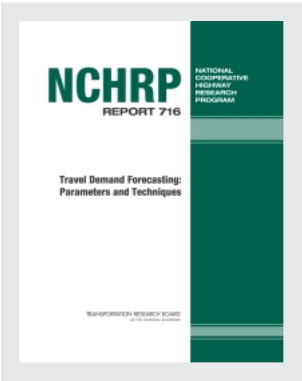

Travel Demand Forecasting: Parameters and Techniques

DETAILS

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NATIONAL COOPERATIVE HIGHWAY RESEARCH PROGRAM

NCHRP REPORT 716

Travel Demand Forecasting: Parameters and Techniques

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NATIONAL COOPERATIVE HIGHWAY RESEARCH PROGRAM

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FOREWORD

By Nanda Srinivasan
Staff Officer
Transportation Research Board

This report is an update to *NCHRP Report 365: Travel Estimation Techniques for Urban Planning* and provides guidelines on travel demand forecasting procedures and their application for solving common transportation problems. The report presents a range of approaches that allow users to determine the level of detail and sophistication in selecting modeling and analysis techniques most appropriate to their situations and addresses straight-forward techniques, optional use of default parameters, and appropriate references to other more sophisticated techniques.

In 1978, TRB published *NCHRP Report 187: Quick-Response Urban Travel Estimation Techniques and Transferable Parameters*. This report described default parameters, factors, and manual techniques for doing simple planning analysis. The report and its default data were used widely by the transportation planning profession for almost 20 years. In 1998, drawing on several newer data sources including the 1990 Census and National Personal Household Travel Survey, an update to *NCHRP Report 187* was published as *NCHRP Report 365: Travel Estimation Techniques for Urban Planning*.

Since *NCHRP Report 365* was published, significant changes have occurred affecting the complexity, scope, and context of transportation planning. Planning concerns have grown beyond "urban" to include rural, statewide, and special-use lands. Transportation planning tools have evolved and proliferated, enabling improved and more flexible analyses to support decisions. The demands on transportation planning have expanded into special populations (e.g., tribal, immigrant, older, and young) and broader issues (e.g., safety, congestion, pricing, air quality, environment, and freight). In addition, the default data and parameters in *NCHRP Report 365* needed to be updated to reflect the planning requirements of today and the next 10 years. Thus, the objective of this research was to revise and update *NCHRP Report 365* to reflect current travel characteristics and to provide guidance on travel demand forecasting procedures and their application for solving common transportation problems.

The research was performed by Cambridge Systematics, Inc. in association with Vanasse Hangen Brustlin, Inc., Gallop Corporation, Dr. Chandra R. Bhat, Shapiro Transportation Consulting, LLC, and Martin/Alexiou/Bryson, PLLC. Information was gathered via literature review, interviews with practitioners, and a database of parameters collected from metropolitan planning organizations as well as from the 2009 National Household Travel Survey. Planners can make use of the information presented in this report in two primary ways: (1) to develop travel model components when local data suitable for model development are insufficient or unavailable and (2) to check the reasonableness of model outputs.

CONTENTS

Note: Many of the photographs, figures, and tables in this report have been converted from color to grayscale for printing. The electronic version of the report (posted on the Web at www.trb.org) retains the color versions.

CHAPTER 1

Introduction

1.1 Background

In 1978, the Transportation Research Board (TRB) published *NCHRP Report 187: Quick-Response Urban Travel Estimation Techniques and Transferable Parameters* (Sosslau et al., 1978). This report described default parameters, factors, and manual techniques for doing planning analysis. The report and its default data were used widely by the transportation planning profession for almost 20 years. In 1998, drawing on several newer data sources, including the 1990 Census and Nationwide Personal Transportation Survey, an update to *NCHRP Report 187* was published in the form of *NCHRP Report 365: Travel Estimation Techniques for Urban Planning* (Martin and McGuckin, 1998).

Since *NCHRP Report 365* was published, significant changes have occurred affecting the complexity, scope, and context of transportation planning. Transportation planning tools have evolved and proliferated, enabling improved and more flexible analyses to support decisions. The demands on transportation planning have expanded into special populations and broader issues (e.g., safety, congestion, pricing, air quality, environment, climate change, and freight). In addition, the default data and parameters in *NCHRP Report 365* need to be updated to reflect the planning requirements of today and the next 10 years.

The objective of this report is to revise and update *NCHRP Report 365* to reflect current travel characteristics and to provide guidance on travel demand forecasting procedures and their application for solving common transportation problems. It is written for "modeling practitioners," who are the public agency and private-sector planners with responsibility for developing, overseeing the development of, evaluating, validating, and implementing travel demand models. This updated report includes the optional use of default parameters and appropriate references to other more sophisticated techniques. The report is intended to allow practitioners to use travel demand forecasting methods to address the full range of transportation planning issues (e.g., environmental, air quality, freight, multimodal, and other critical concerns).

One of the features of this report is the provision of transferable parameters for use when locally specific data are not available for use in model estimation. The parameters presented in this report are also useful to practitioners who are modeling urban areas that have local data but wish to check the reasonableness of model parameters estimated from such data. Additionally, key travel measures, such as average travel times by trip purpose, are provided for use in checking model results. Both the transferable parameters and the travel measures come from two main sources: the 2009 National Household Travel Survey (NHTS) and a database of model documentation for 69 metropolitan planning organizations (MPOs) assembled for the development of this report. There are two primary ways in which planners can make use of this information:

1. Using transferable parameters in the development of travel model components when local data suitable for model development are insufficient or unavailable; and
2. Checking the reasonableness of model outputs.

This report is written at a time of exciting change in the field of travel demand forecasting. The four-step modeling process that has been the paradigm for decades is no longer the only approach used in urban area modeling. Tour- and activity-based models have been and are being developed in several urban areas, including a sizable percentage of the largest areas in the United States. This change has the potential to significantly improve the accuracy and analytical capability of travel demand models.

At the same time, the four-step process will continue to be used for many years, especially in the smaller- and medium-sized urban areas for which this report will remain a valuable resource. With that in mind, this report provides information on parameters and modeling techniques consistent with the four-step process and Chapter 4, which contains the key information on parameters and techniques, is organized consistent with the four-step approach. Chapter 6 of this report presents information relevant to advanced modeling practices, including activity-based models and traffic simulation.

This report is organized as follows:

- **Chapter 1**—Introduction;
- **Chapter 2**—Planning Applications Context;
- **Chapter 3**—Data Needed for Modeling;
- **Chapter 4**—Model Components:
  - Vehicle Availability,
  - Trip Generation,
  - Trip Distribution,
  - External Travel,
  - Mode Choice,
  - Automobile Occupancy,
  - Time-of-Day,
  - Freight/Truck Modeling,
  - Highway Assignment, and
  - Transit Assignment;
- **Chapter 5**—Model Validation and Reasonableness Checking;
- **Chapter 6**—Emerging Modeling Practices; and
- **Chapter 7**—Case Studies.

This report is not intended to be a comprehensive primer for persons developing a travel model. For more complete information on model development, readers may wish to consult the following sources:

- "Introduction to Urban Travel Demand Forecasting" (Federal Highway Administration, 2008);
- "Introduction to Travel Demand Forecasting Self-Instructional CD-ROM" (Federal Highway Administration, 2002);
- *NCHRP Report 365: Travel Estimation Techniques for Urban Planning* (Martin and McGuckin, 1998);
- *An Introduction to Urban Travel Demand Forecasting—A Self-Instructional Text* (Federal Highway Administration and Urban Mass Transit Administration, 1977);
- FSUTMS Comprehensive Modeling Online Training Workshop (http://www.fsutmsonline.net/online_training/index.html#w1l3e3); and
- *Modeling Transport* (Ortuzar and Willumsen, 2001).

1.2 Travel Demand Forecasting: Trends and Issues

While there are other methods used to estimate travel demand in urban areas, travel demand forecasting and modeling remain important tools in the analysis of transportation plans, projects, and policies. Modeling results are useful to those making transportation decisions (and analysts assisting in the decision-making process) in system and facility design and operations and to those developing transportation policy.

NCHRP Report 365 (Martin and McGuckin, 1998) provides a brief history of travel demand forecasting through its publication year of 1998; notably, the evolution of the use of models from the evaluation of long-range plans and major transportation investments to a variety of ongoing, everyday transportation planning analyses. Since the publication of *NCHRP Report 365*, several areas have experienced rapid advances in travel modeling:

- The four-step modeling process has seen a number of enhancements. These include the more widespread incorporation of time-of-day modeling into what had been a process for modeling entire average weekdays; common use of supplementary model steps, such as vehicle availability models; the inclusion of nonmotorized travel in models; and enhancements to procedures for the four main model components (e.g., the use of logit destination choice models for trip distribution).
- Data collection techniques have advanced, particularly in the use of new technology such as global positioning systems (GPS) as well as improvements to procedures for performing household travel and transit rider surveys and traffic counts.
- A new generation of travel demand modeling software has been developed, which not only takes advantage of modern computing environments but also includes, to various degrees, integration with geographic information systems (GIS).
- There has been an increased use of integrated land use-transportation models, in contrast to the use of static land use allocation models.
- Tour- and activity-based modeling has been introduced and implemented.
- Increasingly, travel demand models have been more directly integrated with traffic simulation models. Most travel demand modeling software vendors have developed traffic simulation packages.

At the same time, new transportation planning requirements have contributed to a number of new uses for models, including:

- The analysis of a variety of road pricing options, including toll roads, high-occupancy toll (HOT) lanes, cordon pricing, and congestion pricing that varies by time of day;
- The Federal Transit Administration's (FTA's) user benefits measure for the Section 5309 New Starts program of transit projects, which has led to an increased awareness of model properties that can inadvertently affect ridership forecasts;

- The evaluation of alternative land use patterns and their effects on travel demand; and
- The need to evaluate (1) the impacts of climate change on transportation supply and demand, (2) the effects of travel on climate and the environment, and (3) energy and air quality impacts.

These types of analyses are in addition to several traditional types of analyses for which travel models are still regularly used:

- Development of long-range transportation plans;
- Highway and transit project evaluation;
- Air quality conformity (recently including greenhouse gas emissions analysis); and
- Site impact studies for developments.

1.3 Overview of the Four-Step Travel Modeling Process

The methods presented in this report follow the conventional sequential process for estimating transportation demand that is often called the "four-step" process:

- **Step 1**—Trip Generation (discussed in Section 4.4),
- **Step 2**—Trip Distribution (discussed in Section 4.5),
- **Step 3**—Mode Choice (discussed in Section 4.7), and
- **Step 4**—Assignment (discussed in Sections 4.11 and 4.12).

There are other components commonly included in the four-step process, as shown in Figure 1.1 and described in the following paragraphs.

The serial nature of the process is not meant to imply that the decisions made by travelers are actually made sequentially rather than simultaneously, nor that the decisions are made in exactly the order implied by the four-step process. For example, the decision of the destination for the trip may follow or be made simultaneously with the choice of mode. Nor is the four-step process meant to imply that the decisions for each trip are made independently of the decisions for other trips. For example, the choice of a mode for a given trip may depend on the choice of mode in the preceding trip.

In four-step travel models, the unit of travel is the "trip," defined as a person or vehicle traveling from an origin to a destination with no intermediate stops. Since people traveling for different reasons behave differently, four-step models segment trips by **trip purpose**. The number and definition of trip purposes in a model depend on the types of information the model needs to provide for planning analyses, the characteristics of the region being modeled, and the availability of data with which to obtain model parameters and the inputs to the model. The minimum number of trip purposes in most models is three: home-based work, home-based nonwork, and nonhome based. In this report, these three trip purposes are referred to as the "classic three" purposes.

The purpose of **trip generation** is to estimate the number of trips of each type that begin or end in each location, based on the amount of activity in an analysis area. In most models, trips are aggregated to a specific unit of geography (e.g., a traffic analysis zone). The estimated number of daily trips will be in the flow unit that is used by the model, which is usually one of the following: vehicle trips; person trips in motorized modes (auto and transit); or person trips by all modes, including both motorized and nonmotorized (walking, bicycling) modes. Trip generation models require some explanatory variables that are related to trip-making behavior and some functions that estimate the number of trips based on these explanatory variables. Typical variables include the number of households classified by characteristics such as number of persons, number of workers, vehicle availability, income level, and employment by type. The output of trip generation is trip productions and attractions by traffic analysis zone and by purpose.

Trip distribution addresses the question of how many trips travel between units of geography (e.g., traffic analysis zones). In effect, it links the trip productions and attractions from the trip generation step. Trip distribution requires explanatory variables that are related to the cost (including time) of travel between zones, as well as the amount of trip-making activity in both the origin zone and the destination zone. The outputs of trip distribution are production-attraction zonal trip tables by purpose.

Models of **external travel** estimate the trips that originate or are destined outside the model's geographic region (the model area). These models include elements of trip generation and distribution, and so the outputs are trip tables representing external travel.

Mode choice is the third step in the four-step process. In this step, the trips in the tables output by the trip distribution step are split into trips by travel mode. The mode definitions vary depending on the types of transportation options offered in the model's geographic region and the types of planning analyses required, but they can be generally grouped into automobile, transit, and nonmotorized modes. Transit modes may be defined by access mode (walk, auto) and/or by service type (local bus, express bus, heavy rail, light rail, commuter rail, etc.). Nonmotorized modes, which are not yet included in some models, especially in smaller urban areas, include walking and bicycling. Auto modes are often defined by occupancy levels (drive alone, shared ride with two occupants, etc.). When auto modes are not modeled separately, **automobile occupancy** factors are used to convert the auto person trips to vehicle trips prior to assignment. The outputs of the mode choice process include person trip tables by mode and purpose and auto vehicle trip tables.

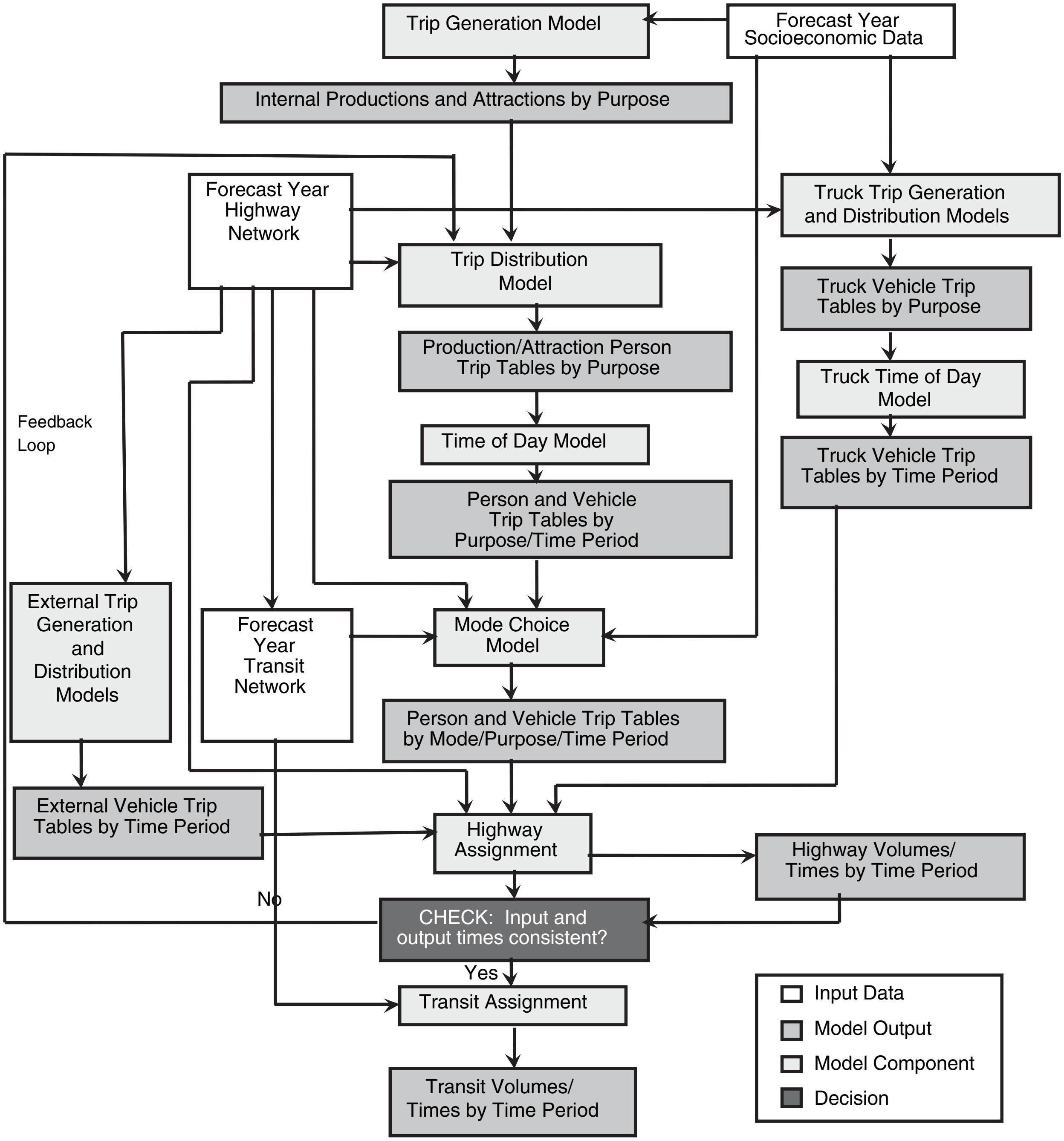

Figure 1.1. Four-step modeling process.

Time-of-day modeling is used to divide the daily trips into trips for various time periods, such as morning and afternoon peak periods, mid-day, and evening. This division may occur at any point between trip generation and trip assignment. Most four-step models that include the time-of-day step use fixed factors applied to daily trips by purpose, although more sophisticated time-of-day choice models are sometimes used.

While the four-step process focuses on personal travel, **commercial vehicle/freight travel** is a significant component of travel in most urban areas and must also be considered in the model. While simple factoring methods applied to personal travel trip tables are sometimes used, a better approach is to model such travel separately, creating truck/commercial vehicle trip tables.

The final step in the four-step process is **trip assignment**. This step consists of separate highway and transit assignment processes. The highway assignment process routes vehicle trips from the origin-destination trip tables onto paths along the highway network, resulting in traffic volumes on network links by time of day and, perhaps, vehicle type. Speed and travel time estimates, which reflect the levels of congestion indicated by link volumes, are also output. The transit assignment process routes trips from the transit trip tables onto individual transit routes and links, resulting in transit line volumes and station/stop boardings and alightings.

Because of the simplification associated with and the resultant error introduced by the sequential process, there is sometimes "feedback" introduced into the process, as indicated by the upward arrows in Figure 1.1 (Travel Model Improvement Program, 2009). Feedback of travel times is often required, particularly in congested areas (usually these are larger urban areas), where the levels of congestion, especially for forecast scenarios, may be unknown at the beginning of the process. An iterative process using output travel times is used to rerun the input steps until a convergence is reached between input and output times. Because simple iteration (using travel time outputs from one iteration directly as inputs into the next iteration) may not converge quickly (or at all), averaging of results among iterations is often employed. Alternative approaches include the method of successive averages, constant weights applied to each iteration, and the Evans algorithm (Evans, 1976).

Although there are a few different methods for implementing the iterative feedback process, they do not employ parameters that are transferable, and so feedback methods are not discussed in this report. However, analysts should be aware that many of the analysis procedures discussed in the report that use travel times as inputs (for example, trip distribution and mode choice) are affected by changes in travel times that may result from the use of feedback methods.

