04535
parking*	-1.342	0.17946
wk_freq*	1.509	0.13135
Constant	0.599	0.54884

* "TDM" variable

Overall Model Fit

To judge overall model fit, the values for ρ^2 and adjusted ρ^2 were computed. This model specification gave a ρ^2 statistic of

$$\rho^2 = 1 - \frac{-1490.019}{-1848.715} = 0.194$$

and an adjusted ρ^2 statistic of

$$adjusted\rho^2 = 1 - \frac{-1490.019 - \left(\frac{8}{2}\right)}{-1848.715} = 0.192$$

The overall fit of this model was comparatively good; however, the model could have some multicollinearity issues. As discussed regarding the home-based work model, there may be some correlation among **income**, **numveh**, and **wk_freq**. Nevertheless, the overall fit of this model was quite acceptable.

OTHER-OTHER MODEL

Model Specification

After the PSTP data had been aggregated to the household level and cases containing no missing data for the specified variables had been selected, 805 households remained that reported making one or more other-other trips during the two-day study period. The mean number of other-other trips per household was 4.5, with a variance of 16.7. A histogram of the number of other-other trips reported is shown in Figure 14. The number of households reporting more than one or two work-other trips per two days was somewhat surprising, but this phenomenon was most likely due to the effects of trip chaining. As shown in the graph, most households reported relatively few trips of this nature.

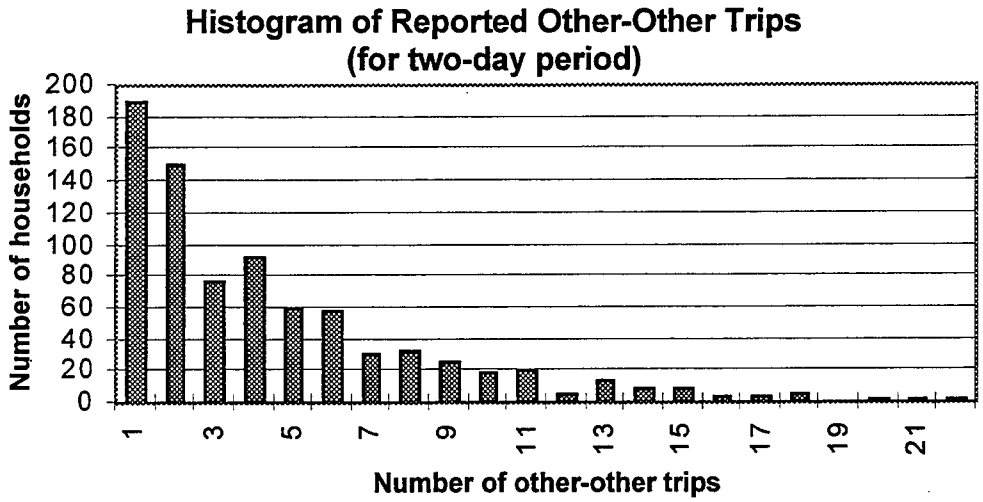


Figure 14: Histogram of Reported Other-Other Trips (for two-day period)

Even though most households made relatively few other-other trips (nearly 78 percent of the households made six or fewer trips of this type), there was a wide range in the number of trips taken. As many as 33 trips by one household over the two-day study period were reported, but the three households reporting more than 22 trips are not shown in Figure 14.

As is the case with several of the other models, the values of the mean and variance of this distribution differed significantly. Because of this difference, the negative binomial regression technique was chosen as the appropriate modeling methodology. To confirm this hypothesis, the t-statistic of the α parameter was examined. A t-statistic value of 8.945 was calculated, corresponding to a significance level of 0.0000. The significance of the α parameter confirmed that the negative binomial regression should be used for this model estimation.

The recommended other-other trip production model was specified with the following four variables, in addition to a constant term.

- **cflag**: If any of a household's other-other trips were produced in a center, this variable equals 1. Otherwise, it equals 0.
- **hhsize**: The total number of household members
- **numveh**: Number of household vehicles
- **wk_freq**: Number of days/week respondent works (average for household)

The values of the coefficient, standard error, mean, and standard deviation for each variable are shown in Table 13.

Table 13: Other-Other Model Specification

Variable	Coefficient	Standard Error	Mean	Standard Deviation
cflag*	0.663	0.071	0.409	0.492
hhsize	0.201	0.033	2.81	1.27
numveh	0.095	0.038	2.32	1.11
wk_freq*	-0.080	0.039	4.71	0.949
Constant	0.565	0.230		

* "TDM" variable

JUSTIFICATION OF VARIABLES

cflag—The positive coefficient of **cflag** indicated that households reporting at least one other-other trip production in a center made more trips than households in which no other-other trips were produced in a center. As was the case with the work-other model, **cflag** did not provide any idea of whether the household was located in a center because this was a non-home based trip type. It is likely that the higher density nature of centers encourages more other-other trips by each household than is the case for non-centers.

hhsize—The positive coefficient of **hhsize** indicated that larger households made more other-other trips than smaller households. This makes sense because members of larger households may be more apt to make multiple shopping or errand-running trips than smaller households.

numveh—The positive sign of the coefficient signified that households with more vehicles were likely to make more other-other trips than households with fewer vehicles. As is the case with other trip purposes that may include discretionary trips, members of households with several vehicles can make trips more easily because they are more likely to have a car at their disposal than households with one or no vehicles.

wk_freq—The negative coefficient of **wk_freq** indicated that as the average work frequency of a household increased, fewer other-other trips were made. This is an interesting relationship, and the significance of this variable can be explained by factors similar to those offered for the same variable in the work-other model. The **wk_freq** variable in the work-other model suggested that those who work more frequently have more opportunities to make work-other trips than those who work less frequently, and the **wk_freq** variable in this model might be explained in that people who work more often have fewer opportunities to make other-other trips. People working frequently could very well make trips to similar destinations as people working infrequently, but a larger proportion of these trips is classified as "work-other" for those who work frequently, and a larger proportion is classified as "other-other" for those who work less frequently.