1.4 Summary of Techniques and Parameters

Chapter 4 presents information on (1) the analytical techniques used in the various components of conventional travel demand models and (2) parameters for these models obtained from typical models around the United States and from the 2009 NHTS. These parameters can be used by analysts for urban areas without sufficient local data to use in estimating model parameters and for areas that have already developed model parameters for reasonableness checking.

While it is preferable to use model parameters that are based on local data, this may be impossible due to data or other resource limitations. In such cases, it is common practice to transfer parameters from other applicable models or data sets. Chapter 4 presents parameters that may be used in these cases, along with information about how these parameters can be used, and their limitations.

1.5 Model Validation and Reasonableness Checking

Another important use of the information in this report will be for model validation and reasonableness checking. There are other recent sources for information on how the general process of model validation can be done. Chapter 5 provides basic guidance on model validation and reasonableness checking, with a specific focus on how to use the information in the report, particularly the information in Chapter 4. It is not intended to duplicate other reference material on validation but, rather, provide an overview on validation consistent with the other sources.

1.6 Advanced Travel Analysis Procedures

The techniques and parameters discussed in this report focus on conventional modeling procedures (the four-step process). However, there have been many recent advances in travel modeling methods, and some urban areas, especially larger areas, have started to use more advanced approaches to modeling. Chapter 6 introduces concepts of advanced modeling procedures, such as activity-based models, dynamic traffic assignment models, and traffic simulation models. It is not intended to provide comprehensive documentation of these advanced models but rather to describe how they work and how they differ from the conventional models discussed in the rest of the report.

1.7 Case Study Applications

One of the valuable features in *NCHRP Report 365* was the inclusion of a case study to illustrate the application of the parameters and techniques contained in it. In this report, two case studies are presented to illustrate the use of the information in two contexts: one for a smaller urban area and one for a larger urban area with a multimodal travel model. These case studies are presented in Chapter 7.

1.8 Glossary of Terms Used in This Report

MPO—Metropolitan Planning Organization, the federally designated entity for transportation planning in an urban area. In most areas, the MPO is responsible for maintaining and running the travel model, although in some places, other agencies, such as the state department of transportation, may have that responsibility. In this report, the term "MPO" is sometimes used to refer to the agency responsible for the model, although it is recognized that, in some areas, this agency is not officially the MPO.

Model area—The area covered by the travel demand model being referred to. Often, but not always, this is the area under the jurisdiction of the MPO. The boundary of the model area is referred to as the **cordon**. Trips that cross the cordon are called **external trips**; modeling of external trips is discussed in Section 4.6.

Person trip—A one-way trip made by a person by any mode from an origin to a destination, usually assumed to be without stops. In many models, person trips are the units used in all model steps through mode choice. Person trips are the usual units in transit assignment, but person trips are converted to vehicle trips for highway assignment.

Trip attraction—In four-step models, the trip end of a home-based trip that occurs at the nonhome location, or the destination end of a nonhome-based trip.

Trip production—In four-step models, the trip end of a home-based trip that occurs at the home, or the origin end of a nonhome-based trip.

Vehicle trip—A trip made by a motorized vehicle from an origin to a destination, usually assumed to be without stops. It may be associated with a more-than-one-person trip (for example, in a carpool). Vehicle trips are the usual units in highway assignment, sometimes categorized by the number of passengers per vehicle. In some models, vehicle trips are used as the units of travel throughout the modeling process.

Motorized and nonmotorized trips—Motorized trips are the subset of person trips that are made by auto or transit, as opposed to walking or bicycling trips, which are referred to as **nonmotorized trips**.

In-vehicle time—The total time on a person trip that is spent in a vehicle. For auto trips, this is the time spent in the auto and does not include walk access/egress time. For transit trips, this is the time spent in the transit vehicle and does not include walk access/egress time, wait time, or time spent transferring between vehicles. Usually, transit auto access/egress time is considered in-vehicle time.

Out-of-vehicle time—The total time on a person trip that is not spent in a vehicle. For auto trips, this is usually the walk access/egress time. For transit trips, this is the walk access/egress time, wait time, and time spent transferring between vehicles. In some models, components of out-of-vehicle time are considered separately, while in others, a single out-of-vehicle time variable is used.

CHAPTER 2

Planning Applications Context

The purpose of developing travel forecasting models is to provide information that can be used to make transportation planning decisions. These decisions may require different kinds of information from the model, depending on the context. The planning context, therefore, should be used to determine the appropriate model structure, parameters, and complexity. This decision, in turn, will ensure that the travel forecasting model is appropriate for each planning context. It is useful to develop a travel forecasting model that meets most (if not all) of an agency's current and future planning needs. This chapter discusses how the planning context affects the model's capabilities and provides examples of different contexts found in U.S. urban areas.

2.1 Types of Planning Analyses

The transportation planning function covers a diverse set of activities that focuses on different transportation modes and systems, timeframes, geographic scales, policy issues, and stakeholder groups. It is critical to gather input from a broad cross section of stakeholders on the types of policy considerations and modal analyses that need to be accounted for in the travel demand model prior to its development. Many planning requirements are directed by federal legislation, such as long-range transportation planning and air quality planning. Federal guidelines and regulations regarding transportation planning are summarized by agency in Appendix A. Planning practices for these requirements are generally consistent across areas of the same population. However, many other aspects of particular planning processes reflect state and local requirements, and actual planning practice varies widely. Many of these transportation planning functions require forecasts of future travel or other model outputs to aid in evaluating the benefits of different plan elements and different plans. The type of analysis being performed guides the design of models and the necessary features required to produce suitable forecasts for decision making (project prioritization, for example). Typical types of transportation planning that require travel forecasts are discussed in the following sections. The planning types are adapted from "Planning and Asset Management" (FHWA, 2009b).

2.1.1 Establishing System Performance Measures

The identification of individual performance measures depends on the complexity of the measures, as well as the size and characteristics of the transportation system. Standard metrics, such as vehicle-miles of travel, vehicle-hours of travel, link-based volume-to-capacity ratios, and travel speeds, can be produced by nearly all models, and some of these measures are used in model validation. (However, a model's ability to produce an output metric does not in itself mean that the model has been validated for that metric, and due care should be taken using the results.) More advanced metrics such as travel time reliability; intersection-based, area-based, or multimodal levels of service; hours of delay; or hours of congestion require both the input data and the model functions to calculate the measure for both a current base year and any horizon years. For example, a model that produces only daily traffic assignments will be unable to produce the data for calculating hours of delay without significant modifications. Transportation system performance measurement is a significant stand-alone topic related to the travel demand forecasting process, but too great to cover in the context of this report. *NCHRP Synthesis 311* (Shaw, 2003) and *TCRP Report 88* (Kittelson and Associates et al., 2003) provide a starting point for understanding the development and application of performance measures.

2.1.2 Long-Range Transportation Planning

Federal statutes require an MPO to prepare a long-range transportation plan (LRTP) and set forth many of the planning guidelines. Chief among these is a typical planning horizon of 20 to 30 years. This is not to say that other horizon years cannot be modeled, but the reliability of forecasts with a planning horizon of more than 30 years is highly questionable. Forecasts of less than 20 years may be appropriate for many of the types of planning activities listed below.

In general, for long-range planning, the model must be capable of analyzing, with reasonable accuracy, the impacts of projects that are included in the LRTP. The types of projects included, of course, vary depending on the characteristics of the urban area and its transportation system. In a large urban area, the plan is likely to include both highway and transit projects; therefore, the model must be capable of analyzing the impacts of projects of all travel modes. If road pricing projects are being considered, the model should be capable of considering the effects of price on travel demand. More detail on the required model features for several project types is provided in Sections 2.1.4 through 2.1.8.

If only a limited number of types of projects are included in the LRTP, which is often the case in smaller urban areas, a simpler modeling approach may be appropriate—unless the model is required to perform other analyses outside the long-range planning context that require additional modeling capabilities.

2.1.3 Policy Planning and Analysis

Tests of different policies can range from simple to complex over several dimensions. Modeling changes in population or employment growth rates require different data than do more complex scenarios, such as congestion pricing, changes in parking costs, fuel costs, assumption of realized mode split targets, or changes in high-occupancy vehicle (HOV) policies. Forecasts for all of the above types of analyses are often conducted for a series of both short- and long-term horizon years. For any of these tests, a more robust model set than one used for typical LRTP preparation is required. The constituencies of many MPOs are already demanding that many of these policies be considered as part of the LRTP development, so the model functionality required to perform these types of analyses is present in many agencies, and quickly being added by others. While it may not always be possible to anticipate all of the specific policies that the model may be used to analyze, it makes sense for model developers to consult with other planners and decision makers who may request certain types of analyses. It is important for the model to include the necessary features to support the analyses required for the policies being examined. If pricing is being analyzed, variables reflecting the pricing of various transportation options (tolls, parking, transit fares, etc.) must be included. If alternative land use patterns are analyzed, then variables reflecting land use patterns, such as density and diversity of development, should be included.

2.1.4 Regional and Corridor Planning

This type of analysis requires greater disaggregation of inputs within the study area, particularly for corridor planning. Facilities that might not be coded in a full regional travel network because they have a lower functional classification must be included for a corridor study, if observed data indicate the volume of traffic using the facilities is relevant to analyzing the corridor. Historically, subarea models have been developed for regional and corridor planning, where the level of detail of the transportation system represented by the networks is finer in the area of interest. Many current models already have a fine level of detail throughout the model area. It may be worthwhile to consider having a fine level of resolution appropriate for regional and corridor planning throughout the entire model, especially in smaller urban areas where the computation and model run time implications of a detailed model are not as likely to be severe. Small- and medium-sized agencies, in particular, must balance this consideration against their available resources to support model development and application.

2.1.5 Project Planning and Development

Forecasting the impacts of transportation projects or investments (and land development projects) is even more focused than corridor planning and requires a corresponding sharper focus and disaggregation of inputs and sometimes outputs. In many project planning studies, it is now common for a refined and study area-focused travel demand forecasting model to be one step in a larger forecasting effort that may take the output model forecasts and subsequently use them as inputs to mesoscopic or microscopic dynamic traffic assignment (DTA) or microscopic travel simulation. In these cases, the model must be able to produce compatible outputs. Even if DTA or microsimulation is not employed for project planning, it is almost inevitable that some sort of post-processing of model results must occur. It is reasonable to assume that for most projects, including studies of specific transportation improvements, either independently or as part of specific land development projects (i.e., traffic impact studies), some analysis will be conducted at the intersection level, requiring model output to be post-processed to produce reasonable intersection volumes and turning movements. This is not to say that a model is required for all such analyses; many traffic impact studies, particularly those looking at short-term forecasts, use simpler analytical methods to produce forecasts that do not require a model.

2.1.6 Transit Planning

At a minimum, forecasts for transit planning require a mode choice model and a transit network, with path building, skimming, and transit assignment capabilities. ["Skimming" sums impedances along selected paths identified as the route or path on the transit network that has the lowest cost for a traveler. Depending on the model structure, cost may be actual dollar values (fares) or monetized values of time, distance, or a combination of these and other price components.] A mode choice model, however, can have one of several different forms and specifications, ranging from a diversion table based on local survey data and a reasonable annual growth factor to a more complex nested logit structure. Regardless of the model form, the mode choice model and the entire model chain must be able to address the existing and potential new markets for transit in the study area, both regionally and for specific projects.

Transit project planning, where the project may use the FTA capital funds, has its own series of guidelines and requirements, but the FTA has been careful to avoid being prescriptive about model specifications and forms when issuing guidance, focusing instead on the properties of good modeling practices. Many of these properties focus on quality assurance and quality checks and rigorous model testing to ensure reliable results; these are characteristics of all good forecasts, not just those related to transit projects. The guidelines and requirements increase based on the potential level of federal capital investment in the project: from lowest to highest, these programs are currently known as Very Small Starts, Small Starts, and New Starts. Much of the current FTA guidance on model properties is included in Appendix A. As with certain types of short-term highway forecasts, forecasts for short-range transit service planning also use analytics that do not require a traditional model.

2.1.7 Road Pricing and Managed Lanes

Various aspects of pricing enter into the estimation of travel demand, including tolls, transit fares, parking costs, and auto/truck operating costs, which include fuel costs. This means that, to produce accurate demand forecasts, the model must be properly sensitive to the effects of price on travel demand. This type of sensitivity might require inclusion of price in all relevant travel choice components [mode, route (i.e., assignment); destination (i.e., trip distribution); time of day, etc.], as well as precise representation of time-cost tradeoffs, which requires accurate estimates of travelers' values of time. It also may require nonconstant implied values of travel time or at least market segmentation to approximate varying values of time. Some types of projects, including congestion pricing and projects where peak spreading is likely to be an issue, may require detailed time-of-day model components.

HOV lanes and carpooling incentives are analyzed in some areas using travel models. This type of analysis requires identification of roadways in the model network that require minimum occupancy levels and trip tables corresponding to each occupancy level allowed to use particular facilities. The mode choice model, therefore, must be capable of outputting these trip tables; and the highway assignment must be capable of assigning HOVs and low-occupancy vehicles to the appropriate facilities. If facilities such as HOT lanes are to be analyzed, the model must include the capabilities of both HOV and pricing analysis.

2.1.8 Nonmotorized Transportation Planning

A variety of analysis techniques is in use to forecast nonmotorized travel. Several factoring methods and sketch-planning techniques, such as aggregate demand models, have been employed to address planning needs. (At the time this report was being prepared, NCHRP Project 08-78, "Estimating Bicycling and Walking for Planning and Project Development," was under way, with a report expected by fall 2012.) The number of agencies fully integrating nonmotorized (bicycle and pedestrian) modes into travel demand forecasting is still small; however, there is continued interest in including nonmotorized treatment as part of good planning practice. Several approaches to incorporating nonmotorized travel into regional travel demand forecasting models are in use. Many major urban areas include nonmotorized travel in their trip generation models. Some agencies then immediately apply factors or models to separate motorized from nonmotorized travel. Other agencies carry nonmotorized travel through trip distribution and mode choice, employing a model that includes nonmotorized modes and delivering as outputs trip tables by mode and purpose. Most such models do not include assignment procedures for nonmotorized trips. Typically, the highway network is used as the basis for both walk and bicycle trips, excluding facilities such as freeways, where pedestrians and bicycles are prohibited. Some areas, however, have opted to develop pedestrian or bicycle networks, at least for some parts of the model region.

2.1.9 Freight Planning

At a minimum, an area planning to produce forecasts for freight will need truck modeling procedures incorporated within the model chain. Areas that observe significant truck traffic should model trucks separately, since passenger modeling procedures are not designed to accurately forecast truck movements.

At least three classes of vehicles could be considered:

1. Trucks carrying freight;
2. Trucks not carrying freight (for example, service vehicles); and
3. Other modes of freight transportation (for example, trains).

Most urban transportation planning contexts are concerned primarily with Classes 1 and 2, although certain specialized studies, such as port or freight terminal studies, may require information on Class 3. A truck model that considers Classes 1 and 2 is, therefore, the most common type of truck/freight model found in urban travel models. The truck trip tables created by the process are assigned along with autos in the highway assignment stage.

Estimates of demand for Classes 1 and 3 could be derived from a multimodal freight model, but this is difficult in urban areas since a high percentage of regional freight movements has an origin and/or destination outside the modeled area. In some states, a statewide freight model might be available to produce estimates of demand for vehicle Classes 1 and 3. However, a multimodal freight model does not consider vehicle Class 2, and so these truck trips must still be estimated.

2.1.10 Land Use Planning

The "transportation-land use" connection is a complex issue that continues to be the subject of a significant amount of research. There are several land use-transportation models that are fully integrated with travel demand models. These models consider the effects of accessibility on land use and location decisions, since travel conditions ultimately impact these choices. While there is no consensus on the best type of land use-transportation model to use, most large urban areas and many smaller ones have integrated some sort of land use modeling process. Land use models have their own data requirements and must be estimated, calibrated, and validated in a process separate from the travel demand model (Parsons Brinckerhoff Quade and Douglas, Inc., 1999).

2.1.11 Environmental Planning

While air quality planning has been established for some time by federal conformity requirements for MPOs, other areas, such as energy planning and carbon footprint forecasts, are still emerging at this time. All are interrelated with the transportation system, but the needs for forecasts are still being developed (or not well understood). Air quality planning can be performed at the regional and corridor level with the use of programs, such as MOBILE, MOVES, and EMFAC [the first two programs were developed by the U.S. Environmental Protection Agency (EPA), and the latter was developed for use in California].

These programs, however, generally require more information than typical travel models produce. Such information includes fleet estimates by vehicle size and fuel type; traffic volume and speed information by hour of the day; the operating modes of vehicles (cold start, running exhaust) at different points in the trip; and external factors such as climatic conditions. To produce the required information, many urban areas use "post-processor" programs to convert model outputs to the required format for input into the air quality analysis program. In addition to regional air quality, global climate change and related energy issues are now considered as part of environmental planning within the transportation context, and an increasing number of agencies explicitly model greenhouse gas (GHG) emissions at a project level [see ICF International (2008) and John A. Volpe National Transportation Systems Center (2009)]. It is likely that some of the guidance on these subjects may become formalized as part of the metropolitan planning process during the next federal reauthorization cycle.

Transferable parameters are more useful for some types of transportation planning than for others. If an area is calibrating a model for long-range transportation planning, land use planning, corridor planning, project site planning, or subarea planning that does not include the evaluation of transportation demand management (TDM) or more than minimal transit service, then transferable parameters are useful for calibrating models that will forecast motorized vehicle use. If planning is required to determine the impact of TDM measures or the diversion of automobile trips to other modes, then transferable parameters may be of reduced value. Other approaches, such as sketch-planning methods, may be of more use for these types of planning [see *TCRP Report 95* (Pratt et al., various years 2003 to 2011) and Cambridge Systematics, Inc. (2000)].

2.2 Urban Area Characteristics Affecting Planning and Modeling

Independent of the type of planning analysis to be performed, many urban area characteristics (e.g., population, employment, density) greatly impact both planning and modeling. Some of these characteristics are discussed in this section, and many of

> *TCRP Report 73: Characteristics of Urban Travel Demand* (Reno et al., 2002) presents a comprehensive set of tables on various aspects of urban travel demand assembled based on data from an MPO survey, the Highway Performance Monitoring System, the National Transit Database, and the 1995 National Personal Travel Survey, including demographics, vehicle ownership, trip generation by mode and trip purpose, trip generation by characteristics or origin and destination, trip making by time of day, truck trip parameters, utilization of facilities, parking, and telecommuting. Although the tables in *TCRP Report 73* contain information largely from the 1990s, it does continue to help illustrate differences among specific metropolitan areas for many of the recorded measures.

them directly inform planning and modeling requirements as set forth by federal planning regulations, which are discussed in detail in Appendix A.

2.2.1 Population and Demographics

Population size (greater than 50,000) is one of the urban area indicators that helps establish the formation of an MPO and the subsequent planning and modeling requirements. A separate threshold of 200,000, along with other guidelines, designates a transportation management area (TMA) and creates additional requirements. In general, the greater the population of an urban area, the more complex are the transportation issues, and thus the planning and modeling efforts. However, population size is not the only issue; in fact, other demographic indicators such as income, race, gender, nonnative status, English as a second language, and household size all have potential impacts on aspects of travel considered in the forecasting process. Many of these characteristics are among the most common variables used in trip generation, trip distribution, and mode choice models.

The average age of the population has been increasing for many years and is expected to continue to do so for the foreseeable future. The aging of the population has significant effects on travel behavior, including the percentage of work-related travel, auto mode share, and time of day of travel. The rate of change in the age of the population differs among urban areas, and analysts should be aware of the expected trends in their regions.

2.2.2 Employment and Housing and Other Land Uses

The types, location, and concentration of housing and employment are key factors in an urban area's travel patterns. For work travel, a significant number of trips flow from home to work in the morning and the reverse in the evening. But as work hours change based on economic and travel conditions and the types of jobs in an area, and as both work and home locations become more dispersed, the travel flows become less temporally and geographically regular. This, in turn, affects nonwork travel traditionally made during off-peak periods. A travel demand model in such an area (or in a region with many such areas) would require the ability to forecast off-peak trips, and ideally would include observed off-peak and nonwork travel data for use in validation.

Urban areas vary in terms of the proportion of employment located in the central business district (CBD). The amount of centralization of employment in CBDs and other major activity centers, along with the size of the region, can impact travel behavior such as trip distance, time of day, and trip chaining.

2.2.3 Geographic Size

As with population size, increases in the geographic size of an urban area usually mean more complex planning and modeling issues. But it is also dependent on the land use and the density associated with the geography. All other features being equal, a large area of relatively uniform land uses and densities is more likely to produce uniform travel patterns (that is, little variability in trip purposes, time-of-day distribution, travel modes, trip distances, and other travel characteristics) than a smaller area with diverse land uses and densities.

2.2.4 Development Density, Diversity, Design, and Destinations

The "four Ds" of development—density, diversity, design, and destinations—can have many different effects on planning and modeling. Population (through housing) and employment density are indicators of land use intensity and, in many urban areas, are accompanied by improved pedestrian amenities, such as sidewalks, and transit options. Land use mix, or diversity, can affect motorized trip making; areas with greater mix often permit a wider variety of needs to be satisfied without needing to drive. Urban design elements, such as street pattern, block size, sidewalk coverage and continuity, and pedestrian and transit amenities, can support higher levels of walking and transit use [see *TCRP Report 95,* Chapter 15, "Land Use and Site Design" (Pratt et al., 2003), and Chapter 17, "Transit Oriented Development" (Pratt et al., 2007)]. Accessibility to a variety of destinations can affect mode shares, trip lengths, and trip chaining.

Higher densities mean more people in the same unit of area, and so the number of person trips would be expected to also be greater. However, this concentration of trip ends can be more efficient to serve with good transit service and nonmotorized transportation facilities leading to differences in the type of travel mode, as compared with less dense areas. Level of density is one of the key indicators used for developing area types in travel forecasting models, and the use of such area types is discussed in Chapter 4.

2.2.5 Natural Geography

Any natural feature that creates a travel barrier—from mountain passes to water crossings to buildable versus unbuildable land (not determined solely by regulation)—affects planning and modeling. Such barriers create good locations for screenlines to be used in model validation and must be key targets for practitioners to model accurately, since the facilities crossing them are likely to be high-profile choke points in the regional transportation system. One difference in this category is coastal versus inland urban areas. (The research team preparing this report tested a relationship between coastal and inland areas and travel characteristics using the 2001 NHTS data during initial data development for this report but found no significant relationship. Such a comparison could still be tested with local data, if available.)

2.2.6 Geographic Location within the United States

Growth and population shifts in the United States since 1945 (excluding international immigration) have generally followed a north-to-south, east-to-west flow. "Newer" urban areas, such as Phoenix and Charlotte, have different travel characteristics than older areas, such as Boston and Philadelphia. Some differences may be evident on a mega-regional level as well: travelers may behave differently in the Southwest than the Northeast, or in the Midwest compared with the East Coast and West Coast.

2.2.7 Climate and Climate Change

Prolonged periods of extreme temperatures, either hot or cold, can have an impact on planning and modeling, particularly if the climate results in degradation of or limitations to the transportation system. As noted in Section 2.1.11, global climate change and its impacts (such as rising sea levels) are now also a consideration in the planning and modeling process. However, these still-developing environmental models are considering time horizons beyond the current capabilities of travel forecasting models, so caution should be exercised when selecting analysis tools.

2.2.8 Resort/Nonresort Visitors

Resort areas that experience a significant number of visitors as a percentage of their total travelers—Las Vegas and Orlando, for example—may have different travel characteristics than areas with fewer visitors. Whether the visitors to the area tend to stay for a single day or multiple days is also an issue.

2.2.9 Presence of Alternative Transportation Modes

The presence of (or desire for) modes other than single-occupant vehicles (SOV) means an urban area should consider mode choice modeling. The complexity and specifications are dependent on the type of mode and type of analysis. The introduction of new fixed-guideway transit into an area has been a frequent application of transferable parameters for use in mode choice estimation, calibration, and validation.

2.2.10 Highway Network and Travel Conditions

Highway mileage, both overall and by functional class, and area travel conditions may lead to different requirements for planning and modeling. Areas with significant congestion will likely need to employ travel time feedback in their models to ensure that they are accurately reflecting the effects of congestion on travel behavior. Less congested areas, where more travel is on arterials rather than freeways, will have different considerations when developing volume-delay functions for their models. One indicator of congestion that can differentiate urban areas is the Annual Urban Mobility Report (mobility.tamu.edu/ums/).

2.2.11 External and Through Travel

The level of external and through travel for an urban area can affect travel conditions and may be a consideration in planning and modeling. Areas with significant through travel may be especially concerned with ways to explore diverting that through travel away from the region to help "free up" congested highways. Regions with large external travel components may need to take particular care in coordinating with neighboring jurisdictions to ensure that necessary current year data are available and that reasonable assumptions are made about future year conditions.

2.2.12 Land Use Control and Governance

The ability to regulate land uses, and at what level of geography, can have an impact on planning and the type of modeling required to test future changes. An urban area with a regional government and an urban growth boundary may have different travel characteristics than an urban area with weak counties and home-rule, with local land use control in the hands of hundreds of small municipal civil divisions, such as boroughs, townships, and other municipalities. The latter case is likely to make realization of aggressive shifts in future land use difficult to achieve even if they are modeled well, so planners should consider an appropriate level of land use sensitivity/modeling as they are building their travel forecasting model.

2.2.13 Presence of Special Generators

Small- and medium-sized urbanized areas that include a major university typically have different travel patterns than similar sized cities without a large campus. Presence of a large university indicates a relatively large number of young adults in the region, likely resulting in a larger percentage of school-related trips and part-time retail worker trips outside the peak period and potentially a larger share of bicycle, walking, and transit trips than other similar sized areas.

The presence of a state capital can also potentially impact travel patterns when compared against a similar sized city with a higher proportion of manufacturing employment. A large state worker labor force could result in additional nonhome-based travel out to lunch and running errands; whereas, factory workers typically have minimal mobility while on a time clock.

Cities with very large hub airports also have different trip characteristics reflected in a larger catchment area for their customers and a significant number of travelers spending the night at hotels in proximity to the airport property. If the airport is a freight hub, it is expected that truck traffic would potentially be higher than otherwise similar urban areas.

CHAPTER 3

Data Needed for Modeling

3.1 Introduction

Many data are required for model development, validation, and application. This chapter briefly describes the data used for these functions. Model application data primarily include socioeconomic data and transportation networks. These data form the foundation of the model for an area, and if they do not meet a basic level of accuracy, the model may never adequately forecast travel. When preparing a model, it is wise to devote as much attention as necessary to developing and assuring the quality of input data for both the base year and for the forecast years. This chapter provides an overview of primary and secondary data sources and limitations of typical data.

3.2 Socioeconomic Data and Transportation Analysis Zones

Socioeconomic data include household and employment data for the modeled area and are usually organized into geographic units called transportation analysis zones (TAZs, sometimes called traffic analysis zones or simply zones). Note that some activity-based travel forecasting models operate at a more disaggregate level than the TAZ (for example, the parcel level); however, the vast majority of models still use TAZs. The following discussion of data sources is applicable to any level of model geography.

TAZ boundaries are usually major roadways, jurisdictional borders, and geographic boundaries and are defined by homogeneous land uses to the extent possible. The number and size of TAZs can vary but should generally obey the following rules of thumb when possible:

- The number of residents per TAZ should be greater than 1,200, but less than 3,000;
- Each TAZ should yield less than 15,000 person trips per day; and
- The size of each TAZ should be from one-quarter to one square mile in area.

The TAZ structure in a subarea of particular interest may be denser than in other areas further away. It is important that TAZs are sized and bounded properly (Cambridge Systematics, Inc. and AECOM Consult, 2007). In general, there is a direct relationship between the size and number of zones and the level of detail of the analysis being performed using the model; greater detail requires a larger number of zones, where each zone covers a relatively small land area.

TAZs are typically aggregations of U.S. Census geographic units (blocks, block groups, or tracts with smaller units preferred), which allows the use of census data in model development.

To facilitate the use of U.S. Census data at the zonal level, an equivalency table showing which zones correspond with which census units should be constructed. Table 3.1 provides a brief example of such a table. Once the zone system is developed and mapped and a census equivalency table is constructed, zonal socioeconomic data can be assembled for the transportation planning process.

Estimates of socioeconomic data by TAZ are developed for a base year, usually a recent past year for which necessary model input data are available and are used in model validation. Forecasts of socioeconomic data for future years must be developed by TAZ and are estimated based on future land use forecasts prepared either using a manual process or with the aid of a land use model. As a key input to the travel demand model, the accuracy of socioeconomic forecasts greatly affects the accuracy of a travel demand forecast.

3.2.1 Sources for Socioeconomic Data

Data availability and accuracy, the ability to make periodic updates, and whether the data can be reasonably forecast into the future are the primary criteria in determining what data

Table 3.1. Example TAZ to Census geography equivalency table.

TAZ	Census Block
101	54039329104320
101	54039329104321
101	54039329104322
102	54039329104323
102	54039329104324

Source: Martin and McGuckin (1998).

will be used in a model.[1] With that consideration and the understanding that in some cases it may be an objective to gather base year data for other planning purposes, the following sources should be evaluated. In general, population and household data come from the U.S. Census Bureau and employment data from the Bureau of Labor Statistics (BLS, part of the United States Department of Labor), as well as their equivalent state and local agencies. Many of the programs are collaborations between the two federal agencies. Socioeconomic input data are also available from a number of private vendors.

Population and Households

Four major data sources for population and household information are described in this subsection: decennial U.S. Census, American Community Survey (ACS), ACS Public Use Microdata Samples (PUMS), and local area population data.

Decennial U.S. Census. The decennial census offers the best source for basic population and household data, including age, sex, race, and relationship to head of household for each individual. The census also provides data for housing units (owned or rented). These data are available at the census block level and can be aggregated to traffic zones. The decennial census survey is the only questionnaire sent to every American household with an identifiable address. The 2010 Census is the first since 1940 to exclude the "long form." Previously, approximately one in every six households received the long form, which included additional questions on individual and household demographic characteristics, employment, and journey-to-work. The absence of the long form means that modelers must obtain these data (if available) from other sources, such as the American Community Survey (see below).

American Community Survey. The ACS has replaced the decennial census long form. Information such as income, education, ethnic origin, vehicle availability, employment status, marital status, disability status, housing value, housing costs, and number of bedrooms may be obtained from the ACS. The ACS content is similar to the Census 2000 long form, and questions related to commuting are about the same as for the long form, but the design and methodology differ.

Rather than surveying about 1 in every 6 households once every 10 years, as had been done with the long form, the ACS samples about 1 in every 40 addresses every year, or 250,000 addresses every month. The ACS uses household addresses from the Census Master Address File that covers the entire country each year. The ACS thus samples about 3 million households per year, translating into a less than 2.5 percent sample per year. As a result of the smaller sample size, multiple years are required to accumulate sufficient data to permit small area tabulation by the Census Bureau in accordance with its disclosure rules. Table 3.2 highlights the ACS products, including the population and geography thresholds associated with each period of data collection. The sample size for the ACS, even after 5 years of data collection, is smaller than the old census long form. Thus, ACS's 5-year estimates have margins of error about 1.75 times as large as those associated with the 2000 Census long form estimates, and this must be kept in mind when making use of the data. AASHTO and the FHWA offer Internet resources providing additional detail on ACS data and usage considerations.

ACS Public Use Microdata Samples. The Census Bureau produces the ACS PUMS files so that data users can create custom tables that are not available through pretabulated data products (U.S. Census Bureau, 2011a). The ACS PUMS files are a set of untabulated records about individual people or housing units. PUMS files show the full range of population and housing unit responses collected on individual ACS questionnaires. For example, they show how respondents answered questions on occupation, place of work, etc. The PUMS files contain records for a subsample of ACS housing units and group quarters persons, with information on the characteristics of these housing units and group quarters persons plus the persons in the selected housing units.

The Census Bureau produces 1-year, 3-year, and 5-year ACS PUMS files. The number of housing unit records contained in a 1-year PUMS file is about 1 percent of the total in the nation, or approximately 1.3 million housing unit records and about 3 million person records. The 3-year and 5-year ACS PUMS files are multiyear combinations of the 1-year PUMS files

[1]The explanatory power of a given variable as it relates to travel behavior must also be considered; however, such consideration is subordinate to the listed criteria. A model estimated using best-fit data that cannot be forecast beyond the base year, for example, provides little long-term value in forecasting.

Table 3.2. ACS data releases.

Data Product	Population Threshold	Geographic Threshold	Years Covered by Planned Year of Release			
			2010	2011	2012	2013
1-year estimates	65,000+	PUMAs, counties, large cities	2009	2010	2011	2012
3-year estimates	20,000+	Counties, large cities	2007–2009	2008–2010	2009–2011	2010–2012
5-year estimates	All areas*	Census tracts, block groups in summary file format	2005–2009	2006–2010	2007–2011	2008–2012

*5-year estimates will be available for areas as small as census tracts and block groups.
Source: U.S. Census Bureau.

with appropriate adjustments to the weights and inflation adjustment factors. They typically cover large geographic areas with a population greater than 100,000 [Public Use Microdata Areas (PUMAs)] and, therefore, have some limits in application for building a socioeconomic database for travel forecasting, but can be helpful because of the detail included in each record. PUMS data are often used as seed matrices in population synthesis to support more disaggregate levels of modeling (such as activity-based modeling). PUMS users may also benefit from looking at Integrated PUMS (IPUMS), which makes PUMS data available for time series going back over decades with sophisticated extract tools.

Local area population data. Some local jurisdictions collect and record some type of population data. In many metropolitan areas, the information is used as base data for developing cooperative population forecasts for use by the MPO as travel model input.

Employment

Obtaining accurate employment data at the TAZ level is highly desirable but more challenging than obtaining household data for a number of reasons, including the dynamic nature of employment and retail markets; the difficulty of obtaining accurate employee data at the site level; and lack of an equivalent control data source, such as the U.S. Census, at a small geographic level. Six potential sources of data are discussed in this subsection.

Quarterly Census of Employment and Wages. Previously called ES-202 data, a designation still often used, the Quarterly Census of Employment and Wages (QCEW) provides a quarterly count of employment and wages at the establishment level (company names are withheld due to confidentiality provisions), aggregated to the county level and higher (state, metropolitan statistical area). Data are classified using the North American Industry Classification System (NAICS). The QCEW is one of the best federal sources for at-work employment information.

State employment commissions. State employment commissions generally document all employees for tax purposes. Each employer is identified by a federal identification number, number of employees, and a geocodable address usually keyed to where the payroll is prepared for the specified number of employees.

Current Population Survey. The Current Population Survey (CPS) is a national monthly survey of about 50,000 households to collect information about the labor force. It is a joint project of the Census Bureau and the BLS. The CPS may be useful as a comparison between a local area's labor force characteristics and national figures.

Market research listings. Many business research firms (e.g., Infogroup, Dun and Bradstreet, etc.) sell listings of all (or major) employers and number of employees by county and city. These listings show business locations by street addresses, as well as post office boxes.

Longitudinal Employer–Household Dynamics. Longitudinal Employer–Household Dynamics (LEHD) (U.S. Census Bureau, 2011b) is a program within the U.S. Census Bureau that uses statistical and computational techniques to combine federal and state administrative data on employers and employees with core Census Bureau censuses and surveys. LEHD excludes some employment categories, including self-employed and federal workers, and data are not generated for all states (i.e., Connecticut, Massachusetts, and New Hampshire as well as the District of Columbia, Puerto Rico, and the U.S. Virgin Islands as of September 2011). Users of LEHD should also be mindful of limitations with the methodology used to assemble the data, including the use of Minnesota data as the basis for matching workers to workplace establishments and the match (or lack of match) with Census Transportation Planning Products (discussed below). Murakami (2007) provides an examination and discussion of LEHD issues for transportation planners. The LEHD Quarterly Workforce Indicators (QWI) report is a useful source for modelers, particularly as a complement to the QCEW.

Local area employment data. Few areas record employment data other than a broad listing of major employers with the highest number of employees locally, typically reported by a local chamber of commerce or similar organization.

Special Sources

Census Transportation Planning Products. Previously called the Census Transportation Planning Package, the Census Transportation Planning Products (CTPP) Program (AASHTO, 2011) is an AASHTO-sponsored data program funded by member state transportation agencies and operated with support from the FHWA, Research and Innovative Technology Administration, FTA, U.S. Census Bureau, MPOs, state departments of transportation (DOTs), and the TRB. CTPP includes tabulations of interest to the transportation community for workers by place of residence, place of work, and for flows between place of residence and place of work. CTPP are the only ACS tabulations that include flow information. Examples of special dimensions of tabulation include travel mode, travel time, and time of departure.

CTPP are most frequently used as an observed data source for comparison during model validation, but are sometimes used as a primary input in model development, particularly in small areas where local survey data are unavailable. The previous CTPP tabulations were based on the decennial census long form. The CTPP 2006 to 2008 is based on the ACS and is available at the county or place level for geography meeting a population threshold of 20,000. The CTPP 2006 to 2010, anticipated to be available in 2013, will provide data at the census tract, CTPP TAZ, and CTPP Transportation Analysis District (TAD) levels. ACS margin of error considerations apply to the CTPP.

Aerial photography. Often aerial or satellite photographs available at several locations on the Internet can be used to update existing land use, which can then be used as a cross-check in small areas to ensure that population and employment data are taking into account changes in land use. It is crucial to know the date of the imagery (when the pictures were taken) prior to using it for land use updates. Aerial photography is also useful in network checking, as discussed later.

Other commercial directories. Some commercial directories provide comprehensive lists of household and employment data sorted by name and address. For households, such information as occupation and employer can be ascertained from these sources. For business establishments, type of business—including associations, libraries, and organizations that may not be on the tax file—can be determined. Other commercial databases provide existing and forecasted households and employment by political jurisdictions.

Other sources. Data on school types, locations, and enrollment are typically obtained directly from school districts and state departments of education (DOE). Large private schools might have to be contacted directly to obtain this information if the state DOE does not maintain records for such schools.

3.2.2 Data Source Limitations

Population

The main data source to establish a residential database is the decennial census. Other sources do not provide comparable population statistics by specific area (i.e., block level). Often, the base year for modeling does not conform to a decennial census. In that case, data from the decennial census should be used as the starting point and updated with available data from the census and other sources to reflect the difference between the decennial census year and the base year.