SIGNIFICANCE OF VARIABLES

Each of the five coefficients included in the final other-other model specification was highly significant. The t-statistics ranged from a low of 2.075 (**wk_freq**) to a high of 9.332 (**cflag**). Excluding the constant term, two of the coefficients represented "traditional variables" (**hhsize** and **numveh**), and two coefficients represented "TDM variables" (**cflag** and **wk_freq**). The specific t-statistics and corresponding significance levels for each variable are shown in Table 14.

Table 14: Significance of Variables in Other-Other Model

Variable Name	t-statistic	Significance Level
cflag*	9.332	0.00000
hhsize	6.011	0.00000
numveh	2.524	0.01162
wk_freq*	-2.075	0.03796
Constant	2.457	0.01400

* "TDM" variable

OVERALL MODEL FIT

To judge overall model fit, the values for ρ^2 and adjusted ρ^2 were computed. This model specification gave a ρ^2 statistic of

$$\rho^2 = 1 - \frac{-1852.105}{-2453.333} = 0.245$$

and an adjusted ρ^2 statistic of

$$adjusted\rho^2 = 1 - \frac{-1852.105 - \left(\frac{5}{2}\right)}{-2453.333} = 0.244$$

The ρ^2 and adjusted ρ^2 values for this model were the highest of any of the models estimated. Especially considering that ρ^2 values tend to be lower than R^2 values, the fit of this model was quite good.

SUMMARY OF SIGNIFICANT VARIABLES AND MODEL FIT

Table 15 shows the significance level of each variable in each model. Blank cells indicate an insignificant variable in a particular model.

Traditional trip generation modeling variables such as **hhsize**, **totadult**, **income**, and **numveh** were found to be significant in each model. The **hhsize** variable was very significant in every model; however, for the home-based work model, **totadult** was a better predictor of number of trips. This makes sense because the adults in a household are

likely to be the ones making work trips. The **income** variable was significant in two of the models, and the **numveh** variable proved to be significant in every model.

Table 15: Significance Levels for Variables in Each Model

Variable	Home-based work	Home-based shopping	Home-based other	Work-other	Other-other
cflag*	0.00029	0.21415		0.00000	0.00000
hhsize		0.00001	0.00000	0.00000	0.00000
income	0.00035			0.02696	
mile*	0.00000	0.16438			
needcar*				0.00023	
numveh	0.03507	0.04116	0.00555	0.04535	0.01162
parking*				0.17946	
totadult	0.00000				
wk_freq	0.05378			0.13135	0.03796
Constant	0.00223	0.29976	0.00000	0.54884	0.01400

* "TDM" variable

The TDM variables were found to be significant in several models. The **cflag** variable was highly significant in three models (home-based work, work-other, and other-other), marginally significant in one (home-based shopping), and insignificant in one (home-based other). This variable was most significant in the models likely to describe mandatory trips, whereas it was less significant in the models that describe a large percentage of discretionary trips.

The **mile** variable was very significant in the home-based work model and somewhat less significant in the home-based shopping model. The significance of this variable is explained by a combination of trip chaining effects and the effects of induced travel.

The **needcar** variable, which may help explain the travel behavior effects of on-site amenities, was highly significant in the work-other model.

The **parking** variable was included in the final work-other model only, but it was not completely insignificant in any model. Pricing strategies would probably be significant in a trip generation model; however, this particular variable had some inherent flaws, as was discussed earlier in the justification for **parking** in the work-other model.

The **wk_freq** variable was significant in the home-based work, work-other, and other-other models; however, it is likely that this variable is useful for describing the effects of TDM strategies in the home-based work model only. Other reasons were offered for the significance of this variable in the work-other and other-other models (see the justification of variables for each of these models).

In addition, the constant term was included in each model, although it was found to be comparatively insignificant in the home-based shopping and work-other models. This term is useful in explaining a "base rate" of trips that every household takes, in addition to accounting for the effects of any unobserved variables that are not included in the model specification.

Table 16 displays the ρ^2 and adjusted ρ^2 statistics for each model, as well as the type of regression analysis (Poisson or negative binomial) used to specify them.

Table 16: Goodness-of-Fit of Each Model

Model	ρ^2	Adjusted ρ^2	Regression type
Home-based work	0.059	0.057	Poisson
Home-based shopping	0.102	0.100	Negative binomial
Home-based other	0.172	0.171	Negative binomial
Work-other	0.194	0.192	Negative binomial
Other-other	0.245	0.244	Negative binomial

The "best" model specification was the other-other model, whereas the "worst" model estimation was the home-based work model. Because of the relatively limited number of variables used in each model specification, the adjusted ρ^2 statistic did not differ

greatly from the ρ^2 statistic in any case. The negative binomial formulation was found to be the appropriate estimation method in four out of the five models.

CHAPTER 6: ELASTICITY ANALYSIS OF TRAVEL DEMAND MANAGEMENT VARIABLES

In this chapter, we examine the elasticity of several of the "TDM variables" to determine the probable extent of the effects that various TDM strategies may have on trip generation rates for specific purposes. For each strategy, the current literature regarding the effectiveness of that particular strategy is summarized, followed by a discussion of the elasticities of the explanatory variables for each model in which the variable was significant. For further information regarding the reasoning for the significance of each variable, refer to the "Justification of Variables" sections for each model in Chapter 5.