Employment

Each of the previously identified data sources has some deficiency in accurately specifying employment for small geographic areas:

- The census provides total labor force by TAZ; however, this represents only employment location of residents and not total employment.
- The census also shows labor force statistics by industry group but does not compile this by employer and specific geographic area (i.e., block).
- The CTPP counts employed persons, not jobs. For persons with more than one job, characteristics on only the principal job are collected.
- Considerations regarding margin of error apply to use of CTPP or ACS data (or any data for that matter).
- The employment commission data may provide accurate employment for each business but only partially list street addresses.
- Market research listings have all employers by street address. Although these listings are extensive, the accuracy is controlled internally and often cannot be considered comprehensive (because of the lack of information regarding

collection methodology), but it offers a check for other data sources.

- The land use data obtained from aerial photography provide a geographic location of businesses but do not provide numbers of employees.
- Employment commission data (as well as other data on employers) often record a single address or post office box of record; employee data from multiple physical locations may be aggregated when reported (i.e., the headquarters of a firm may be listed with the total employment combined for all establishments).
- Government employment is not included in some data sources (including market research listings) or is included incompletely. Government employment sites are often either double-counted in commercially available data sources or "lumped" (i.e., multiple sites reported at one address). For example, public school employees are not always assigned to the correct schools.

Employment data are the most difficult data component to collect. None of the data sources alone offers a complete inventory of employment by geographic location. Therefore, the methodology for developing the employment database should be based on the most efficient and accurate method by which employment can be collected and organized into the database file. All data must be related to specific physical locations by geocoding. Planning for supplementary local data collection remains the best option for addressing deficiencies in source data on employment; however, this effort must be planned several years in advance to ensure that resources can be made available for survey development, administration, and data analysis. For all sources of socioeconomic data, users must be aware of disclosure-avoidance techniques applied by the issuing agency and their potential impact on their use in model development.

3.2.3 Base and Forecast Year Control Totals for the Database

The control totals for the database should be determined before compilation of the data. The source of the control totals for population should be the decennial census. Control totals for employment at the workplace location are more difficult to establish; however, the best source is usually the QCEW or state employment commission data.

When the most recent census data are several years old, it may be desirable to have a more recent base year for the model, especially in faster growing areas. This means that some data may not be available at the desired level of detail or segmentation—for example, the number of households for a more recent year may be available, but not the segmentation by income level. Analysts often use detailed information from the most recent year for which it is available to update segmentations, such as applying percentages of households by segment from the census year to the total number of households for a more recent year. In some cases, estimates of totals (for example, employment by type) may not be available at all for the base year. Other data sources, such as building permits, may be used to produce estimates for more recent years, building upon the known information for previous years.

Census data are, of course, unavailable for forecast years. Some of the agencies discussed above—as well as state agencies, counties, and MPOs—produce population, housing, and employment forecasts. Such forecasts are often for geographic subdivisions larger than TAZs, and other types of segmentation may also be more aggregate than in data for past years. This often means that analysts must disaggregate data for use as model inputs. Data are typically disaggregated using segmentation from the base year data, often updated with information about land use plans and planned and proposed future developments.

3.3 Network Data

The estimation of travel demand requires an accurate representation of the transportation system serving the region. The most direct method is to develop networks of the system elements. All models include a highway network; models that include transit elements and mode choice must also include a transit network. Sometimes, a model includes a bicycling or a walk network. Accurate transportation model calibration and validation require that the transportation networks represent the same year as the land use data used to estimate travel demand.

3.3.1 Highway Networks

The highway network defines the road system in a manner that can be read, stored, and manipulated by travel demand forecasting software. Highway networks are developed to be consistent with the TAZ system. Therefore, network coding is finer for developed areas containing small zones and coarser for less-developed areas containing larger zones. The types of analyses, for which the model will be used, determine the level of detail required. A rule of thumb is to code in roads one level below the level of interest for the study. One highway network may be used to represent the entire day, but it may be desirable to have networks for different periods of the day that include operational changes, such as reversible lanes or peak-period HOV lanes. Multiple-period networks can be stored in a single master network file that includes period or alternative-specific configurations for activation and deactivation.

Each TAZ has a centroid, which is a point on the model network that represents all travel origins and destinations in a zone. Zone centroids should be located in the center of activity (not necessarily coincident with the geographic center) of the zone, using land use maps, aerial photographs, and local knowledge. Each centroid serves as a loading point to the highway and transit systems and, therefore, must be connected to the model network.

Sources for Network Data

Digital street files are available from the Census Bureau (TIGER/Line files), other public sources, or several commercial vendors and local GIS departments. Selecting the links for the coded highway network requires the official functional classification of the roadways within the region, the average traffic volumes, street capacities, TAZ boundaries, and a general knowledge of the area. Other sources for network development include the FHWA National Highway Planning Network, Highway Performance Monitoring System (HPMS), Freight Analysis Framework Version 3 (FAF3) Highway Network, National Transportation Atlas Database, and various state transportation networks. All of these resources may be useful as starting points for development or update of a model network. However, there are limitations with each in terms of cartographic quality; available network attributes; source year; and, especially with commercial sources, copyrights, which should be considered when selecting a data source to use.

In states where the state DOT has a database with the roadway systems already coded, the use of the DOT's coded network can speed up the network coding process. Questions can be directed to the DOT; and such a working relationship between DOT and MPO helps the modeling process because both parties understand the network data source.

Highway Network Attributes

Highway links are assigned attributes representing level of service afforded by the segment and associated intersections. Link distance based on the true shape of the roadway (including curvature and terrain), travel time, speed, link capacity, and any delays that will impact travel time must be assigned to the link. Characteristics, such as the effect of traffic signals on free-flow travel time, should be considered (see Parsons Brinckerhoff Quade & Douglas, 1992). Three basic items needed by a transportation model to determine impedance for the appropriate assignment of trips to the network are distance, speed, and capacity. Additional desirable items may include facility type and area type.

Facility Type and Area Type

The link attributes facility type and area type are used by many agencies to determine the free-flow speed and per-lane hourly capacity of each link, often via a two-dimensional look-up table.

Area type refers to a method of classifying zones by a rough measure of land use intensity, primarily based on population and employment density. A higher intensity of land use generally means more intersections, driveways, traffic signals, turning movements, and pedestrians, and, therefore, slower speeds. Sometimes, roadway link speeds and capacities are adjusted slightly based on the area type where they are located. Common area type codes include central business district (CBD), CBD fringe, outlying business district, urban, suburban, exurban, and rural. The definition of what is included in each area type is somewhat arbitrary since each study area is structured differently. In some models, area type values are assigned during the network building process on the basis of employment and population density of the TAZ centroid that is nearest to the link (Milone et al., 2008). Note that, since area type definitions are aggregate and "lumpy," their use in models may result in undesirable boundary effects. In many cases, use of continuous variables will be superior to use of aggregate groupings of zone types.

Facility type is a designation of the function of each link and is a surrogate for some of the characteristics that determine the free-flow capacity and speed of a link. Facility type may be different from functional classification, which relates more to ownership and maintenance responsibility of different roadways. Table 3.3 provides common facility types used by some modeling agencies. Features, such as HOV lanes, tolled lanes, and reversible lanes, are usually noted in network coding to permit proper handling but may not be facility types per se for the purposes of typical speed/capacity look-up tables.

Link Speeds

Link speeds are a major input to various model components. The highway assignment process relates travel times and speeds on links to their volume and capacity. This process requires what are commonly referred to as "free-flow" speeds. Free-flow speed is the mean speed of passenger cars measured during low to moderate flows (up to 1,300 passenger cars per hour per lane).

Free-flow link speeds vary because of numerous factors, including:

- Posted speed limits;
- Adjacent land use activity and its access control;
- Lane and shoulder widths;

Table 3.3. Typical facility type definitions.

Facility Type	Definition	Link Characteristics
Centroid Connectors	Links that connect zones to a network that represent local streets or groups of streets.	High capacity and low speed
Freeways	Grade-separated, high-speed, high-capacity links. Freeways have limited access with entrance and exit ramps.	Top speed and capacity
Expressways	Links representing roadways with very few stop signals serving major traffic movements (high speed, high volume) for travel between major points.	Higher speed and capacity than arterials, but lower than freeways
Major Arterials	Links representing roadways with traffic signals serving major traffic movements (high speed, high volume) for travel between major points.	Lower speed and capacity than freeways and expressways, but more than other facility types
Minor Arterials	Links representing roadways with traffic signals serving local traffic movements for travel between major arterials or nearby points.	Moderate speed and capacity
Collectors	Links representing roadways that provide direct access to neighborhoods and arterials.	Low speed and capacity
Ramps	Links representing connections to freeways and expressways from other roads.	Speeds and capacity between a freeway and a major arterial

- Number of lanes;
- Median type;
- Provision of on-street parking;
- Frequency of driveway access; and
- Type, spacing, and coordination of intersection controls.

Transportation models can use any of several approaches to simulate appropriate speeds for the links included in the network. Speeds should take into account side friction along the road, such as driveways, and the effect of delays at traffic signals.

One way to determine the free-flow speed is to conduct travel time studies along roadways included in the network during a period when traffic volumes are low and little if any delay exists. This allows the coding of the initial speeds based on observed running speeds on each facility. Speed data are also available from various commercial providers (e.g., Inrix); and in some jurisdictions, speed information on certain facilities is collected at a subsecond level. An alternative approach is to use a free-flow speed look-up table. Such a table lists default speeds by area and facility type, which are discussed later.

Although regional travel demand forecasting validation generally focuses on volume and trip length-related measures, there is often a desire to look at loaded link speeds and travel times. The analyst should be cognizant that "model time" may differ from real-world time due to the many network simplifications present in the modeled world, among other reasons. Looking at changes in time and speed can be informative (e.g., by what percentage are speeds reduced/travel times increased). When looking at such information for the validation year, a variety of sources may be available for comparative purposes, including probe vehicle travel time studies, GPS data collection, and commercial data.

Link Capacity

In its most general sense, capacity is used here as a measure of vehicles moving past a fixed point on a roadway in a defined period of time; for example, 1,800 vehicles per lane per hour. In practice, models do not uniformly define capacity. Some models consider capacity to be applied during free-flow, uncongested travel conditions, while others use mathematical formulas and look-up tables based on historical research on speed-flow relationships [e.g., Bureau of Public Roads (BPR) curves and other sources] in varying levels of congestion on different types of physical facilities. Throughout this report, the authors have tried to specify what is meant for each use of "capacity."

The definitive reference for defining highway capacity is the *Highway Capacity Manual* (Transportation Research Board, 2010), most recently updated in 2010. "Capacity" in a traffic engineering sense is not necessarily the same as the capacity variable used in travel demand model networks. In early travel models, the capacity variable used in such volume-delay functions as the BPR formula represented the volume at Level of Service (LOS) C; whereas, in traffic engineering, the term "capacity" traditionally referred to the volume at LOS E. The *Highway Capacity Manual* does contain useful information for the computation of roadway capacity, although many of the factors that affect capacity, as discussed in the manual, are not available in most model highway networks.

Link capacities are a function of the number of lanes on a link; however, lane capacities can also be specified by facility and area type combinations. Several factors are typically used to account for the variation in per-lane capacity in a highway network, including:

- Lane and shoulder widths;
- Peak-hour factors;
- Transit stops;
- Percentage of trucks[2];
- Median treatments (raised, two-way left turn, absent, etc.);
- Access control;
- Type of intersection control;
- Provision of turning lanes at intersections and the amount of turning traffic; and
- Signal timing and phasing at signalized intersections.

Some models use area type and facility type to define per lane default capacities and default speed. The number of lanes should also be checked using field verification or aerial or satellite imagery to ensure accuracy.

Some networks combine link capacity and node capacity to better define the characteristics of a link (Kurth et al., 1996). This approach allows for a more refined definition of capacity and speed by direction on each link based on the characteristics of the intersection being approached. Such a methodology allows better definition of traffic control and grade separation at an intersection.

Typical Highway Network Database Attributes

The following highway network attributes are typically included in modeling databases:

- Node identifiers, usually numeric, and their associated x-y coordinates;
- Link identifiers, either numeric, defined by “A” and “B” nodes, or both;
- Locational information (e.g., zone, cutline, or screenline location);
- Link length/distance;
- Functional classification/facility type, including the divided or undivided status of the link’s cross section;
- Number of lanes;
- Uncongested (free-flow) speed;
- Capacity;
- Controlled or uncontrolled access indicator;
- One-way versus two-way status;
- Area type; and
- Traffic count volume (where available).

3.3.2 Transit Networks

Most of the transit network represents transit routes using the highways, so the highway network should be complete before coding transit. Transit network coding can be complex. Several different modes (e.g., express bus, local bus, light rail, heavy rail, commuter rail, bus rapid transit) may exist in an area; and each should have its own attribute code. Peak and off-peak transit service likely have different service characteristics, including headways, speeds, and possibly fares; therefore, separate peak and off-peak networks are usually developed. The transit networks are developed to be consistent with the appropriate highway networks and may share node and link definitions.

Table 3.4 is a compilation of transit network characteristics that may be coded into a model’s transit network. Characteristics in italics, such as headway, must be included in all networks, while the remaining characteristics, such as transfer penalty, may be needed to better represent the system in some situations.

Transit networks representing weekday operations in the peak and off-peak periods are usually required for transit modeling; sometimes, separate networks may be required for the morning and afternoon peak periods, as well as the mid-day and night off-peak periods.

The development of bus and rail networks begins with the compilation of transit service data from all service providers in the modeled area. Transit networks should be coded for a typical weekday situation, usually represented by service provided in the fall or spring of the year.

Two types of data are needed to model transit service: schedule and spatial (the path each route takes). Although the data provided by transit operators will likely contain more detail than needed for coding a transit network, software can be used to calculate, for each route, the average headway and average run time during the periods for which networks are created.

Transit Line Files

Local bus line files are established “over” the highway network. Sometimes nodes and links, which are coded below the grain of the TAZ system, must be added to the highway network so that the proximity of transit service to zonal

[2]Facilities experiencing greater-than-typical truck traffic (say, greater than 5 percent for urban facilities; greater than 10 percent for nonurban facilities) have an effective reduction in capacity available for passenger cars (i.e., trucks reduce capacity available by their passenger car equivalent value, often a simplified value of 2 is used). Trucks in this context are vehicles F5 or above on the FHWA classification scheme, the standard *Highway Capacity Manual* definition.

Table 3.4. Transit network characteristics and definitions.

Transit Network Characteristic	Description
Drive access link	A link that connects TAZs to a transit network via auto access to a park-and-ride or kiss-and-ride location.
*Effective headway**	The time between successive transit vehicles on multiple routes with some or all stops in common.
Headway	The time between successive arrivals (or departures) of transit vehicles on a given route.
Local transit service	Transit service with frequent stops within a shared right-of-way with other motorized vehicles.
Mode number	Code to distinguish local bus routes from express bus, rail, etc.
Park-and-ride-to-stop link	A walk link between a park-and-ride lot and a bus stop, which is used to capture out-of-vehicle time associated with auto access trips, and also for application of penalties associated with transfers.
Premium transit service	Transit service (e.g., bus rapid transit, light rail transit, heavy rail, commuter rail) with long distances between infrequent stops that may use exclusive right-of way and travel at speeds much higher than local service.
Route description	Route name and number/letter.
Run time	The time in minutes that the transit vehicle takes to go from the start to the finish of its route and a measure of the average speed of the vehicle on that route.
Transfer link	A link used to represent the connection between stops on two transit lines that estimates the out-of-vehicle time associated with transfers, and also for application of penalties associated with transfers.
Transfer penalty	Transit riders generally would rather have a longer total trip without transfers than a shorter trip that includes transferring from one vehicle to another; therefore, a penalty is often imposed on transfers to discourage excess transfers during the path-building process.
Walk access link	A link that connects TAZs to a transit network by walking from a zone to bus, ferry, or rail service; usually no longer than one-third mile for local service and one-half mile for premium service (some modeling software distinguishes access separately from egress).
Walking link	A link used exclusively for walking from one location to another. These links are used in dense areas with small TAZs to allow trips to walk between locations rather than take short transit trips.

*Italics indicate characteristics that must be included in all networks.

activity centers can be more accurately represented. These subzonal highway links, which are used to more accurately reflect transit route alignments, should be disallowed from use during normal highway path-building and highway assignments. Local bus stops are traditionally coded at highway node locations.

Transit line files can be designated for different types of service or different operators using mode codes, which designate a specific provider (or provider group) or type of service. Premium transit line files that operate in their own right-of-way are coded with their own link and node systems rather than on top of the highway network. Some modeling software requires highway links for all transit links, thus, necessitating the coding of "transit only" links in the highway network. The modeler may not be provided with detailed characteristics for transit services that do not already exist in the modeled area and may need guidance with regard to what attribute values should be coded for these new services (FTA, 1992). Each transit line can be coded uniquely and independently so that different operating characteristics by transit line can be designated.

Transit line files contain information about transit lines, such as the headway, run time, and itinerary (i.e., the sequence of nodes taken by the transit vehicle as it travels its route). Some models compute the transit speed as a function of underlying highway speed instead of using a coded run time. Line files are time-of-day specific, so there is a set of line files for each time period for which a network is coded. One can usually designate stops as board-only or alight-only (useful for accurately coding express bus service). Similarly, one can code run times for subsections of a route, not just for the entire route; a feature useful for the accurate depiction of transit lines that undergo extensions or cutbacks, or which travel through areas with different levels of congestion. One can also store route-specific comments (such as route origin, route destination, and notes) in line files.

Access Links

It is assumed that travelers access the transit system by either walking or driving. Zone centroids are connected to the transit system via a series of walk access and auto access paths. In the past, modeling software required that walk access and auto access links be coded connecting each zone centroid to the transit stops within walking or driving distance. These separate access links are still seen, particularly in models that have been converted from older modeling software packages. Current modeling software generally allows walk or auto access paths to be built using the highway network links, including, where appropriate, auxiliary links that are not available to vehicular traffic (such as walking or bicycle paths).

Walk paths are coded to transit service that is within walking distance of a zone to allow access to and egress from transit service. The maximum walking distance may vary depending on urban area, with larger urban areas usually having longer maximum walk distances although generalizations about typical values could be misleading. The best source for determining maximum walk distances is an on-board survey of transit riders. Some models may classify "short" and "long" walk distances.

Auto access paths are used to connect zones with park-and-ride facilities or train stations. Auto access paths are coded for zones that are not within walking distance (as classified by that model) of transit service but are deemed to be used by transit riders from a zone. A rule-based approach (for example, maximum distance between the zone centroid and the stop) is often used to determine which zones will have auto access to which stops. Again, the best source for determining which zones should have auto access is an on-board survey of transit riders.

Travel Times and Fares

The time spent on transit trips—including time spent riding on transit vehicles, walking or driving to and from transit stops, transferring between transit lines, and waiting for vehicles—must be computed. This computation is done by skimming the transit networks for each required variable (for example, in-vehicle time, wait time, etc.). In-vehicle times are generally computed from the network links representing transit line segments, with speeds on links shared with highway traffic sometimes computed as a function of the underlying (congested) highway speed. Wait times are usually computed from headways with one-half of the headway representing the average wait time for frequent service and maximum wait times often used to represent infrequent service where the travelers will know the schedules and arrange their arrival times at stops accordingly. Auto access/egress times are often computed from highway networks. Walk access/egress times are sometimes computed assuming average speeds applied to distances from the highway networks.

Transit fares used in the mode choice process must be computed. The process may need to produce multiple fare matrices representing the fare for different peak and off-peak conditions. This can be done in multiple ways. If the fare system is distance based, then transit fares can be calculated by the modeling software by skimming the fare over the shortest path just as the time was skimmed. Systems that use one fare for all trips in the study area can assign a fare to every trip using transit. More complex systems with multiple fare tariffs will require unique approaches that may be a combination of the previous two or require the use of special algorithms. Some transit systems require transfer fares that are applied whenever a rider switches lines or from one type of service to another.