TELECOMMUNICATIONS AND ALTERNATIVE WORK SCHEDULE STRATEGIES

SUMMARY OF CURRENT KNOWLEDGE

TELECOMMUNICATIONS STRATEGIES

The effectiveness of telecommunications strategies (specifically telecommuting) is highly dependent on the number of workers who participate in a telecommuting program. Nationwide, about 2 percent of the work force telecommutes on any given day of the week, but larger metropolitan areas such as Los Angeles and San Francisco report telecommuting rates of 7.6 percent and 8.1 percent, respectively. (WSDOT, 1996) The Southern California Association of Governments, which includes the Los Angeles area, has set a goal to have 10.4 percent of the area work force participate in a telecommuting or work-at-home program. (The Urban Transportation Monitor, 1997)

Work Trips. Obviously, telecommuting decreases the number of work trips made. The Puget Sound Telecommuting Demonstration Project reported a decrease of 1.4

commute trips on telecommuting days for telecommuters versus workers who did not telecommute. (Koenig et al., 1996) This finding is consistent with data from the State of California Telecommuting Pilot Project, which showed an average elimination of 1.5 commute trips for telecommuters on telecommuting days. (Koenig et al., 1996)

Non-Work Trips. The generation of additional non-work trips by telecommuters has been hypothesized as a potential negative impact of telecommuting. The empirical evidence to date has been mixed, but in no cases do the effects of additional non-work travel outweigh the effects of reduced work travel. The Puget Sound and State of California telecommuting studies referenced above indicated a small increase in the number of non-work trips made by telecommuters on telecommuting days. The Puget Sound study noted an increase in non-work travel of 0.3 trips, and the State of California study cited an increase in non-work travel of 0.5 trips. (Koenig et al., 1996)

However, Mokhtarian asserted that non-work trips do not increase as a result of telecommuting. Furthermore, she stated that "non-commute trips actually decrease, and in some cases trip making has been observed to decrease for telecommuters' household members as well." (Mokhtarian, 1991) She also offered several reasons why non-commute travel may decrease for telecommuters, including "(for telecommuters) a tendency to anchor non-work activities to the commute trip, and the threshold costs associated with getting dressed to leave the house; (for household members) a desire to be at home with the telecommuter; and (for everyone) a heightened awareness on the part of the household of the need for reducing travel and/or traveling more efficiently." (Mokhtarian, 1991)

Though the evidence is mixed regarding the impacts of telecommuting on non-work travel, as stated earlier, most research notes that any minor increases in non-work trip generation will not offset the decreases in work trip generation.

ALTERNATIVE WORK SCHEDULES

In comparison to telecommuting, few case studies have documented the trip generation impacts of compressed work weeks. One prominent study performed by Ho and Stewart involved a "before and after" case study of a compressed work week program in Southern California. Under this program, employees worked four 10-hour days per week, instead of the more traditional five 8-hour days per week.

The total number of weekly trips taken by employees in this program decreased by approximately 9 percent. Increases in the number of trips made were reported on Friday and Saturday, and decreases were reported for every other day. These results are shown in Table 17.

Table 17: Trip Generation Effects of a Compressed Work Week (CWW) Schedule

	Number of Trips per Respondent		
Day	Before CWW	After CWW	Percent change
Saturday	3.26	3.29	+1.1
Sunday	3.09	2.96	-4.2
Monday	3.56	2.96	-20.0
Tuesday	3.84	3.02	-26.9
Wednesday	3.52	3.14	-12.2
Thursday	3.61	3.07	-17.6
Friday	3.63	4.01	+9.3
Week	24.51	22.46	-9.1

The results of the second survey indicated that after the implementation of the compressed work week schedule, more trips were made on Friday than on any other day. However, even though the compressed work week schedule encouraged people to make more trips on Friday, the increase was overshadowed by a reduction in the number of trips being taken on most other days, resulting in a net reduction in the number of weekly trips.

Evidence also suggests that more non-work-related trips might be taken in the non-peak periods as a result of a compressed work week schedule. Results of this study

showed an increase in the number of trips made during the peak period on workdays, as well as an increase in the number of trips made around noon. The morning and evening trips can be interpreted as commute trips, and the midday trips were interpreted as "either errand or lunch trips made from work." The *before* survey noted fewer errand trips in general between Monday and Thursday. On Friday, the number of trips made before 8:00 AM or after 3:00 PM decreased, indicating that errand trips were shifted out of the peak period. (Ho and Stewart, 1992)

Overall, the number of trips made on Fridays (employee's day off) increased by 9.3 percent. Obviously, fewer trips were made to work, but trips to other destinations (shopping, running errands, and other) increased, accounting for the overall increase. This indicates that the respondents were using their day off to tend to personal matters and to run errands. However, the percentage of all trips from home decreased in comparison to a Friday before the compressed work week schedule had been enacted, indicating that trip chaining played a larger role in the respondents' travel behavior. Trip chaining also led to a reduction in the average distance traveled on Friday, even though the number of "trips" increased. This implies that the effects of trip chaining are quite significant and should be taken into account in trip generation models. (Ho and Stewart, 1992)

Ho and Stewart noted that the proportion of work trips almost doubled for workdays (Monday through Thursday) under a compressed work week scheme; however, these work trips were not *commute* trips per se because the percentage of trips to home decreased substantially. Instead, the increased percentage and number of trips to work can be accounted for by trips made during the workday when the respondents returned to work from, for example, lunch or an errand. (Ho and Stewart, 1992)

This evidence indicates that compressed work week schedules affect not only home-based work trips but also other home-based and possibly even non-home-based

trips. As is the case with telecommuting, even if there is some increase in non-work travel, it is outweighed by the decrease in work travel.

Elasticity in Home-Based Work Model

The average elasticity of the **wk_freq** variable, which can account for both telecommuting and compressed work week strategies, was computed as approximately 0.29 in the home-based work model. In rough terms, this means that a 1 percent decrease in the average work frequency will result in a 0.29 percent decrease in the number of home-based work trips. It seems that there should be a higher elasticity than this, but as discussed earlier, the number of "home-based work" trips is not necessarily the same as the number of trips to and from work because of the effects of trip chaining. This elasticity is likely capturing these effects in addition to the reduction in the total number of trips due to TDM strategies.

Elasticity in Work-Other Model

The average elasticity of the **wk_freq** variable in the work-other model was calculated as about 0.45, meaning that a 1 percent decrease in the average work frequency should result in roughly 0.45 percent fewer work-other trips. This elasticity is higher than the elasticity for the same variable in the home-based work model, which is interesting. It is likely that rather than explaining the effects of TDM strategies, this elasticity value relates to the effects of trip chaining. As stated in the justification for this variable, people who work less often have fewer opportunities to make work-other trips. They do not necessarily make fewer trips, but fewer trips are classified as work-other trips.

Elasticity in Other-Other Model

In the other-other model, the average elasticity of the **wk_freq** variable was computed as approximately -0.38. This means that a 1 percent decrease in the average work

frequency should result in roughly 0.38 percent *more* other-other trips. As was the case for this variable, this elasticity is more likely explaining the effects of trip chaining than the impacts of TDM strategies. It was noted above that people who work less often do not necessarily make fewer trips than those who work more frequently, but fewer trips are classified as work-other trips. Perhaps the negative elasticity of **wk_freq** in this model suggests that some of the work-other trips of those who work more frequently are other-other trips for those who work less frequently.

SUMMARY OF ELASTICITIES FOR TELECOMMUTING AND ALTERNATIVE WORK SCHEDULES

Although the **wk_freq** variable was significant in three models, it likely explained the impacts of TDM strategies in the home-based work model only. The existing empirical evidence is mixed regarding the effects of these strategies on non-work trips, and this variable was not significant in either the home-based shopping or home-based other models, perhaps lending additional support to the hypothesis that telecommuting and compressed work week schedules have a negligible impact on non-work trips. The statistical summary for the computed elasticities of **wk_freq** is shown in Table 18.

Table 18: Statistical Summary of Elasticities of **wk_freq** Variable

Model	Average Elasticity	Minimum	Maximum	Standard Deviation	Number of Cases
Home-based work	0.28857	0.1179	0.4128	0.034077	736
Work-other	0.45304	0.09206	0.6445	0.056699	619
Other-other	-0.37830	-0.5627	0.0000	0.076279	805

ON-SITE AMENITIES

SUMMARY OF CURRENT KNOWLEDGE

As with compressed work weeks, few case studies document the trip generation effects of on-site amenities. The most prominent case study, performed by Davidson in 1993, is described below.

An activity diary was distributed to employees at two large companies in Brentwood, Tennessee (suburban Nashville): Comdata Corporation and Service Merchandise Company. Respondents were asked to identify all of their daily on-site activities, the mode of travel that would have been used to access each service had it not been available on-site, and their estimated miles of travel to perform each activity off-site. Also, several socioeconomic questions were posed. (Davidson, 1995) The activity diary was used to collect information for one week (five work days).

Amenities available on-site at Comdata included a 150-seat, full-service cafeteria; a break room with microwave, icemaker, and vending machine; an automated teller machine; a fitness center open 24 hours a day; direct payroll deposit; college-level classes; a company store with logo merchandise; and dry cleaning pick-up. In addition, a child care center was located adjacent to the Comdata site. Comdata had an active TDM program in other areas as well, including ridematching services and flexible work hours. Fifty employees from Comdata completed diaries in July 1993.

Amenities available on-site at Service Merchandise Company included a full-service cafeteria; a break room with vending machines; a company store that offered company logo items and an automated order center for Service Merchandise catalog items; an automated teller machine; direct deposit; a travel agency for personal use; a newsstand; dry cleaning pick-up; post office; and a first-aid clinic. Service Merchandise Company also offered other TDM programs, including ridesharing incentives and an appointed employee transportation

coordinator. One hundred and twenty-seven employees from Service Merchandise completed diaries in August 1993.

The travel behavior effects of the on-site amenities were expressed primarily in terms of VMT reductions. However, we can also make some conclusions regarding the actual changes in the number of trips taken as a result of the amenities.

Davidson reported that the survey participants (from both companies) eliminated 2,528 miles of travel per week as a result of the presence of on-site amenities. This amount corresponds to a mean weekly reduction of 14.3 miles per respondent. The amenities at Comdata that helped eliminate the most VMT were the cafeteria, education, fitness facility, and automated teller machine. At Service Merchandise, the most influential amenities were the cafeteria, automated teller machine, direct deposit, stamp machine, dry cleaning pick-up, and travel agency. The Service Merchandise cafeteria enabled the reduction of 665 miles per week, corresponding to about 27 trips avoided per day.

Davidson concluded, "Amenities proved to be a substitute for trip-making. They allowed non-poolers to contribute to trip reduction be removing weekly miles that non-poolers would have traveled as part of the home-based work trip, mid-day trip or a later home-based non-work trip. The most influential amenity on trip elimination at both work sites was the cafeteria." (Davidson, 1995)

ELASTICITY IN WORK-OTHER MODEL

The **needcar** variable was used to help evaluate the potential impacts of on-site amenities. However, because it is a categorical variable, the elasticity can not be easily interpreted. The important characteristic of this variable is the negative sign of the coefficient, which was discussed earlier in the justification for this variable. This sign helps lend support to the positive trip reduction potential of on-site amenities.

PRICING STRATEGIES

SUMMARY OF CURRENT KNOWLEDGE

Pricing schemes can take on many forms, such as parking pricing, tolls, congestion pricing, increased gasoline prices, and taxes (such as a VMT tax). The main issue surrounding this strategy as it relates to trip generation is whether pricing incentives and disincentives will cause a change in trip generation rates, a change in destination, a change in mode, or even a change in route. It seems likely that regionwide pricing strategies, such as taxes, may influence trip generation rates more than site-specific charges, such as parking charges (unless parking charges are implemented uniformly regionwide). Site-specific strategies, on the other hand, seem more likely to affect trip distribution or mode choice characteristics. However, more research is needed to prove or disprove this hypothesis. The parking charge variable was the only pricing variable used in this study.