3.3.3 Updating Highway and Transit Networks

Transportation networks change over time and must be coded to represent not only current conditions for the base year, but also forecasting scenarios so that models can be used to forecast the impact of proposed changes to the highway network. Socioeconomic data and forecasts must also be updated, and these can affect network attributes (for example, area type definitions that depend on population and employment density).

It is good transportation planning practice to have a relatively up-to-date base year for modeling, particularly when there are major changes to the supply of transportation facilities and/or newer socioeconomic data available. Many of the same data sources, such as digitized street files, aerial photographs, and state and local road inventories, can be used to update the network to a new base year. A region's Transportation Improvement Program (TIP) and state and local capital improvement programs (CIPs) are also very useful for updating a network representing an earlier year to a more recent year. Traffic volumes and transit ridership coded in the network should also be updated for the new base year.

Most MPOs and many local governments use models to evaluate short- and long-range transportation plans to determine the effect of changes to transportation facilities in concert with changes in population and employment and urban structure on mobility and environmental conditions in an area. Updating the transportation network to a future year requires some of the same data sources, as well as additional ones. In addition to TIPs and CIPs, master plans, long-range transportation plans, comprehensive plans, and other planning documents may serve as the source of network updates.

3.3.4 Network Data Quality Assurance

Regardless of the sources, network data should be checked using field verification or an overlay of high-resolution aerials or satellite imagery.

Visual inspection cannot be used to verify certain link characteristics, such as speed and traffic volume, which may often be verified using databases and GIS files available from state DOTs or other agencies. One approach used to verify coded distances is to use the modeling software to build two zone-to-zone distance matrices: the first using airline distance calculated using the x-y coordinates for each centroid, and the second using the over-the-road distance calculated from paths derived using the coded distance on each link. If one matrix is divided by the other, the analyst can look at the results and identify situations where the airline distance is greater than the over-the-road distance, or where the airline distance is much lower. These situations should be investigated to determine if they are the result of a coding error.

Coded speeds can be checked in a similar fashion by creating skim trees (time between zone matrices) for each mode and dividing them by the distance matrix. Resulting high or low speeds should be investigated to determine if they are the result of coding errors.

There are other data sources that may be used for reasonableness checking of roadway networks. For example, the HPMS has network data that may be used to check model networks.

Quality assurance applies to transit networks, as well as highway networks. Local data sources may be available to check the networks against. For example, transit operators can often provide line-level data on run times, service hours, and service miles, which can be compared to model estimates of the same.

The *Travel Model Validation and Reasonableness Checking Manual, Second Edition* (Cambridge Systematics, Inc., 2010b) includes detailed discussions of other transit network checking methods, including comparing modeled paths to observed paths from surveys and assigning a trip table developed from an expanded transit survey to the transit network.

3.4 Validation Data

Model validation is an important component of any model development process. As documented in the *Travel Model Validation and Reasonableness Checking Manual, Second Edition* (Cambridge Systematics, Inc., 2010b), planning for validation and ensuring that good validation data are available are tasks that should be performed as an integral part of the model development process.

Model validation should cover the entire modeling process, including checks of model input data and all model components. While reproduction of observed traffic counts and transit boardings may be important validation criteria, they are not sufficient measures of model validity. Adjustments can be made to any model to reproduce base conditions. Pendyala and Bhat (2008) provide the following comments regarding travel model validation:

> There is no doubt that any model, whether an existing four-step travel demand model or a newer tour- or activity-based model, can be adjusted, refined, tweaked, and—if all else fails—hammered to replicate base year conditions. Thus, simply performing comparisons of base year outputs from four-step travel models and activity-based travel models alone (relative to base year travel patterns) is not adequate . . . the emphasis needs to be on capturing travel behavior patterns adequately from base year data, so that these behavioral patterns may be reasonably transferable in space and time.

3.4.1 Model Validation Plan

The development of a model validation plan at the outset of model development or refinement is good model development practice. The validation plan should establish model validation tests necessary to demonstrate that the model will produce credible results. Such tests depend, in part, on the intended uses of the model. Validation of models intended for support of long-range planning may have increased focus on model sensitivity to key input variables and less focus on the reproduction of traffic counts or transit boardings. Conversely, models intended for support of facility design decisions or project feasibility probably require a strong focus on the reproduction of traffic counts or transit boardings.

The validation plan should identify tests and validation data for all model components. A good approach for the development of a validation plan is to identify the types of validation tests and the standards desired (or required) prior to identifying whether the required validation data are available. Then, once the tests and required data have been identified, the available validation data can be identified and reviewed. Data deficiencies can then be pinpointed and evaluated against their importance to the overall model validation, as well as the cost, time, and effort required to collect the data.

3.4.2 Example Model Validation Tests

Ideally, model validation tests should address all model components. The list of tests shown in Table 3.5 was developed by a panel of travel modeling experts who participated in the May 2008 Travel Model Improvement Program Peer Exchange on Travel Model Validation Practices (Cambridge Systematics, Inc., 2008b). The table is intended to provide examples of tests and sources of data that may be used to validate travel models.

Table 3.5. Example primary and secondary model validation tests.

Model Component	Primary Tests	Secondary Tests	Potential Validation Data Sources
Networks/Zones	• Correct distances on links • Network topology, including balance between roadway network detail and zone detail • Appropriateness of zone size given spatial distribution of population and employment • Network attributes (managed lanes, area types, speeds, capacities) • Network connectivity • Transit run times	• Intrazonal travel distances (model design issue) • Zone structure compatibility with transit analysis needs (model design issue) • Final quality control checks based on review by end users • Transit paths by mode on selected interchanges	• GIS center line files • Transit on-board or household survey data
Socioeconomic Data/Models	• Households by income or auto ownership • Jobs by employment sector by geographic location • Locations of special generators • Qualitative logic test on growth • Population by geographic area • Types and locations of group quarters • Frequency distribution of households and jobs (or household and job densities) by TAZ	• Dwelling units by geographic location or jurisdiction • Households and population by land use type and land use density categories • Historical zonal data trends and projections to identify "large" changes (e.g., in autos/ household from 1995 to 2005)	• Census SF-3 data • QCEW • Private sources, such as Dun & Bradstreet
Trip Generation	• Reasonableness check of trip rates versus other areas • Logic check of trip rate relationships	• Checks on proportions or rates of nonmotorized trips • Reasonableness check of tour rates • Cordon lines by homogeneous land use type	• Chapter 4 of this report • Traffic counts (or intercept survey data) for cordon lines • Historic household survey data for region • NHTS (2001 or 2009)
Trip Distribution	• Trip length frequency distributions (time and distance) by market segments • Worker flows by district • District-to-district flows/desire lines • Intrazonal trips • External station volumes by vehicle class	• Area biases (psychological barrier—e.g., river) • Use of k-factors (Design Issue) • Comparison to roadside intercept origin-destination surveys • Small market movements • Special groups/markets • Balancing methods	• ACS/CTPP data • Chapter 4 of this report • Traffic counts (or intercept survey data) for screenlines • Historic household survey data for region • NHTS (2001 or 2009)

(continued on next page)

Table 3.5. (Continued).

Model Component	Primary Tests	Secondary Tests	Potential Validation Data Sources
Time of Day of Travel	• Time of day versus volume peaking • Speeds by time of day	• Cordon counts • Market segments by time of day	• Permanent traffic recorder data • NHTS (2001 or 2009) • Historic household survey data for region • Transit boarding count data
Mode Choice	• Mode shares (geographic level/market segments) • Check magnitude of constants and reasonableness of parameters • District-level flows • Sensitivity of parameters to LOS variables/elasticities	• Input variables • Mode split by screenlines • Frequency distributions of key variables • Reasonableness of structure • Market segments by transit service • Existence of "cliffs" (cutoffs on continuous variables) • Disaggregate validation comparing modeled choice to observed choice for individual observations	• Traffic counts and transit (or intercept survey data) for screenlines • CTPP data • Chapter 4 of this report • Transit on-board survey data • NHTS (2001 or 2009) • Household survey data (separate from data used for model estimation)
Transit Assignment	• Major station boardings • Bus line, transit corridor, screenline volumes • Park-and-ride lot vehicle demand • Transfer rates	• Kiss-and-ride demand • Transfer volumes at specific points • Load factors (peak points)	• Transit boarding counts • Transit on-board survey data • Special surveys (such as parking lot counts)
Traffic Assignment	• Assigned versus observed vehicles by screenline or cutline • Assigned versus observed vehicles speeds/times (or vehicle hours traveled) • Assigned versus observed vehicles (or vehicle miles traveled) by direction by time of day • Assigned versus observed vehicles (or vehicle miles traveled) by functional class • Assigned versus observed vehicles by vehicle class (e.g., passenger cars, single-unit trucks, combination trucks)	• Subhour volumes • Cordon lines volumes • Reasonable bounds on assignment parameters • Available assignment parameters versus required assignment parameters for policy analysis • Modeled versus observed route choice (based on data collected using GPS-equipped vehicles)	• Permanent traffic recorders • Traffic count files • HPMS data • Special speed surveys (possibly collected using GPS-equipped vehicles)

Source: Cambridge Systematics, Inc. (2008b).

CHAPTER 4

Model Components

4.1 Introduction

This chapter presents information on the analytical techniques used in various components of conventional travel demand models and on parameters for these models obtained from typical models around the United States and from the 2009 NHTS. These parameters can be used by analysts for urban areas with insufficient local data with which to estimate model parameters. They may also be used, in areas that have already developed model parameters, to check these parameters for reasonableness. Chapter 5 discusses the use of the parameters presented in this chapter for model validation and reasonableness checking.

4.1.1 Information Sources

There are two primary sources of information in this chapter:

1. The **NHTS** is administered by the FHWA. It provides information to assist transportation planners and policy makers who need comprehensive data on travel and transportation patterns in the United States. The 2009 NHTS updates information gathered in the 2001 NHTS and in prior Nationwide Personal Transportation Surveys (NPTS) conducted in 1969, 1977, 1983, 1990, and 1995. Data were collected from a nationwide sample of households on trips taken within a 24-hour period and include:
   - Trip purpose (work, shopping, etc.);
   - Means (mode) of transportation used (car, bus, light rail, walk, etc.);
   - How long the trip took, i.e., travel time;
   - Time of day and day of week when the trip took place; and
   - If a private vehicle trip:
     – Number of people in the vehicle, i.e., vehicle occupancy;
     – Driver characteristics (age, sex, worker status, education level, etc.); and
     – Vehicle attributes (make, model, model year, amount of miles driven in a year).

   The 2009 NHTS was used to obtain selected parameters including trip generation rates, average trip lengths, and time-of-day percentages. The information included in this report from the NHTS uses the weekday sample only. This information was estimated by urban area population range, using the urbanized area identifier in the data set. The population ranges available in the NHTS data set are as follows:
   - Over 1 million population with subway/rail;
   - Over 1 million population without subway/rail;
   - 500,000 to 1 million population;
   - 200,000 to 500,000 population;
   - 50,000 to 200,000 population; and
   - Not in an urban area.

   It was found that many of the parameters estimated from NHTS data did not vary by population range, varied only between some ranges, or had only minor fluctuations that showed no trends and appeared to be related to survey sampling. In these cases, parameters are presented for aggregated population ranges and, in cases where there was no variation among population ranges or only minor fluctuations, for all areas together.
2. **A database of information from model documentation** from 69 MPOs[4] was used to obtain information on selected model parameters. While all of the documents did not include information on every parameter of interest, information was again summarized by urban area population range where sufficient data were available.

[4]While the term "MPOs" is used here for convenience to describe the agencies maintaining travel models, it is recognized that some agencies maintaining models are not actually metropolitan planning organizations.

This database is referred to throughout the chapter as the "MPO Documentation Database." The metropolitan areas are organized by population range, as follows:

- Over 1 million population;
- 500,000 to 1 million population;
- 200,000 to 500,000 population; and
- 50,000 to 200,000 population.

The areas included in the MPO Documentation Database are shown in Table 4.1, organized by population category. Again, some parameters did not vary by population range, varied only between some ranges, or had only minor fluctuations. For some parameters, there was insufficient information for some population ranges. In these cases, parameters are presented for aggregated population ranges and for all areas together, in cases where there was no variation among population ranges, or only minor fluctuations.

A few supplementary sources were used to fill gaps where neither of the primary sources could be used. These sources are identified where they are used throughout the chapter.

4.1.2 Chapter Organization

This chapter comprises 12 sections. The first section after this introduction is a brief description of the logit model, a formulation that is used in several of the model components described later in the chapter. Each of the remaining 10 sections corresponds to a specific model component and includes the following subsections:

- **Model Function**—A brief summary of the function of the model component and how it fits into the overall modeling process.
- **Best Practices**—A brief description of the typical method(s) representing best practice. This subsection may include alternative methods that may be appropriate in different contexts. For example, trip generation might include methods to estimate total person trips, total motorized person trips, or total vehicle trips. This subsection does not include a complete discussion of the theory behind the methods and the model estimation procedures; rather, references to the already extensive existing literature documenting these items are provided.
- **Basis for Data Development**—The basis for the development of the data presented in the subsection and in typical modeling practice.
- **Model Parameters**—Model parameters classified by urban area category (including tables and figures as appropriate), with explanations of how they can be used in model estimation, validation and reasonableness checking, and parameter transfer.

Model Components

The methods presented in this chapter follow the conventional sequential process for estimating transportation demand. It is often called the "four-step" process where the principal steps are:

- Step 1—Trip Generation;
- Step 2—Trip Distribution;
- Step 3—Mode Choice; and
- Step 4—Assignment.

This chapter discusses the following components of conventional travel modeling:

- Vehicle Availability (Section 4.3)—Estimating the number of automobiles available to households;
- Trip Generation (Section 4.4)—Estimating the number of passenger trips that are made from origin zones and to destination zones, classified as trip productions and trip attractions;
- Trip Distribution (Section 4.5)—Estimating the number of passenger trips that are made between origins and destinations;
- External Travel (Section 4.6)—Estimating the travel that has at least an origin or a destination external to the area being covered by the transportation model;
- Mode Choice (Section 4.7)—Estimating the mode to be used for passenger travel between origins and destinations;
- Automobile Occupancy (Section 4.8)—Estimating the number of vehicles required to accommodate passenger trips by automobile between origins and destinations;
- Time-of-Day Characteristics (Section 4.9)—Estimating the time of the day during which passenger trips are made;
- Freight/Truck Modeling (Section 4.10)—Estimating the number of freight and other trucks that travel in addition to passenger trips between origins and destinations;
- Highway Assignment (Section 4.11)—Estimating the volume of trips on the highway segments that result from accommodating the passenger automobile and truck trips between origins and destinations; and
- Transit Assignment (Section 4.12)—Estimating the volume of trips on transit vehicles and lines that result from accommodating the passenger transit trips between origins and destinations.

One of the primary reasons for the development of this report is the presentation of transferable parameters for use in urban areas where there is insufficient local data with which to estimate models. In such cases it has been common practice to transfer parameters from other models or data sets. In preparing this report, a literature review of transferability of model parameters was undertaken (the results

Table 4.1. MPOs classified using year 2000 population.

Metropolitan Planning Organization	Region Served
MPOs with Population greater than 1,000,000 (25 MPOs)	
Atlanta Regional Commission	Atlanta, Georgia
Baltimore Regional Transportation Board	Baltimore, Maryland
Capital Area Metropolitan Planning Organization	Austin, Texas
Central Transportation Planning Staff	Boston, Massachusetts
Chicago Area Transportation Study	Chicago, Illinois
Denver Regional Council of Governments	Denver, Colorado
Durham-Chapel Hill-Carrboro MPO	Durham, North Carolina
Greater Buffalo/Niagara Falls Regional Transportation Council	Buffalo/Niagara Falls, New York
Hampton Roads MPO	Hampton Roads, Virginia
Maricopa Association of Governments	Phoenix, Arizona
Mecklenburg-Union MPO	Charlotte, North Carolina
Metropolitan Council of the Twin Cities	Minneapolis-St. Paul, Minnesota
Metropolitan Transportation Commission	San Francisco, California
Mid-America Regional Council	Kansas City, Missouri
Metropolitan Washington Council of Governments	Washington, D.C.
North Central Texas Council of Governments	Dallas-Fort Worth, Texas
Puget Sound Regional Council	Seattle, Washington
Regional Transportation Commission of Southern Nevada	Las Vegas, Nevada
Sacramento Area Council of Governments[a]	Sacramento, California
San Diego Association of Governments	San Diego, California
Shelby County MPO	Memphis, Tennessee
Southeast Michigan Council of Governments	Detroit, Michigan
Southeastern Wisconsin Regional Planning Commission	Milwaukee, Wisconsin
Southern California Association of Governments	Los Angeles, California
Wasatch Front Regional Council	Salt Lake City, Utah
MPOs with Population between 500,000 and 1,000,000 (8 MPOs)	
Akron Metropolitan Area Transportation Study	Akron, Ohio
Capital District Transportation Committee	Albany, New York
Capitol Region Council of Governments	Hartford, Connecticut
Council of Fresno County Governments	Fresno County, California
Genesee Transportation Council	Rochester, New York
Kern County Council of Governments	Bakersfield, California
Mid-Region Council of Governments	Albuquerque, New Mexico
Nashville Metropolitan Planning Organization	Nashville, Tennessee
MPOs with Population between 200,000 and 500,000 (18 MPOs)	
Brown County Planning Commission	Green Bay, Wisconsin
Chatham Urban Transportation Study	Savannah, Georgia
Chattanooga-Hamilton County Regional Planning Agency	Chattanooga, Tennessee
Des Moines MPO	Des Moines, Iowa
East Central Wisconsin Regional Planning Commission	Appleton-Oshkosh, Wisconsin
Knoxville Regional Transportation Planning Organization	Knoxville, Tennessee
Lane Council of Governments	Eugene, Oregon
Madison Area MPO	Madison, Wisconsin
Mid-Willamette Valley Council of Governments	Salem, Oregon

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Table 4.1. (Continued).