Apogee Research cited several studies indicating that parking pricing may potentially reduce the number of work trips by 2.5 percent and the number of non-work trips by 5.4 percent. These figures were based on research by Cameron and Bhatt, as well as research by Harvey and Deakin. The figure for work parking was based on parking rate increases of about $2.00 per day, while the figure for non-work parking was based on charges ranging from $0.60 per hour up to $3.00 per day. However, it was not clear from the literature whether the potential trip reduction figures were based on regionwide parking charges or charges at individual sites.Apogee Research, 1994)

A number of cities have implemented higher parking charges, and although many of them have reported a decrease in the number of parked cars, few provide evidence as to whether the affected people changed modes, changed parking location, or eliminated the trip altogether. Especially in the case of work trips, it seems unlikely that people will eliminate the trip entirely. The City of Madison, Wisconsin, imposed a peak-period

surcharge of $1.00 at four parking facilities and instituted new shuttle service. Five to 8 percent of commuters switched to transit, but 22 percent simply shifted parking location, and 6 percent parked after the peak period. The City of Eugene, Oregon, reported a similar phenomenon. After parking rates had been raised at two municipal garages and several surface lots, the number of cars in these location decreased significantly. Approximately half of the parkers joined a carpool or rode a free shuttle; however, the other half appeard to have simply changed parking locations. (Federal Transit Administration, 1992)

SENSITIVITY IN WORK-OTHER MODEL

The elasticity of the **parking** variable was used to evaluate the potential trip reduction impacts of parking charges. The average elasticity was calculated as approximately -0.011, indicating that a 1 percent increase in parking charges should result in roughly 0.011 percent fewer home-based work trips. More realistically, a 25 percent increase would result in roughly 0.28 percent fewer trips. As discussed earlier, the **parking** variable has some inherent weaknesses, but this elasticity at least lends support to the hypothesis that regionwide pricing strategies can be an effective trip-making deterrent, especially in comparison to site-specific pricing strategies. A statistical summary of the elasticity of the **parking** variable is in Table 19.

Table 19: Statistical Summary of Elasticity of **parking** Variable

Model	Average Elasticity	Minimum	Maximum	Standard Deviation	Number of Cases
Work-other	-0.011636	-0.5662	0.0000	0.047547	619

LAND-USE STRATEGIES

SUMMARY OF CURRENT KNOWLEDGE

A number of studies have evaluated the trip generation impacts of higher density or mixed-use neighborhoods in comparison to typical low density, single-use neighborhoods.

Kitamura et al. referred to a study completed by the White Mountain Survey Company in Portsmouth, New Hampshire. This study found that a multi-use neighborhood in that city exhibited trip generation rates that were "considerably lower than the general averages contained in the ITE Trip Generation Handbook." (Kitamura et al., 1997) On the other hand, in a study that used Puget Sound data, Frank found that trip generation rates were "significantly positively related to urban form for work trips but not for shopping trips. This positive relationship indicated that the number of trips per person increased as density and land-use mix increased." (Frank, 1994) However, in a study using data from several areas in Florida, Ewing et al. found that "residential density, mixed use, and accessibility appear to have negligible effects on household trip rates." Nevertheless, the authors also stated that "land use and accessibility variables may still have some effect on household trip rates, indirectly through their effect on automobile ownership." (Ewing et al., 1996) Clearly, research regarding the effects of land-use strategies on trip generation rates is inconclusive.

For the analysis below, elasticities for the **cflag** variable were not computed because the elasticity of a binary (0/1) variable has no immediate interpretation. However, elasticities for the **mile** variable were computed and interpreted. For further discussion regarding the significance of these variables in each model, refer to the justification of each variable in Chapter 5.

Elasticity in Home-Based Work Model

As noted earlier, the significance of the **mile** variable in the home-based work model is more likely attributable to the effects of trip chaining than to TDM strategies. Nevertheless, the elasticity of this variable was computed. The average elasticity of **mile** in the home-based work model was calculated as approximately -0.15, meaning a 1 percent decrease in the average household distance from home to work will result in a roughly 0.15

percent increase in the number of home-based work trips. However, because work trips are generally mandatory, the increase in the number of home-based work trips is likely offset by a decrease in non-home-based trips.

Elasticity in Home-Based Shopping Model

The elasticity of **mile** in the home-based shopping model was computed as about -0.07, indicating that a 1 percent decrease in the average distance from home to work should result in a roughly 0.07 percent increase in the number of home-based shopping trips. As noted earlier, this may be due in some extent to the effects of trip chaining; however, there is also evidence that this variable addresses the effects of induced demand. People with shorter trips seem likely to take more shopping trips. Although the impacts of induced demand may theoretically affect home-based other trips as well, this variable was not significant in the home-based other model.

Summary of Elasticities for Land-Use Strategies

The **mile** variable was significant in both the home-based work and the home-based shopping model; however, in the case of the home-based work model, this variable does not appear to address the impacts of land-use strategies. The increase in the number of home-based work trips as the average distance from home to work decreases is likely offset by a decrease in non-home-based trips. However, for the home-based shopping model, there is evidence that induced demand may play a role in the increased number of home-based shopping trips for those that live closer to work. A statistical summary of the elasticities in these two models is shown in Table 20.

Table 20: Statistical Summary of Elasticities of **mile** Variable

Model	Average Elasticity	Minimum	Maximum	Standard Deviation	Number of Cases
Home-based work	-0.14939	-0.6567	-0.004568	0.10167	736
Home-based shopping	-0.072628	-0.3109	-0.004506	0.053214	719

CHAPTER 7: APPLICATION OF MODELS IN A NETWORK-BASED MODELING APPROACH

As noted in Chapter 3, the traditional four-step modeling process has some notable deficiencies related to evaluating TDM strategies. This section further discusses these shortcomings and also offers suggestions regarding the adjustments to the modeling process that would be necessary to incorporate trip generation models similar to the ones estimated for this study. The following issues are addressed:

- trip chaining effects
- adjustments needed in other "steps"
- feedback mechanisms
- aggregation issues.

In addition, the appropriateness of the variables used in this study to describe the TDM strategies is discussed. Although the variables used here do explain the effects of TDM strategies to some extent, they may also capture effects that are not specifically related to TDM strategies. Recommendations for improving the variables used in this study are offered.

TRIP CHAINING EFFECTS

Many recent research efforts have evaluated trip-making characteristics by using trip chains rather than a series of independent trips. People often combine individual trips to different destinations as one "tour." However, current trip generation models analyze each trip independently, without accounting for the interrelationships that exist among many of the trips. Activity-based modeling is intended to address this issue, especially with regard to non-work travel. Although non-work travel accounts for the largest share of urban area

travel, non-work travel models generally perform worse than work trip models. (Cambridge Systematics et al., 1994)

The issue of trip chaining seems to become even more prominent as additional trip purposes are modeled. Recently developed trip generation models include a number of other purposes in addition to the three traditional trip types of home-based work, home-based other, and non-home-based trips.

In this study, the changes in the number of trips that were modeled as a result of the "TDM variables" may not necessarily have been due to the TDM strategies themselves, especially in the case of non-work travel. Preliminary evidence from this study indicates that people who live farther away from their worksite may be more apt to chain trips together than those who live closer to their worksite. Note that the trip chaining phenomenon does not necessarily decrease the number of trips made; rather, the same trips are made with different trip ends. As was noted in the justification for several of the variables in Chapter 5, a decrease in the number of trips for one purpose as a result of a "TDM variable" may result in an increase in the number of trips for another purpose. Thus, the TDM variable actually may not explain the effects of the TDM strategy but rather a shift in the number of trips that are estimated for specific purposes.

To fully understand whether the "TDM variables" are in fact explaining TDM strategies, a modeling approach should be used that accounts for the effects of trip chaining. Activity-based modeling (see discussion in Chapter 3) is geared toward the evaluation of trip chains, and the use of these types of models is anticipated to increase. Still, it should be possible to incorporate the effects of trip chaining into the traditional four-step process, which would allow for a better understanding of the true impacts of TDM strategies.

EFFECTS ON OTHER "STEPS"

The inclusion of TDM strategies, particularly land-use strategies, in trip generation models may necessitate adjustments to the models used in the other "steps." Evidence indicates that higher densities and mixed land use may actually encourage more trips than would be produced in a low-density, single land use area. However, these additional trips are typically short-distance trips and may be more apt to occur by modes other than the automobile.

The distribution of the additional trips should be adequately handled by the gravity formula, because areas with higher densities and mixed land use seem likely to be modeled with a greater number of attractions than low-density, single use areas. The low travel time for those living in areas of mixed land use will also be taken into account in the gravity formula through an increased friction factor.

With regard to mode choice, walking and bicycling are more feasible as modes of transportation in higher-density areas, and thus, these modes should be included in the mode choice model in addition to the traditional automobile and transit modes. The impedance formulas for each of these modes should take into account the differences in cost of the trip and travel time between non-motorized modes and motorized modes in order to produce reasonable mode splits for higher-density areas.

Also, the effects of site-specific TDM strategies such as parking charges at individual lots should be examined with reference to trip distribution and mode choice models in addition to trip generation. Existing data indicate that parking charges at individual sites do not affect the number of trips generated as much as they affect trip distribution and mode choice. Even though **parking** was significant in the work-other model, this may in fact be explaining distributional or mode choice effects rather than trip generation impacts. More study is warranted regarding the impacts of site-specific TDM strategies on trip distribution and mode choice.

FEEDBACK MECHANISMS

The traditional four-step process assumes that each traveler makes decisions sequentially, using the following hierarchy:

1. travelers decide whether to make a trip (trip generation)
2. they decide where to go (trip distribution)
3. they decide what mode they want to take to get there (mode choice)
4. they decide which route they want to use (trip assignment).

However, travelers do not always make decisions according to this hierarchy. Cambridge Systematics stated, "Inter-relationships between travel decisions at various levels of the hierarchy are not represented [in the four-step process]. Many trip-makers may consider both alternative destinations and alternative modes simultaneously, for example: whether to make a shopping trip using transit to the CBD, or auto to a suburban shopping center." (Cambridge Systematics, 1996) In addition to this shortcoming, "trip generation models are independent of any level of service variables. Thus, variations in accessibility, as measured in trip distribution and mode choice models, are not associated with variations in the number of trips made." (Cambridge Systematics, 1996)

These deficiencies certainly can affect the modeling of TDM strategies. As is discussed elsewhere in this report, site-specific TDM strategies (such as parking charges at individual lots) may actually affect trip distribution and mode choice more so than trip generation, even if the "TDM variable" is found to be significant in a trip generation model. Furthermore, there are many other TDM strategies that are not discussed in this paper because they are more appropriately modeled in one of the steps other than trip generation, even though decisions based on these strategies may still affect trip generation.

In short, travelers do not make their decisions in the sequential order implied by the traditional modeling process, and to gain a better understanding of the actual travel

decisions that are made, some type of feedback mechanism should be employed. This feedback mechanism would iterate between trip assignment and the previous steps in the process to try to find a consistent measure of level of service. For example, under the current scheme, a trip is generated regardless of what the cost of the trip is determined to be in the mode choice model. Even if a trip to the grocery store costs $1000, it is still generated. In reality, however, more likely than not the person will not make this trip. If some type of feedback mechanism could iterate the cost of the trip back into the trip generation model, the trip would (more appropriately) not be generated. Feedback between the various steps is especially important with regard to pricing strategies.

AGGREGATION ISSUES

In this study, we examined disaggregate, household-level data. However, when incorporated into a regional travel demand model, the household-level data are aggregated into zonal-level data. Thus, the variability of the "TDM variables" at the household level is sacrificed, and only the variability between individual zones can be included in the regional model. This may not be as big an issue as it seems, however. The TDM strategies discussed here are basically regionwide strategies (with the exception of site-specific parking charges). On-site amenities are implemented at individual sites, but if offering such amenities were to become widespread practice, this would also become a regionwide strategy. The effectiveness of TDM strategies is also usually analyzed at a regionwide level (or at least a level that is more aggregate than the household). Furthermore, because TDM strategies are usually evaluated in a "before versus after," rather than a "household versus household" context, the most important consideration should be the significance of the "TDM variables" at the zonal level, rather than the variability associated with them. Nevertheless, more research is needed to look at the variability and significance of the "TDM variables" at an aggregate level.

RECOMMENDATIONS FOR IMPROVED MODELING PRACTICE OF SPECIFIC STRATEGIES

TELECOMMUNICATIONS STRATEGIES AND ALTERNATIVE WORK SCHEDULES

The **wk_freq** variable was used to describe both telecommuting strategies and alternative work schedules. Although this variable was found to be significant in three of the models, some improvements could be made to this variable that might potentially increase its ability to describe the trip-making effects of telecommuting and alternative work schedules. These improvements are discussed below.