Metropolitan Planning Organization	Region Served
North Front Range Metropolitan Planning Organization	Fort Collins, Colorado
Pima Association of Governments	Tucson, Arizona
Poughkeepsie-Dutchess County Transportation Council	Poughkeepsie, New York
San Joaquin Council of Governments	Stockton, California
Spokane Regional Transportation Council	Spokane, Washington
Stanislaus Council of Governments	Modesto, California
Syracuse Metropolitan Transportation Council	Syracuse, New York
Tri-County Regional Planning Commission	Harrisburg, Pennsylvania
Tulare County Association of Governments	Visalia, California
MPOs with Population between 50,000 and 200,000 (31 MPOs)	
Adirondack-Glens Falls Transportation Council	Glens Falls, New York
Association of Monterey Bay Area Governments	Monterey, California
Bay-Lake Regional Planning Commission	Sheboygan, Wisconsin
Binghamton Metropolitan Transportation Study	Binghamton, New York
Bristol Metropolitan Planning Organization	Bristol, Tennessee
Butte County Association of Governments	Chico, California
Chittenden County Metropolitan Planning Organization	Burlington, Vermont
Clarksville-Montgomery County Regional Planning Agency	Clarksville, Tennessee
Cleveland Area MPO	Cleveland, Tennessee
Columbus-Phenix City Metropolitan Planning Organization	Muscogee, Georgia - Russell, Alabama
Elmira-Chemung Transportation Council	Elmira, New York
Fond du Lac MPO	Fond du Lac, Wisconsin
Grand Valley MPO	Grand Junction, Colorado
Herkimer-Oneida County Transportation Study	Utica, New York
Ithaca Tompkins County Transportation Council	Ithaca, New York
Jackson Municipal Regional Planning Commission	Jackson, Tennessee
Janesville MPO	Janesville, Wisconsin
Johnson City Metropolitan Planning Organization	Johnson City, Tennessee
Kings County Association of Governments	Lemoore, California
Kingsport Transportation Department	Kingsport, Tennessee
La Crosse Area Planning Committee	La Crosse, Wisconsin
Lakeway Area Metropolitan Transportation Planning Organization	Morristown, Tennessee
Madera County Transportation Commission	Madera, California
Merced County Association of Governments	Merced, California
San Luis Obispo Council of Governments	San Luis Obispo, California
Santa Barbara County Association of Governments	Santa Barbara, California
Shasta County Regional Transportation Planning Agency	Redding, California
Siouxland Interstate Metropolitan Planning Council	Sioux City, Iowa
Thurston Regional Planning Council	Olympia, Washington
Ulster County Transportation Council	Kingston, New York
West Central Wisconsin Regional Planning Commission	Eau Claire, Wisconsin

[a]The documentation reviewed for the Sacramento Area Council of Governments was for its trip-based model, not its current activity-based model.

of this review are presented in Appendix B). This review found mixed results: while transferability was valid in some studies, its validity could not be demonstrated in others. In general, transferability was demonstrated for trip generation and mode choice in some cases but not others while the literature on transferability of other parameters, including trip distribution, time of day, and freight/truck modeling, was insufficient to draw any conclusions. More research into model transferability, the conditions under which transferability is most likely to be valid, and ways in which the validity of transferred parameters could be improved, is needed.

While the literature to date has not provided conclusive guidelines for transferability across geographic areas, it appears that transferability would be improved with a transfer approach that involves transfer scaling of coefficients using limited data from the application context (the area to which parameters are to be transferred). Appendix B includes several references that describe methods for scaling that could be used if the limited data (possibly from a small household activity/travel survey or NHTS samples in the model region) were available.

However, it is recognized that many areas, especially smaller urban areas, will not have even the limited data needed, or the required resources and expertise, to perform scaling of transferred parameters. In such cases, the parameters presented in this chapter, or parameters from specific models that could provide estimation contexts, will serve as the best available parameters to use in the local models.

Regardless of the transfer approach used, validation and reasonableness testing of results based on the transferred models should be performed. Validation and reasonableness testing are described in Chapter 5 and in the *Travel Model Validation and Reasonableness Checking Manual, Second Edition* (Cambridge Systematics, Inc., 2010b). It will be particularly important to perform validations for two points in time, if possible, and to apply reasonableness tests to travel forecasts. While models based on transferred parameters may be validated to base year conditions, the transferred models may have different sensitivities to changed conditions and scenarios than might be expected in an area.

Trip Purposes

In four-step travel models, the unit of travel is the "trip," defined as a person or vehicle traveling from an origin to a destination with no intermediate stops. Because people traveling for different reasons behave differently, four-step models segment trips by **trip purpose**. The number and definition of trip purposes in a model depends on the types of information the model needs to provide for planning analyses, the characteristics of the region being modeled, and the availability of data with which to obtain model parameters and the inputs to the model.

Trip purposes are defined by the type of activity taking place at each end of the trip (home, work, school, etc.). Because most trips begin or end at home, many trip purposes are defined as "home based" (e.g., home-based work, which would include trips from home to work and from work to home). Nonhome-based trips are most often not segmented further, but some models further categorize these as work based or nonwork based ("other based").

The minimum number of trip purposes in most models is three: home-based work, home-based nonwork, and nonhome based. In this report, these three trip purposes are referred to as the "classic three" purposes. Other commonly used home-based trip purposes are school, shopping, social-recreational, escorting (pickup/dropoff), and university. Models use a "home-based other" trip purpose to represent home-based trips not to or from an activity type defined by one of the other trip purposes. While the convention varies for different model documents, in this report "home-based nonwork" is used rather than "home-based other" for models that have only one home-based trip purpose besides work.

Throughout this chapter, model parameters and other data are presented for the classic three trip purposes. In some cases, where the data are sufficient, figures for the home-based school purpose are presented separately because of the unique nature of school travel, which is mainly made by children. In these cases, a home-based other trip purpose that represents all home-based nonwork and nonschool trips is included. To clarify, "home-based other" represents all home-based trips except work and school trips, and "home-based nonwork" represents all home-based trips except work trips. Depending on whether the analyst is including a separate home-based school purpose, he or she should use the information stratified by trip purpose in one of the following ways:

- For the classic three purposes (home-based work, home-based nonwork, and nonhome based) or
- For the following four purposes: home-based work, home-based school, home-based other, and nonhome based.

Throughout Chapter 4, tables of transferable parameters are presented. The longer tables can be found in Appendix C and are referred to in the text of this chapter by table number (e.g., Table C.1).

4.2 The Logit Model

This section describes the logit model, the most commonly used discrete choice analysis method in travel forecasting. This background is provided for understanding the parameters of logit models described in this chapter, rather than to provide a detailed discussion of logit model estimation, validation, and application. The principles and the basic mathematical formulation are presented, and the ways it can be used for choice analysis in travel demand modeling are discussed. For more detailed information about logit models, the reader may wish to consult Ben-Akiva and Lerman (1985) and Koppelman and Bhat (2006).

The basic idea underlying modern approaches to travel demand modeling is that travel is the result of choices made by individuals or collective decision-making units such as households. Individuals choose which activities to do during the day and whether to travel to perform them, and, if so, at which locations to perform the activities, when to perform them, which modes to use, and which routes to take. Many of these choice situations are discrete, meaning the individual has to choose from a set of mutually exclusive and collectively exhaustive alternatives.

The presentation of discrete choice analysis uses the principle of utility maximization. Briefly, a decision maker is modeled as selecting the alternative with the highest utility among those available at the time a choice is made. An operational model consists of parameterized utility functions in terms of observable independent variables and unknown parameters.

The utility represents the individual's value for each option, and its numerical value depends on attributes of the available options and the individual. In practice, it is not unusual for apparently similar individuals (or even the same individual, under different conditions) to make different choices when faced with similar or even identical alternatives. Models in practice are therefore random utility models, which account for unexplained (from the analyst's perspective) variations in utility.

The utility function, U, can be written as the sum of the deterministic (known) utility function specified by the analyst, V, and an error term, e. That is: $U = V + e$. An analyst never knows the true utility function. In effect, the analyst always measures or estimates utility with error, and an error term of unknown size is always present in the analyst's specification of the utility function. This error term accounts for variables that are not included in the data set, or that the analyst chooses to omit from the model (e.g., because he cannot forecast them well), or that are completely unknown to the analyst.

When the true utilities of the alternatives are random variables, it is not possible to state with certainty which alternative has the greatest utility or which alternative is chosen. This inability is because utility and choice depend on the random components of the utilities of the available alternatives, and these components cannot be measured. The most an analyst can do is to predict the probability that an alternative has the maximum utility and, therefore, the probability that the alternative is chosen. Accordingly, the analyst must represent travel behavior as being probabilistic.

In logit formulations used in most travel demand models, the utility function for each alternative is a linear combination of variables affecting the choice. The utility equations have the form:

$$V_n = \beta_{n0} + \sum_k \beta_{nk} * x_k \tag{4-1}$$

where:

n = Alternative number;
V_n = (Deterministic) utility of alternative n;
β_{n0} = The statistically estimated constant associated with alternative n, essentially the effects of variables that influence the choice that cannot be included in the model due to inability to quantify or forecast, lack of data from the surveys used in model estimation, etc.;
β_{nk} = The statistically estimated coefficient indicating the relative importance of variable x_k on choice n; and
x_k = The value of decision variable k.

Variables in utility functions may be *alternative specific*, meaning that the coefficients must be different in each utility function (i.e., the values of β_{nk} cannot be equal for all values of n), or they may be *generic*, meaning that β_{nk} is the same for each alternative. In a logit model, the utility of one alternative matters only in terms of its value relative to the utilities of other alternatives.

Logit is the most widely used mathematical model for making probabilistic predictions of mode choices. The simplest function used is the multinomial logit formulation. In the multinomial logit model, the probability of each alternative is expressed as:

$$P_n = \frac{\exp(V_n)}{\sum_{Alternatives\_n'} \exp(V_{n'})} \tag{4-2}$$

where:

P_n = The probability that alternative n is chosen;
$\exp()$ = The exponential function; and
V_n = (Deterministic) utility of alternative n (from Equation 4-1).

Another logit model form that is often used for mode choice is the nested logit model. Under a nested structure, the model pools together alternatives that share similarities, and the choice is represented as a multistep decision. Consider an example with three alternatives, labeled *1A, 1B,* and *2,* where *1A* and *1B* are more similar to each other than either is to alternative *2.* In the upper level of the nested model, the probability that an individual would choose alternative 1 (one of alternative *1A* or alternative *1B*) is given by Equation 4-3.

$$P_1 = \frac{\exp(V_1)}{\exp(V_1) + \exp(V_2)} \tag{4-3}$$

The probability of choosing alternative *1A conditional* on choosing *1* is equal to:

$$P_{1A/1} = \frac{\exp(V_{1A})}{\exp(V_{1A}) + \exp(V_{1B})} \tag{4-4}$$

Thus, the probability of choosing alternative 1A is equal to:

$$P_{1A} = P_{1A/1} \times P_1 \tag{4-5}$$

In a nested model, the utility of an alternative in an upper level is a function of the utilities of its subalternatives. The utility for a nest m includes a variable that represents the expected maximum utility of all of the alternatives that compose the nest. This variable is known as the logsum and is given by the formula:

$$\text{Logsum}_{nest\ m} = \ln \sum_{All\_M\_in\_nest\_m} \exp(U_M) \tag{4-6}$$

As an example, consider a model with a simple nest with two alternatives. If the utility of each alternative is the same, say 3.00 (indicating the choice probability of each is 50 percent), then the logsum is equal to ln [exp(3.00) + exp(3.00)] = 3.69, higher than the utility of either alternative. But if the utilities are, say, 5.00 for one alternative and 0.05 for the other (indicating a choice probability for the first alternative of over 99 percent), the logsum is equal to ln [exp(5.00) + exp(0.05)] = 5.01, only slightly higher than the utility of the superior alternative. Thus, the inclusion of a competitive alternative in a nest increases the expected maximum utility of all alternatives while the inclusion of a substantially inferior alternative has little effect on the logsum value.

Note that the logsum is equal to the natural logarithm of the denominator of the logit probability function (Equation 4-2) for the alternatives in nest *m*. A "nesting coefficient" of the logsum term is used in the utility function for nest *m*. This coefficient must be between zero and one and should be statistically significantly different from zero and one.

The primary advantage of nested logit models over (non-nested) multinomial logit models is that nested logit models enable one to reduce the intensity of the "independence of irrelevant alternatives" (IIA) assumption by nesting related choices. The IIA assumption, which is characteristic of all multinomial logit models as well as the lowest level nests in nested logit models, states that the probability of choices does not depend on alternatives that are not relevant. For example, assume in a mode choice model that there are three alternatives—car, red bus, and blue bus—with equal utilities. Most people would choose between car and any bus, not distinguishing between the bus choices simply due to their color (i.e., they would be perfect substitutes for one another). But, given equal utility for all three of these choices, in a multinomial logit model framework the choice probabilities for each of the three choices would calculate as equal (⅓), leading to a greater probability of choosing any bus than the car alternative simply because the choice is being made among three equal alternatives rather than two (i.e., respecting the IIA assumption means one must not construct such choice sets with irrelevant alternatives).

4.3 Vehicle Availability

The number of motor vehicles available to a household has a major impact on the travel behavior of the members of the household. As a result, some travel demand models have incorporated components modeling household vehicle availability or automobile ownership. Vehicle availability models estimate the number of vehicles available to households based on characteristics of the households themselves, the areas in which they are located, and the accessibilities of those areas via various transportation modes. These models are most commonly used in larger urban areas and often are not used in small or mid-size regions. While the estimation of vehicle availability is not one of the four "classic" steps of traditional travel demand models, the availability of vehicles to households can influence trip generation, trip distribution, and mode choice.

The advantage of modeling vehicle availability, rather than simply estimating it from trends or assuming that vehicle availability levels remain constant across scenarios and forecast years, is to consider the effects of changes in demographics, such as household size and income, on vehicle ownership. Furthermore, accessibility by various transportation modes and changes in land use patterns, both of which can be affected by transportation planning policies, have been shown to affect vehicle availability, and these effects can be included in vehicle availability models. To produce credible forecasts of travel demand, it is therefore desirable not only to have accurate estimates of the households and employment for traffic analysis zones, but also to have accurate estimates of the number of autos (vehicles) available to these households.

4.3.1 Model Function

The function of a vehicle availability model is to estimate the number of households with zero, one, two, etc., vehicles. In the context of a four-step travel demand model, this estimate is done through an aggregate process where the shares of households for each vehicle availability level are applied to the total households in each zone. These shares may be obtained from a disaggregately estimated model (i.e., a logit model).

The reason to have the households in each zone segmented into vehicle availability levels based on the number of vehicles is to allow later steps in the modeling process to use different parameters for market segments based on these levels. These segments may be based solely on the number of vehicles (zero, one, two, etc.) or on variables that incorporate interactions between the number of vehicles and another variable, such as the number of persons or number of workers in the household. Examples of these types of interactions include the following:

- For **trip productions**, model parameters representing the number of person trips per household (as discussed in Section 4.4) are applied for combinations of two or three input variables, such as number of persons by number of vehicles. If one of the variables is the number of vehicles, the segmentation of households may be achieved through a vehicle availability model, assuming that the segmentation of the other variable(s) is performed through another means.

- For **trip distribution** and **mode choice**, models may be applied separately for household market segments defined simply by the number of vehicles (zero, one, two, etc.) or for segments defined by combinations of two or three input variables. Examples include households where the number of vehicles is less than, equal to, or greater than the number of workers. The use of such segmentation requires that the information needed to define the segmentation levels is available from the trip generation model. For example, segmentation comparing the number of vehicles to the number of workers could be used if the trip production model uses a cross-classification of number of vehicles by number of workers.

It is not necessary that the segmentation scheme be the same for every trip purpose. In some models, segmentation might be used only for some trip purposes such as home-based work.

Some aggregate models compute the shares for each vehicle availability level from curves fitted against observed data and do not base these shares on household, area, or accessibility characteristics. On the other hand, a logit vehicle availability model might include such variables, as discussed in Section 4.3.2.

4.3.2 Best Practices

There are two commonly used approaches in vehicle availability modeling: aggregate approaches and discrete choice models (Cambridge Systematics, Inc., 1997b). Both approaches estimate the number of households owning zero, one, two, etc., vehicles. Aggregate approaches estimate the percentage of households in each vehicle availability category while discrete choice (i.e., logit) models estimate the probabilities of having zero, one, two, etc., vehicles. These probabilities are used either as aggregate percentages applied to different segments of households or as probabilities used in simulation models. The most common number of vehicle availability categories is four (i.e., zero, one, two, or three or more vehicles), although some models have three or five categories.

Aggregate approaches estimate the percentages of households for each vehicle ownership category at the zonal level, sometimes for segments of households within zones (such as income levels). In these approaches, curves are fitted to match distributions of households by number of vehicles available. The observed distributions that the curves attempt to match usually come from U.S. Census data. These models do not necessarily use mathematical formulas; rather, points on the curves can be determined, and "smooth" curves fitting the points are derived. There are therefore no mathematical parameters to derive or transfer for these types of models.

Logit models of vehicle availability have been in use for some time. In these models, a utility function for each vehicle availability level is developed, including variables that affect vehicle availability.

Examples of the decision variables in the utility functions include the following:

- Household characteristics:
  - Persons per household;
  - Workers per household;
  - Household income; and
  - Single or multifamily dwelling.
- Geographic (zone) characteristics:
  - Urban area type;
  - Residential and/or commercial density; and
  - Pedestrian environment.
- Transportation accessibility:
  - Accessibility via highway;
  - Accessibility via transit; and
  - Accessibility via walking/bicycling.

Accessibility may be expressed as the amount of activity (for example, trip attractions) within a certain travel time by the corresponding mode or may be a more sophisticated variable that does not depend on a defined travel time cutoff. An example of the latter is provided in Figure 4.1.

A multinomial logit formulation is commonly used for vehicle availability models, although ordered response and nested models are sometimes used. Variables in vehicle availability models are alternative specific (see Section 4.2). For simplicity, therefore, the coefficient for one alternative is set to zero for each variable. It is most efficient (and easiest to interpret the results) if this is the same alternative for each variable and for the alternative-specific constant β_{n0}. So, typically, the entire utility for one alternative, most often the zero-vehicle alternative, is set to zero (i.e., all coefficients and constants for this alternative are equal to zero).

4.3.3 Basis for Data Development

When sufficient local data are available, best practice for vehicle availability models is to estimate the models from local household activity/travel survey data. Data on vehicle availability are required for model validation and usually are obtained from U.S. Census data for the urban area.

Because there are only a few alternatives (three to five) and, usually, several thousand households in the sample, typical

A_i = Auto accessibility during the peak hours for zone TSZ_i.

$$A_i = \ln(1 + \sum_j TotEmp_j \times \exp^{-2\times T_{ij} / \hat{T}_i})$$

where:

$TotEmp_j$ = Total employment in TSZ_j;

T_{ij} = Peak non-HOV auto travel time from TSZ_i to TSZ_j; and

$$\hat{T}_i = (\sum_j T_{ij}) / J$$

where J = Total number of TSZ_i to TSZ_j pairs.

TR_i = Transit accessibility during the peak hours for TSZ_j.

$$TR_i = \ln(1 + \sum_j TotEmp_j \times R_{ij} \exp^{-2\times S_{ij} / \hat{S}_i})$$

where:

$TotEmp_j$ = Total employment in TSZ_j.

R_{ij} = 1 if TSZ_i to TSZ_j has transit access, 0 otherwise.

S_{ij} = Peak non-park-and-ride transit total travel time from TSZ_i to TSZ_j.

$$\hat{S}_i = (\sum_j R_{ij} \times S_{ij}) / K$$

where K = Total number of TSZ_i to TSZ_j pairs having transit access.

Acc_i = Ratio of auto accessibility during the peak hours to transit accessibility during the peak hours.

$$Acc_i = A_i / (1 + TR_i)$$

Source: This function was recommended by a Travel Model Improvement Program Peer Review Panel and was successfully implemented for the Southern California Association of Governments.

Figure 4.1. Example accessibility variable.

urban area household surveys include sufficient data for estimation of logit vehicle availability models. It might also be possible to estimate these models using data from the NHTS, although sample sizes for urban areas that are not included in NHTS add-on areas are probably insufficient.

Usually, the main issue is whether the survey data set contains sufficient samples of zero-vehicle households, which are the smallest category in nearly all U.S. urban areas. According to data from the ACS, the percentage of zero-vehicle households in U.S. metropolitan statistical areas (MSAs) ranges from about 3 to 14 percent, with areas in Puerto Rico having 20 to 24 percent zero-vehicle households and the New York area having about 30 percent (U.S. Census Bureau, 2011a). The percentages of households with zero, one, two, and three or more vehicles from the ACS are presented in Table C.1.