The **wk_freq** variable was derived from the following question, which was asked in the PSTP person survey: "How many days a week do you normally work?" However, this question does not differentiate between the number of days spent working at the office and the number of days spent working at home. To better address telecommuting patterns, this question could be changed to something like, "How many days a week do you normally work (not including work-at-home days)?" Then, to determine the extent of telecommuting, a question such as, "How many days a week do you normally work at home?" could be asked. Although a question in the PSTP person survey asked whether a person worked at home, it was simply a yes/no question and did not address the extent to which that person worked at home.

The question "How many days a week do you normally work (not including work-at-home days)?" could also be used to eliminate any ambiguity with regard to compressed work week strategies, although this is less of an issue than it is for telecommuters.

RECOMMENDATIONS

To better address telecommuting, a question such as "How many days a week do you normally work at home?" should be included in the person survey. A new

telecommuting-specific variable, such as **telecom**, could then be derived from the results of this question.

To better address compressed work week schedules, the existing "work frequency" question should be modified slightly to eliminate any ambiguity that might be perceived by those completing the survey. A question such as, "How many days a week do you normally work (not including work-at-home days)?" is appropriate. The current **wk_freq** variable could still be used, as long as it was derived from the modified "work frequency" question.

On-Site Amenities

The **needcar** variable was derived from two other variables, **freqerrd** and **freqpers**, in the PSTP attitude survey. These two variables were defined as "Frequency needing car for other personal errands (aside from dropping off or picking up children) before or after work" and "Frequency needing car for personal trips during day," respectively. One of the major ambiguities with regard to the **freqpers** variable is that it fails to clearly differentiate between personal trips and business trips. Because no question in the panel survey dealt specifically with the number of business trips taken during the day, respondents might have been unclear about whether they should include business trips in their response to the **freqpers** question. Because on-site amenities cater mainly to personal trips, the inclusion of business trips in the response to this question might have introduced some bias with regard to the ability of this variable to explain the trip-making impacts of on-site amenities.

Also, because these variables are categorical variables, their elasticity is not easily interpreted, which precludes analysis of the contribution of this variable to the overall model. If count data were used, the interpretation of this variable would be much easier.

Furthermore, the current variables only consider the frequency with which someone needs a car to make personal trips. No consideration is given to the fact that people may use other modes to make personal trips. The existence of on-site amenities should affect the number of personal trips made regardless of mode.

Recommendations

To clear up any ambiguities as well as to try to capture the effects of on-site amenities in a single question, the **needcar** variable should be defined by something such as, "Number of personal (non-business) trips made before, during, and after work during the week." This formulation of the question is not mode-specific, and it does not use the categories associated with the current scheme.

Pricing Strategies

The treatment of pricing strategies in this study was limited to an assessment of parking charges incurred on particular trips. Obviously, there are many other types of pricing strategies, and these should also be tested for significance in trip generation models. However, the major difficulty associated with testing strategies such as an increased VMT tax or congestion pricing is the lack of data that are available to use in the estimation of these variables. Furthermore, because of the regionwide nature of these types of strategies, it might not be proper to include them as specific variables in a model. Instead, a series of models should be developed—each one corresponding to whether a VMT tax is in place, different levels of congestion pricing, and other factors.

As discussed earlier, the site-specific pricing strategies, such as charges at specific parking areas, may affect the other steps of the four-step process more so than trip generation. Thus, the significance of variables such as **parking** should be treated with caution.

Recommendations

To properly model regionwide pricing strategies such as taxes, it is probably more feasible to develop a series of trip generation models based on various levels of pricing levels than to include the strategies as explicit variables in one trip generation model. Site-specific pricing strategies may be more appropriate as explicit variables, but these strategies may be more applicable in other stages of the four-step process.

Land-Use Strategies

As discussed earlier, there is little consensus in the literature regarding the effects of strategies such as mixed land use and higher density levels on trip-making characteristics. This study indicated that land-use strategies may have some impact on trip generation rates; however, the results are inconclusive. The evaluation of land-use strategies as an explicit variable in trip generation models does not seem to be the most effective methodology with which to examine the trip-making characteristics of these strategies. Ideally, a series of trip generation models could be developed for areas with distinct density and land-use mixture levels. The "centers" defined by PSRC have much potential as a means to test the trip generation impacts of areas of differing land uses. The centers could be further subdivided into such categories as "urban centers" or "suburban centers." Unfortunately, there were not enough data from households located within the centers to develop separate trip generation models for centers and non-centers. If future surveys addressed this issue and surveyed more households located within centers, perhaps the development of a series of trip generation models would be more feasible.

Recommendations

Land-use strategies do not seem especially suited for inclusion in trip generation models as an explicit variable. For this reason, more data should be obtained from

households located within the "centers," with the intention of developing a series of trip generation models that correspond to areas of different density levels and land-use mixture.

CHAPTER 7: CONCLUSIONS

RESEARCH FINDINGS

This research has provided evidence that TDM strategies can be incorporated into regional travel demand models through the traditional four-step modeling process. The five TDM strategies that may potentially affect trip generation rates were evaluated by using variables that describe the effects of these strategies, and this technique had varying degrees of effectiveness for the different strategies.

TELECOMMUTING AND ALTERNATIVE WORK SCHEDULES

An explicit variable called **wk_freq**, which was defined as the average number of days per week the respondent works, was used to describe the effects of telecommuting and alternative work schedules (specifically compressed work weeks). This variable was significant in three models: home-based work, work-other, and other-other.

As expected, the **wk_freq** variable had a negative coefficient in the home-based work model, meaning that the fewer days per week the respondent works, the fewer home-based work trips the respondent makes. The reasoning for the significance of this variable in the home-based work model seems clear; however, the significance of this variable in the work-other and other-other models is not as obvious.

In the work-other model, the **wk_freq** variable had a positive coefficient, indicating that as a person's work frequency increases, that person is likely to make more work-other trips. However, this relationship is not necessarily due to the effects of telecommuting or alternative work week schedules. The more often a person works, the more opportunities that person has to make a trip that is classified as a "work-other" trip. If

a person works less frequently, that person does not necessarily make fewer trips, but fewer of the trips are classified as "work-other" trips.

The **wk_freq** variable had a negative coefficient in the other-other model, meaning that as a person's work frequency increases, the number of "other-other" trips made by that person decreases. As was the case with the work-other model, the significance of this variable is not necessarily due to the impacts of TDM strategies, but could be attributable to the effects of trip chaining and the classification of trips by specific purposes. Those who work more often have increased opportunities to make work-other trips, and consequently, may have fewer opportunities to make other-other trips.

ON-SITE AMENITIES

In an attempt to model the potential effect of on-site amenities, a variable called **needcar** was defined. This variable was derived from two other variables in the PSTP panel survey and was defined as the average value of "frequency needing car for personal trips during the workday" and "frequency needing car for other personal errands before or after work." This variable was significant in the work-other model.

In the work-other model, **needcar** had a negative coefficient, which means that as a person needs a car less often for personal trips or errand-running, that person makes fewer work-other trips. This relationship makes sense and agrees with the travel behavior changes that on-site amenities are designed to encourage. If more on-site amenities are available to a worker, that person needs a car less often to run errands, and thus, fewer work-other trips are made.

PRICING STRATEGIES

There are many types of pricing strategies; however, this study examined parking charges only. The variable used to represent parking charges, **parking**, was simply the

parking charges that a person paid on any particular trip. This variable was found to be significant in the work-other model.

The **parking** variable had a negative coefficient, meaning that as parking charges increase, the number of work-other trips decrease. This relationship makes sense; however, these results should be treated with caution. Compared to the significance of other variables, this variable was only marginally significant, and research has indicated that site-specific parking charges may have a bigger impact on trip distribution or mode choice than trip generation. Nevertheless, the significance of this variable serves as an indicator that other, more regionwide pricing strategies might be even more significant in trip generation models.

LAND-USE STRATEGIES

The treatment of land-use strategies was the least clear of any of the TDM strategies tested in this study. Two variables were used that may help explain the trip generation effects of land-use strategies: **cflag** and **mile**. The **cflag** variable was a binary (0/1) variable that equalled 1 if a household reported any trips for a particular purpose that were produced in a *center*, an area designated by PSRC that is generally higher in density and has a more diverse mixture of land uses than surrounding areas. If no trips were produced in a center, 0 was assigned. The hypothesis behind this variable is that centers produce more trips than non-centers, and trips taken in centers may encourage additional trips in the centers. The **mile** variable, which was defined as the average household distance from home to work, does not explicitly represent any type of land-use strategy but may act as a surrogate for the effects of more high-density, mixed-use development in which workers are able to live closer to their jobs. The **cflag** variable was significant in the home-based work, home-based shopping, work-other, and other-other models, and **mile** was significant in the home-based work and home-based shopping models.

The **cflag** variable had a positive coefficient in each of the four models in which it was significant, meaning that households reporting at least one production in a center tended to make more trips of each purpose. This finding does not necessarily mean that centers lead to an increase in VMT; instead, center-based trips are likely to be shorter in distance than non-center-based trips, and the use of alternative modes may be more feasible for center-based trips.

The **mile** variable had a negative coefficient in both the home-based work and home-based shopping models, meaning that as the distance from home to work increases, fewer trips of these respective types are made. But especially in the case of home-based work trips, it seems unlikely that the significance of **mile** is attributable to differences in land use. Rather, it seems more likely that people living farther away from work are apt to chain their work trip with other trips. Thus, they do not necessarily make fewer trips to work, but fewer trips are classified as "home-based work" trips. The same idea is true to some degree with home-based shopping trips. However, there is some evidence that the effects of induced demand may also be at work with respect to home-based shopping trips. People with a longer work commute seem to make fewer trips when shopping is the destination (either home-based or non-home-based).

RESEARCH IMPLICATIONS AND FUTURE RESEARCH

A number of implications for future research can be derived from this study. One of the most significant issues is the treatment of trip chaining in the four-step modeling process. Researchers seem to agree that this is an important consideration, but until recently, little research had been conducted regarding trip chaining. In this study, the significance of several of the variables designed to emulate the effects of TDM strategies can be attributed to the effects of trip chaining, rather than to the implementation of TDM

strategies. The issue of trip chaining becomes even larger as an increased number of trip purposes are evaluated, which has been the recent trend.

Although this study examined various TDM strategies through the inclusion of explicit variables, it is likely that some TDM strategies (such as land-use strategies) may not be well-suited for evaluation as a specific variable. Instead, it might be more practical to develop a series of trip generation models, each one corresponding to a different type of land use. However, to attempt this, more data from the "centers" are needed.

Another consideration is the effects that these TDM strategies may have on other steps of the four-step process. Some TDM strategies (such as telecommuting) affect only trip generation; however, other strategies (such as pricing strategies) may affect trip distribution, mode choice, and even trip assignment in addition to trip generation. Some type of feedback mechanism should be incorporated into the modeling process to account for the fact that the decision to travel is not made in the strict sequence implied by the four-step process.

To implement a regional travel demand model that includes the effects of TDM strategies, data sufficient in quality and quantity are needed. However, some strategies, such as regionwide pricing schemes, have been implemented only rarely, resulting in a lack of empirical data that can be used to develop the models. Because of the lack of empirical data, stated preference methods have emerged as a possible method with which to measure the potential effectiveness of TDM strategies. Stated preference data could likely play a major role in examining the trip generation impacts of strategies such as regionwide pricing schemes; therefore, additional research efforts should be devoted to the application of stated preference data in a network-based modeling framework.

This study addresses the incorporation of TDM strategies into trip generation modeling only. There are many other TDM strategies that affect the trip distribution, mode choice, and trip assignment stages of the four-step process. The incorporation of other

TDM strategies into other phases of the four-step process certainly merits some research attention; in addition, more research could certainly improve the modeling methodology developed for this study. However, this thesis provides evidence that the traditional four-step planning process can be a viable mechanism to use for evaluating the travel impacts related to TDM strategies.

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