Another possible source for vehicle availability model estimation data is the U.S. Census PUMS. This data source, which is now based on the ACS, can provide household-level records that include most household and person characteristics that would be used in vehicle availability models. The main limitation of PUMS data is that geographic resolution is only to the PUMA, an area of approximately 100,000 in population. These areas contain many travel analysis zones and are too large to estimate accessibility, pedestrian environment, or area-type variables.

There are relatively few U.S. urban area models for which vehicle availability model documentation is available, and most of those that have been documented are for larger urban areas. Nor have there been studies of transferability of vehicle availability model parameters. Ryan and Han

(1999) compared parameters estimated using PUMS data for the same model specification across seven large urban areas in the United States. They concluded that transferability was likely due to similarity in the estimated parameters but did not test specifically for transferability. Given the lack of information on transferability, it therefore is preferable not to transfer vehicle availability models if local data (i.e., household travel/activity survey) to estimate models are available.

However, if an area does not have the necessary local data and wishes to take advantage of the benefits of modeling vehicle availability, transferring an existing model from another location may be considered. Section 4.3.4 presents parameters from four models as examples that could be considered in urban areas where the survey data to estimate such a model is unavailable.

4.3.4 Model Parameters

Tables C.2 through C.4 in Appendix C show parameters for four U.S. urban area vehicle availability models, for the one-vehicle, two-vehicle, and three-or-more-vehicle utilities respectively. The urban areas for which these models were developed are summarized as follows:

- **Model 1**—Western metro area, 1 to 2 million population range, about 1.9 vehicles per household;
- **Model 2**—Southern metro area, over 3 million population range, about 1.8 vehicles per household;
- **Model 3**—Southern metro area, 1 to 2 million population range, about 1.7 vehicles per household; and
- **Model 4**—Eastern metro area, 1 to 2 million population range, about 1.5 vehicles per household.

In these specifications, the parameters are presented as the zero-vehicle alternative having a total utility of zero. These four models were chosen for the following reasons:

- All are multinomial logit models with four alternatives: zero, one, two, and three or more vehicles;
- All are associated with four-step models (activity-based models usually have household and person variables not usually available in four-step models);
- All were estimated since 2000 using household activity/travel survey data; and
- The variable specifications are somewhat similar.

Some important points to note regarding the variable definitions in these tables:

- The variables representing the number of persons, number of workers, and income levels are indicator variables, taking a value of one if the household has the indicated characteristic and zero otherwise. For example, when the model is applied to two-person, one-worker, high-income households, the values of the two-person, one-worker, and high-income variables would be equal to one, and the values of the other person, worker, and income indicator variables would be zero.
- The income groups are intended to represent quartiles, but the income-level definitions are different for every model. Because they were estimated in various places at different times, they are not directly comparable.
- The accessibility ratio for Model 2 is the same as the one shown in Figure 4.1.

The columns in Tables C.2 through C.4 correspond to the parameters β_{nk} in the utility functions (see Equation 4-1) of the four models (β_{n0} represents the alternative-specific constants). So, for example, in Model 2, the utility function for the one-vehicle alternative is:

$$
\begin{aligned}
U_1 = {} & 1.58 \\
& + 1.84 * \text{Low-medium income} \\
& + 2.54 * \text{High-medium income} \\
& + 0.72 * \text{High income} \\
& + 0.06 * \text{Accessibility ratio}
\end{aligned}
$$

A low-medium–income household in a zone with an accessibility ratio of 2.0 would therefore have a utility of owning one vehicle of 1.58 + 1.84 + 0.06 (2.0) = 3.54. If the household has three persons, the probabilities of the alternatives for two and three or more vehicles can be computed, using Equation 4-1, as:

$$U_2 = -1.90 + 2.78 + 3.02 + 0.089\ (2.0) = 4.08$$

$$U_3 = -12.38 + 3.04 + 4.14 + 0.12\ (2.0) = -4.96$$

The probabilities of owning zero, one, two, etc., vehicles are computed using Equation 4-2:

$$
\begin{aligned}
P_0 &= \exp(0)/\left[\exp(0) + \exp(3.54) + \exp(4.08) + \exp(-4.96)\right] \\
&= 1.06 \text{ percent}
\end{aligned}
$$

$$
\begin{aligned}
P_1 = {} & \exp(3.54)/\left[\exp(0) + \exp(3.54) + \exp(4.08)\right. \\
& \left. + \exp(-4.96)\right] = 36.43 \text{ percent}
\end{aligned}
$$

$$
\begin{aligned}
P_2 = {} & \exp(4.08)/\left[\exp(0) + \exp(3.54) + \exp(4.08)\right. \\
& \left. + \exp(-4.96)\right] = 62.51 \text{ percent}
\end{aligned}
$$

$$
\begin{aligned}
P_3 = {} & \exp(-4.96)/\left[\exp(0) + \exp(3.54) + \exp(4.08)\right. \\
& \left. + \exp(-4.96)\right] = 0.01 \text{ percent}
\end{aligned}
$$

In model application, these probabilities would be computed and applied separately to segments of households of each type as defined by the variables (number of persons, income level, etc.), and the probabilities for each segment applied to the households in each segment.

Because no two of the models presented in Tables C.2 through C.4 have identical specifications, the values for specific coefficients may differ significantly between models. The presence or absence of other variables in a model can affect the coefficients of other variables. So it is much more valid to transfer individual models rather than composites of models with different variables.

As discussed previously, there is little experience with which to guide planners in transferring vehicle availability models, or even to determine how transferable the parameters of such models are. The best guidance that can be provided if one wished to transfer one of the models shown in Tables C.2 through C.4 is to choose one of the models based on the similarity to the metro areas based on the characteristics provided above (location within the United States, population, and average vehicles per household). Because of the differences in model specification, a composite of two or more of these models cannot be created. If the chosen model proves difficult to calibrate, perhaps another model could be chosen for transfer.

4.4 Trip Generation

Trip generation is commonly considered as the first step in the four-step modeling process. It is intended to address the question of how many trips of each type begin or end in each location. It is standard practice to aggregate trips to a specific unit of geography (e.g., a traffic analysis zone).[5] The estimated numbers of trips will be in the unit of travel that is used by the model, which is usually one of the following:

- Vehicle trips;
- Person trips by motorized modes (auto and transit); or
- Person trips by all modes, including both motorized and nonmotorized (walking, bicycling) modes.

Trip generation models require explanatory variables that are related to trip-making behavior and functions that estimate the number of trips based on these explanatory variables. While these functions can be nonlinear, they are usually assumed to be linear equations, and the coefficients associated with these variables are commonly called trip rates. Whether the function is linear or nonlinear, it should always estimate zero trips when the values of the explanatory variables are all zero. Mathematically, this is equivalent to saying that the trip generation equations should include no constant terms.

4.4.1 Model Function

The purpose of trip generation is to estimate the number of average weekday trip ends by purpose for each zone. In four-step models, the trip ends of home-based trips are defined as productions, representing the home ends of trips, and attractions, representing the nonhome end, regardless of whether home is the origin or destination. In other words, for home-based trips, the production end may be the destination and the attraction end, the origin if the trip-maker is returning home. For nonhome-based trips, for convenience the production end is defined as the trip origin and the attraction end as the trip destination.

For home-based trips, the number of trip productions in a zone is, naturally, based on the number of households in the zone. Household characteristics can affect trip making; therefore, in trip production models, households are usually classified by some of these characteristics, which often include the number of persons, workers, children, or vehicles, or the household income level. The trip rates for each purpose vary depending on the household classifications, which may not be the same for all trip purposes.

Trip attractions are based on other variables besides households, because several types of activities (commercial, employment, residential, etc.) are often located at the nonhome trip end. The type of activity that affects the number of trip attractions depends on the trip purpose. For example, home-based work trip attractions are usually estimated best by using employment as the explanatory variable. Other purposes typically use different sets of variables (school enrollment or employment for home-based school trips, retail employment for home-based shopping trips, etc.). Home-based nonwork, home-based other, and nonhome-based trip attraction models usually use a linear combination of several different variables (employment by type, households, etc.).

The number of nonhome-based trips made in a region does depend on the number of households, but unlike home-based trips, they need not have one end in the zone where the household of the trip-maker is located. One way in which models deal with this issue is to use household-based nonhome-based trip production rates to estimate regional productions and to allocate this regional total to zones based on other variables. A common convention is to assume that the regional nonhome-based trips are allocated to each zone based on the number of nonhome-based trip attractions in the zone.

[5] While the geographic units of some travel models are not zones, the term "zones" is used in the remainder of the chapter for convenience.

Special Generators

While estimates of passenger trip activity based on rates applied to household or employment in a zone can address the majority of conditions, there are special conditions when these rates are insufficient to accurately estimate trip activity. These conditions might be because the trip activity is due to considerations not directly related to the number of employees or households in a zone—for example, trips to airports, hospitals, colleges, or large recreational facilities. Additional estimates of trip activity may also be necessary because the trip generation rates are for average conditions that are not applicable to specialized conditions—for example, shopping productions or attractions to "big box" retail stores that have shopping trip rates per employee that are higher than typical retail employment. These activity locations are often referred to as "special generators."

The term "special generators" is somewhat misleading in that the different travel behavior associated with them is not limited to trip generation. While it is true that the number of trips generated by these sites is not readily modeled using conventional trip attraction models, the sensitivity of trip distribution (see Section 4.5) and mode choice (see Section 4.7) to variables such as time and cost is also different than that of other trips. Ideally, such travel should be treated as a separate trip purpose so that separate models for trip generation, trip distribution, and mode choice could be applied, but unless there are detailed surveys of the special generator with a sufficient sample size for model estimation, it is unlikely that this could be done.

Trip rates are not developed for special generators. Rather, the numbers of trips attracted to these locations are exogenously estimated using separate data sources, such as surveys or counts conducted at the special generators. Hence there are no parameters for trip generation at special generators, and default parameters cannot be provided. It is important to consider how special generator travel is considered relative to the trip purposes used in the model. Generally, trips attracted to special generators are estimated separately from the attractions for the trip purposes used in the model, but the special generator attractions must be considered in examining the balance between productions and attractions. Since separate trip distribution, time-of-day, and mode choice models are not available for special generator travel, the analyst must decide how these features will be modeled for special generators (for example, using the models for home-based nonwork or nonhome-based travel).

Balancing Productions and Attractions

The regional totals of productions and attractions for each trip purpose are equal because each trip has one production end and one attraction end. However, the model results may not be equal because productions and attractions are estimated separately. While trip distribution models (see Section 4.5) can often be applied with different production and attraction totals, certain types of model formulations (such as the gravity model) produce better results if productions and attractions are equal, or close to equal.

Because trip productions are estimated for the household, which is the same as the basis of the sampling frame of the surveys from which trip generation models are estimated, trip production models are generally estimated using records representing individual households, for which the total number of trips should be reported in the household survey. Trip attractions, on the other hand, occur at locations for which a complete set of survey records comprising all trips to the attractor will not be available. It is therefore common convention to adjust trip attractions to match productions by purpose at the regional level. This "balancing" of productions and attractions must take into account trips with one end outside the region (see Section 4.6 on external travel) and trips attracted to special generators.

It is good practice to review the ratio between unbalanced attractions and productions as a large difference might indicate problems with employment estimates, trip rates, etc. Most literature on best practices recommends that the difference between unbalanced regional attractions and productions be kept to +/−10 percent for each purpose, although a review of model validation reports shows that this standard is often exceeded. Upwards of +/−50 percent difference at the regional level might be considered acceptable under certain conditions and trip purposes.

4.4.2 Best Practices

Trip Productions

While other model forms are sometimes used, the most common form of trip production model is the cross-classification model. The households in each zone are classified by two or more variables, and the number of households in each category is multiplied by the appropriate "trip rate," representing the average number of trips per household for the category. Mathematically, the number of trips generated in a zone is given by:

$$P_i^p = \sum_k P\ rate_{pk} * h_{ik} \tag{4-7}$$

where:

P_i^p = Number of trip ends produced for purpose p in zone i;

$P rate_{pk}$ = The production trip rate for purpose p per household for category k; and

h_{ik} = The number of households in category k in zone i.

The state of the practice for trip production models is to create tables of trip rates by two or more dimensions, for example by household income and by household size (number of persons). Most commonly, trip production models are two-dimensional, although three-dimensional models are sometimes used, especially in larger areas where more data are available. The households in each zone are segmented along the two dimensions, and the trip rate is estimated for each combination of the two variables. For example, a cross-classification of households by three income levels (say, low, medium, and high) and number of persons (1, 2, 3, and 4+) would have the number of households divided into 12 segments, one for each income level–number of persons combination, and would use 12 corresponding trip production rates.

Trip Attractions

Accurately estimating trip attractions can be significantly more difficult and problematic than estimating trip productions. Whether trip attraction model parameters are estimated from local data or are transferred, they are usually derived from household survey data, which collects travel information at the production end of trips. Such surveys do not provide control totals at trip attraction locations. It is common practice to estimate the parameters, such as coefficients in linear regression equations, at an aggregate level such as districts (groups of zones), implying that the results may not be as accurate at more disaggregate spatial levels (such as zones). Some regions have attempted to address this issue through the use of establishment surveys, where the data are collected at the attraction end of trips, but the wide variety of establishment types and the expense of obtaining sufficient sample sizes at each type means that accuracy issues are not completely resolved. It is therefore recommended that analysts use the information provided here (indeed, locally derived trip attraction information as well) with extreme caution and to be prepared to adjust parameters to produce more reasonable results as needed.

Trip attraction models are most often linear equations with variables representing the amount of activity in a zone—typically employment by type, student enrollment at school sites, and households or population—and coefficients reflecting the effects of these variables on trip making to the zone for the appropriate purpose. The equations follow the form:

$$A_i^p = \sum_k A\,rate_{pk} * v_{ik} \qquad (4\text{-}8)$$

where:

A_i^p = Attraction of trip ends for purpose p in zone i;
$Arate_{pk}$ = Rate of attraction trip ends for purpose p per unit of variable k; and
v_{ik} = Value of variable k in zone i.

To summarize, the model parameters for trip generation are the trip production and attraction rates, represented by $Prate_{pk}$ in Equation 4-7 and $Arate_{pk}$ in Equation 4-8.

4.4.3 Basis for Data Development

When sufficient local data are available, best practice for the development of trip generation models is to estimate the model parameters from household activity/travel survey data using statistical techniques such as linear regression. Typically, sample sizes for these surveys are sufficient for model estimation, although the required amount of data depends on factors such as:

- The number of parameters to be estimated, such as the number of cells in cross-classification models;
- The number of households occurring in each cross-classification cell in the population, and in the survey sample; and
- The resolution of the geographic units (e.g., zones) at which the models will be applied.

If local data for model estimation are not available, parameters may be transferred from another model. Transferable parameters for general use are presented in Section 4.4.4.

Trip Productions

For trip productions, cross-classification trip rates were estimated from the 2009 NHTS for the classic three trip purposes, for urban areas stratified by population. Additionally, trip rates for home-based school trips are presented, along with a home-based other trip purpose that represents all home-based nonwork and nonschool trips. These rates represent average weekday person trips, including both motorized and nonmotorized trips, and were estimated using the weighted NHTS data. Initially, separate rates were estimated for the six urban area population ranges, but, in many cases, the rates did not vary by population category, and combined rates for multiple population ranges are presented.

Note that the 2009 NHTS does not include travel for children younger than five years old. If an analyst wishes to model the travel of younger children and to use the information provided in this chapter, he/she should be prepared to slightly adjust the trip rates for all purposes except home-based work upward, with a more substantial increase in home-based school trips (if that purpose is modeled and includes pre-school/day care travel).

Trip Attractions

Documented trip attraction models from a number of MPOs were available in the MPO Documentation Database.

One conclusion from the review is that there is little commonality among MPOs regarding the variables to include in trip attraction models. The variables ranged from employment stratified by three basic groups to employment stratified by seven or eight groups. In a number of trip attraction models, school enrollment was included. The number of trip purposes and the variables used for each trip purpose also varied substantially.

Different model calibration methods also added to the variation among models. Some of the models were estimated using regression techniques that could produce somewhat surprising results. For example, regression model calibration techniques can result in negative coefficients for some of the variables. A home-based shop trip attraction model could have, say, a positive coefficient for retail employment and a negative coefficient for basic employment. Such occurrences might be explained as "second-level" relationships—each retail employee attracts a certain number of home-based shop trips during the day, but as the amount of basic employment increases around the retail location, the number of home-based shop trips decreases due to unattractiveness of, say, an industrial area.

However, some illogical regression results were also observed in the review. An example is a home-based work model using multiple employment categories as independent variables with some of the coefficients being positive and some negative. Since each employee should attract a reasonable average number of home-based work trips each day, a negative model coefficient for an employment category is not logical.

4.4.4 Model Parameters

Trip Productions

The household trip production rates classified by variables representing household characteristics were estimated from the 2009 NHTS data. These rates represent the number of person trips, including both motorized and nonmotorized trips, per household. To determine the best variables to use for the rates provided here, trip rates were summarized for the following variables:

- Number of persons,
- Number of workers,
- Income level, and
- Number of vehicles.

The number of persons categories ranged from 1 to 5+. The number of workers categories ranged from 0 to 3+. The number of vehicles categories ranged from 0 to 3+. The household income levels (in 2008 dollars) were defined as:

- $0 to $9,999;
- $10,000 to $24,999;
- $25,000 to $49,999;
- $50,000 to $100,000; and
- Over $100,000.

To determine which variables best explained trip generation behavior in the NHTS data, an analysis of variance (ANOVA) was performed to explore the explanatory power of the variables. This parametric statistical technique provides a basis to identify the most statistically significant cross-classification of explanatory variables for each trip purpose and thereby select dimensions across which the trip production rates were categorized.

The ANOVA results indicate that all of the independent variables have significant effects on home-based work trip production rates. However, among all interaction effects, the household vehicles versus household workers variable appears to be the strongest predictor of the home-based work trip production rate. For home-based nonwork and home-based other trips, household workers versus household persons appears to be the strongest predictor of the trip production rate. For the nonhome-based trip purpose, the ANOVA results suggest that household workers by household persons is again found to be the strongest predictor of the trip production rate.

The MPO Documentation Database indicated that two other cross-classifications are commonly used: number of persons by income level and number of persons by number of vehicles. Parameters for these cross-classifications, also estimated from the NHTS data set, are presented for all trip purposes.

For home-based school trips, trip rates were estimated for the cross-classification of number of persons by number of children. Since some modeling agencies do not forecast the number of children, trip rates were also estimated for number of persons by income level and number of persons by number of vehicles.

Tables C.5 through C.9 in Appendix C show the trip rates by purpose cross-classified by the preferred pairs of variables, based on 2009 NHTS data, for home-based work, home-based nonwork, nonhome-based, home-based school, and home-based other trips, respectively. The NHTS data showed nearly the same trip rates for all population ranges for most trip purposes, apparently due at least in part to the relatively low sample sizes and resulting large errors associated with some of the cells. For home-based nonwork and home-based other trips, the NHTS data indicated lower trip rates for urban areas under 500,000 in population and nonurban areas, and so separate rates are presented for such areas for these trip purposes.

Use of a cross-classification trip production model requires that the households in each zone are classified along the same dimensions as the model. For example, if the first model in

Table 4.2. Example number of households by numbers of persons and autos.

	Persons					
Autos	**1**	**2**	**3**	**4**	**5+**	**Total**
0	10	10	10	0	0	**30**
1	50	100	70	20	10	**250**
2	0	150	200	100	50	**500**
3+	0	0	40	80	100	**220**
Total	**60**	**260**	**320**	**200**	**160**	**1,000**

Table C.5 is used, the households in each zone must be cross-classified by number of workers (0, 1, 2, and 3+) and number of autos (0, 1, 2, and 3+). If the demographic estimates available to the modeler are not already classified in the required manner, there are procedures that may be used to estimate the percentages in each cell and to apply them to the total households. Common sources for these percentages include the CTPP, NHTS, and local survey data. Depending on sample sizes, however, these sources may not provide statistically significant percentages at the zone level, and it may be necessary to estimate percentages for groups of zones based on area type and location within the region.

Example Calculations

Consider a zone with 1,000 households located in an urban area of under 500,000 in population where a trip production model with the classic three trip purposes is being developed. The MPO has estimated the number of households in the zone cross-classified by number of persons and number of vehicles, as depicted in Table 4.2.

For home-based work trips, the number of households in each cell is multiplied by the trip rate from the second section of Table C.5, yielding the number of home-based work trips in each cell of the cross-classification in Table 4.3.

So this zone produces 1,839 home-based work trips. Similarly, home-based nonwork and nonhome-based trip productions can be computed using the fourth section of Table C.6 and the second section of Table C.7, performing the same type of calculations.

Reasonableness checks of the trips per household by purpose estimated from trip production model results can be performed. Information on the national sample represented by the NHTS, as represented by Tables C.5 through C.7, indicate that the average household in urban areas of greater than 500,000 in population makes 10.0 person trips: 1.4 home-based work trips, 5.6 home-based nonwork trips, and 3.0 nonhome-based trips. The average household in urban areas of less than 500,000 in population makes 9.5 person trips: 1.4 home-based work trips, 5.1 home-based nonwork trips, and 3.0 nonhome-based trips. The range of person trips per household in the MPO Documentation Database is about 1.3 to 2.0 home-based work trips, 2.6 to 5.9 home-based nonwork trips, and 1.6 to 4.5 nonhome-based trips. Total person trips per household range from 7.0 to 11.5.

Trip Attractions

Table 4.4 summarizes average daily trip attraction rates for the classic three trip purposes from the analyses of the models in the MPO Documentation Database. These rates were all estimated from local or statewide household travel surveys. While all of these models used person trips as the unit of travel, some used person trips in motorized modes while others used total person trips, including those by walking and bicycling.

While Table 4.4 shows average rates for commonly defined models, achieving commonality required substantial processing. Although trip attraction models are defined for the classic three trip purposes, development of rates for home-based nonwork and nonhome-based trips often required aggregation of more purpose-specific submodels. For example, if a region used both home-based shop and home-based other (representing nonwork and nonshopping travel) trip attraction models, the trip rates per retail employee were added in the composite home-based other trip attraction model. If

Table 4.3. Example number of home-based work trips.

	Persons					
Autos	**1**	**2**	**3**	**4**	**5+**	**Total**
0	2	7	11	0	0	20
1	30	80	84	34	15	243
2	0	195	400	200	115	910
3+	0	0	104	232	330	666
Total	**32**	**282**	**599**	**466**	**460**	**1,839**

Table 4.4. Trip attraction rates from selected MPOs (person trips per unit).

	Number of MPO Models Summarized	Households[a]	School Enrollment[b]	Employment			Total
				Basic[c]	Retail[d]	Service[e]	
All Person Trips							
Home-Based Work							
Model 1	16						1.2
Home-Based Nonwork							
Model 1	2	1.2	1.4	0.2	8.1	1.5	
Model 2	8	2.4	1.1		7.7	0.7	
Model 3	2	0.7		0.7	8.4	3.5	
Nonhome Based							
Model 1	5	0.6		0.5	4.7	1.4	
Model 2	8	1.4			6.9	0.9	
Motorized Person Trips							
Home-Based Work							
Model 1	8						1.2
Home-Based Nonwork							
Model 1	1	0.4	1.1	0.6	4.4	2.5	
Model 3	4	1.0		0.3	5.9	2.3	
Nonhome Based							
Model 1	6	0.6		0.7	2.6	1.0	

[a] The number of households in a zone.
[b] The number of elementary, high school, or college/university students in a zone.
[c] Employment primarily in two-digit North American Industry Classification System (NAICS) codes 1–42 and 48–51 [Standard Industrial Classification (SIC) codes 1–51].
[d] Employment primarily in two-digit NAICS codes 44–45 (SIC codes 52–59).
[e] Employment primarily in two-digit NAICS codes 52–92 (SIC codes 60–97).

Source: MPO Documentation Database.

a region stratified trip attraction rates by area type, averages of the trip rates were estimated. If data were available for the various strata that had to be combined, weighted averages were estimated; where data were not available for weighted averages, simple averages were used. Finally, composite trip rates were estimated for three main employment groups: basic employment, retail employment, and service employment.

Since the presence or absence of other variables in a model can affect the coefficient for a specific model variable, Table 4.4 shows sets of trip rates for trip attraction models with common independent variables. Rates are provided for all person trips and motorized person trips only. Note that there are some combinations of variables that none of the models in the database used for motorized person trip attraction models.

To use the information in Table 4.4 to obtain parameters for trip attraction models, the analyst should choose a model that is consistent with the unit of travel (motorized or nonmotorized trips) and variables that are available for use in model application. The number of attractions can then be computed for each zone. For example, for a zone with 20 households, no school enrollment, 200 basic employees, 10 retail employees, and 100 service employees, the home-based nonwork trip attractions computed from Model 3 are: $0.7 * 20 + 0.7 * 200 + 8.4 * 10 + 3.5 * 100 = 588$.

Table 4.4 shows substantial variation in the trip attraction rates for the various model forms. The variation may reflect the different sizes of urban areas, different travel characteristics, and different development densities or area types, as well as the impact of variables included or excluded from the different model forms. It should be noted that no trends in trip attraction models by urban area population were evident; although the number of models examined is small, this is consistent with previous documentation efforts such as *NCHRP Report 365* (Martin and McGuckin, 1998).

The trip attraction rates shown in Table 4.4 may provide reasonable starting points for models for areas lacking the locally collected data necessary to develop trip attraction models. The selection of the specific model forms to be used could be made based on the types of independent data available for model application. The results of such initial model specifications should be reviewed to ensure that they reflect known travel conditions and behave reasonably for a region. Three examples are provided in the following paragraphs. These examples all use the models for "all person trips" in the upper portion of Table 4.4.

Example 1. Suppose the trip attraction rates from home-based work model 1, home-based nonwork model 3, and nonhome-based model 1 are applied for a region. In a review of traffic assignment results, it is discovered that too many trips are crossing the cordon boundary around the CBD. In such a case, it might be reasonable to reduce the home-based nonwork and nonhome-based trip attraction rates for retail and service employment in the CBD and to balance those reductions in the CBD trip rates with increases of the values for the rates for non-CBD zones. However, before making such adjustments, other checks should be performed, including the accuracy of CBD socioeconomic data, mode shares to the CBD, and comparison of CBD through traffic to observed origin-destination data.

Example 2. Suppose a region has forecasts for only households, retail employment, and nonretail employment available. None of the three home-based nonwork model forms match the independent variables available for the region. In this case, it might be reasonable to test both home-based nonwork models 2 and 3, ignoring the coefficients for the missing variables. Careful attention should be paid to traffic assignment results around industrial areas and educational facilities. The "best performing" model in terms of reproducing traffic volumes would be selected. If neither model performed well, it might be appropriate to mix the rates to address the issues.

Example 3. Again, suppose a region has employment stratified only by retail and nonretail at the zone level. If regional totals for basic and service employment can be determined, nonretail attraction rates for the home-based nonwork and nonhome-based trip purposes can be estimated by applying home-based nonwork model 1 (or model 3) at the regional level and estimating a weighted average trip rate for nonretail employment. The same procedure could be applied using rates from nonhome-based model 1 to develop a weighted average nonretail employment trip rate. If the regional totals for basic and service employment are not available, the straight averages of the rates for basic and service employment could be used. For example, if using model 3 for home-based nonwork attractions for motorized trips, one could use the average of the basic and service employment coefficients (1.3) as the coefficient for nonretail employment.

It is difficult to perform reasonableness checks of trip attraction model results for most trip purposes because the models are multivariate. The coefficients of a model that has the same variables could be compared to those in one of the models in Table 4.4, but having the same or different coefficients as one other model would not provide confirmation of the reasonableness or unreasonableness of the model. For home-based work trips, the vast majority of attraction models in the MPO Documentation Database have coefficients for total employment in the range of 1.0 to 1.5, and so coefficients in this range may be considered reasonable.

4.5 Trip Distribution

Trip distribution is the second step in the four-step modeling process. It is intended to address the question of how many of the trips generated in the trip generation step travel between units of geography, e.g., traffic analysis zones. These trips are in the same units used by the trip generation step (e.g., vehicle trips, person trips in motorized modes, or person trips by all modes including both motorized and non-motorized modes). Trip distribution requires explanatory variables that are related to the impedance[6] (generally a function of travel time and/or cost) of travel between zones, as well as the amount of trip-making activity in both the origin zone and the destination zone.

The inputs to trip distribution models include the trip generation outputs—the productions and attractions by trip purpose for each zone—and measures of travel impedance between each pair of zones, obtained from the transportation networks. Socioeconomic and area characteristics are sometimes also used as inputs. The outputs are trip tables, production zone to attraction zone, for each trip purpose. Because trips of different purposes have different levels of sensitivity to travel time and cost, trip distribution is applied separately for each trip purpose, with different model parameters.

4.5.1 Model Function

The gravity model is the most common type of trip distribution model used in four-step models. In Equation 4-9, the denominator is a summation that is needed to normalize the gravity distribution to one destination relative to all possible destinations. This is called a "doubly constrained" model because it requires that the output trip table be balanced to attractions, while the numerator already ensures that it is balanced to productions.

[6]The term "impedance" is used in this report to represent the generalized cost of travel between two zones. In most cases, the primary component of generalized cost is travel time, and so impedance is often expressed in time units such as minutes.

Gravity Model

$$T_{ij}^{p} = P_i^p * \frac{A_j^p * f(t_{ij}) * K_{ij}}{\sum_{j' \in Zones} A_{j'}^p * f(t_{ij'}) * K_{ij'}} \qquad (4\text{-}9)$$

where:

T_{ij}^p = Trips produced in zone i and attracted to zone j;
P_i^p = Production of trip ends for purpose p in zone i;
A_j^p = Attraction of trip ends for purpose p in zone j;
$f(t_{ij})$ = Friction factor, a function of the travel impedance between zone i and zone j, often a specific function of impedance variables (represented compositely as t_{ij}) obtained from the model networks; and
K_{ij} = Optional adjustment factor, or "K-factor," used to account for the effects of variables other than travel impedance on trip distribution.

Destination Choice

Trip distribution can be treated as a multinomial logit choice model (see Section 4.2) of the attraction location. In such a formulation, the alternatives are the attraction zones, and the choice probabilities are applied to the trip productions for each zone. The utility functions include variables related to travel impedance and the number of attractions (the "size variable"), but other variables might include demographic or area-type characteristics.

A logit destination choice model is singly constrained since the number of attractions is only an input variable, not a constraint or target. Sometimes such a model is artificially constrained at the attraction end using zone-specific constants or post processing of model results.

Development of Travel Impedance Inputs

Zone-to-zone (interzonal) travel impedance. One of the major inputs to trip distribution is the zone-to-zone travel impedance matrices. The first decision is on the components of the travel impedance variable. The simplest impedance variable is the highway (in-vehicle) travel time, which is often an adequate measure in areas without a significant level of monetary auto operating cost beyond typical per-mile costs—for example, relatively high parking costs or toll roads—or extensive transit service. In some areas, however, other components of travel impedance should be considered. These may include distance, parking costs, tolls, and measures of the transit level of service. These measures, and the relative weights of each component, are often computed as part of utility functions in mode choice (Section 4.7).

The individual components of travel impedance are computed as zone-to-zone matrices through "skimming" the highway and transit networks using travel modeling software. The components may be combined through a simple weighting procedure, which might be appropriate if all components are highway related, or through the use of a logsum variable, which can combine highway- and transit-related variables. In this case, the logsum represents the expected maximum utility of a set of mode choice alternatives and is computed as the denominator of the logit mode choice probability function. The logit mode choice model is discussed in Section 4.7.

Terminal times and costs. The highway assignment process (discussed in Section 4.11) does not require that times be coded on the centroid connectors since those links are hypothetical constructs representing the travel time between the trip origin/destination and the model networks, including walking time. However when the skim times from a network assignment are used in trip distribution, the travel time representing travel within zones, including the terminal time, which may include the time required to park a vehicle and walk to the final destination, must be included. If the distribution model includes consideration of impedance based on travel times, this same consideration should also be made for the centroid-based terminal considerations.

Intrazonal impedance. Network models do not assign trips that are made within a zone (i.e., intrazonal trips). For that reason, when a network is skimmed, intrazonal times are not computed and must be added separately to this skim matrix.

There are a number of techniques for estimating intrazonal times. Some of these methods use the average of the skim times to the nearest neighboring zones and define the intrazonal time as one-half of this average. Various mechanisms are used to determine which zones should be used in this calculation, including using a fixed number of closest zones or using all zones whose centroids are within a certain distance of the zone's centroid. Other methods compute intrazonal distance based on a function of the zone's area, for example, proportional to the square root of the area. Intrazonal time is computed by applying an average speed to this distance.

Friction factors. There are two basic methods for developing and calibrating friction factors for each trip purpose:

- A mathematical formula and
- Fitted curves/lookup tables.

Three common forms of mathematical formulas are shown below, where F_{ij}^p represents the friction factor and t_{ij} the travel impedance between zones i and j:

- **Power function**, given by the formula $F_{ij}^p = t_{ij}^a$. A common value for the exponent a is 2.

- **Exponential**, given by the formula $F^p_{ij} = \exp(-m * t_{ij})$. An advantage of this formula is that the parameter m represents the mean travel time.
- **Gamma function**, given by the formula:

$$F^p_{ij} = a * t^b_{ij} * \exp\left(c * t_{ij}\right) \tag{4-10}$$

The parameters a, b, and c are gamma function scaling factors. The value of b should always be negative. The value of c should also generally be negative (if a positive value of c is used, the function should be carefully inspected across the full expected range of input impedance values to ensure that the resulting friction factors are monotonically decreasing). The parameter a is a scaling factor that does not change the shape of the function. Section 4.5.4 presents some typical values for the parameters b and c. These factors may be adjusted during model calibration to better fit the observed trip length frequency distribution data (usually from household travel surveys). This adjustment is commonly done on a trial-and-error basis.

Some modeling software packages allow the input of a lookup table of friction factors for each trip purpose, with some providing the capability of fitting these factors to best fit observed trip length frequency distributions.

4.5.2 Best Practices

While best practice for trip distribution models would be considered to be a logit destination choice model, the gravity model is far more commonly used, primarily because the gravity model is far easier to estimate, with only one or two parameters in the friction factor formulas to calibrate (or none, in the case of factors fitted directly to observed trip length frequency distributions), and because of the ease of application and calibration using travel modeling software.

There is no consensus on whether it is better to always have a singly constrained or doubly constrained trip distribution model. For home-based work trips, some type of attraction end constraint or target seems desirable so that the number of work trip attractions is consistent with the number of people working in each zone. For discretionary travel, however, the number of trip attractions can vary significantly between two zones with similar amounts of activity, as measured by the trip attraction model variables. For example, two shopping centers with a similar number of retail employees could attract different numbers of trips, due to differences in accessibility, types of stores, etc. A doubly constrained model would have the same number of shopping attractions for both shopping centers, and a doubly constrained trip distribution model would attempt to match this number for both centers. So it might be reasonable to consider singly constrained models for discretionary (nonwork, nonschool) trip purposes, although implied zonal attraction totals from such distribution models should be checked for reasonableness.

Besides segmentation by trip purpose, it is considered best practice to consider further segmentation of trip distribution using household characteristics such as vehicle availability or income level, at least for home-based work trips. This additional segmentation provides a better opportunity for the model to match observed travel patterns, especially for work trips. For example, if the home-based work trip distribution model is segmented by income level, work trips made by households of a particular income level can be distributed to destinations with jobs corresponding to that income level.

However, it may be difficult to segment attractions by income or vehicle availability level since the employment variables used in trip attraction models are not usually segmented by traveler household characteristics. Often, regional percentages of trips by income level, estimated from the trip production models, are used to segment attractions for every zone, especially for nonwork travel, but this method clearly is inaccurate where there are areas of lower and higher income residents within the region.

Methods to estimate household incomes by employee at the work zone have begun to be used but are not yet in widespread practice. Kurth (2011) describes a procedure used in the Detroit metropolitan area. This procedure consists of estimating the (regional) proportions of workers by worker earnings level based on industry, calculating the shares of workers by worker earnings group for each industry by area type, and calculating the shares of workers by household income for each worker earnings group by area type. The model is applied using the workers by industry group for each zone.

Some advantages to segmentation by vehicles rather than income level include:

- Often, a better statistical fit of the cross-classification trip production models;
- Avoidance of the difficulty in accurate reporting and forecasting of income;
- Avoidance of the need to adjust income for inflation over time and the difficulty of doing so for forecasting;
- Avoidance of the need to arbitrarily define the cutoffs for income levels because income is essentially a continuous variable; and
- Likelihood that vehicle availability has a greater effect on mode choice, and possibly trip distribution as well.

That being said, there are also advantages to using income level for segmentation, which is a more common approach in U.S. travel models. Perhaps the main advantage is that the trip attractions can be more easily segmented by income level. For example, home-based work trip attractions at the zone level are usually proportional to employment, and employment is easier to segment by income level than by number of autos. Some employment data sources provide information on income levels for jobs; no such information exists for vehicle availability levels. [However, it should be noted that income for a specific work attraction (job) is not the same as household income, which includes the incomes of other workers in the household.]

No one method for developing friction factors is considered "best practice." Some analysts find the gamma function easier to calibrate, because it has two parameters to calibrate compared to a single parameter for power and exponential functions. Since the exponential function's parameter is the mean travel time, this value can be easily obtained from observed travel data (where available), but matching the mean observed travel time does not necessarily mean that the entire trip length frequency distribution is accurate.

It is important to understand that matching average observed trip lengths or even complete trip length frequency distributions is insufficient to deem a trip distribution model validated. The modeled orientation of trips must be correct, not just the trip lengths. The ability to calibrate the origin-destination patterns using friction factors is limited, and other methods, including socioeconomic segmentation and K-factors, often must be considered.

4.5.3 Basis for Data Development

The best practice for the development of trip distribution models is to calibrate the friction factors and travel patterns using data from a local household activity/travel survey. If such a survey is available, it is straightforward to determine observed average trip lengths and trip length frequency distributions for each trip purpose and market segment. Calibrating friction factors to match these values is an iterative process that is usually quick and may be automated within the modeling software.[7] Household survey data can also be used as the basis for estimating observed travel patterns for use in validation, although sample sizes are usually sufficient to do this only at a more aggregate level than travel analysis zones.

The question is what to do if there is insufficient local survey data to develop the estimates of the observed values. Data sources such as the NHTS have insufficient sample sizes for individual urban areas to develop trip length frequency estimates for each trip purpose (although if an urban area is located in an NHTS add-on area, the sample size might be sufficient). Trip length distributions can vary significantly depending on the geography of a model region and its extent, which can often depend on factors such as political boundaries, the size of the region, physical features such as bodies of water and mountain ranges, and the relative locations of nearby urban areas. Therefore, simply using friction factors from another model may result in inaccurate trip distribution patterns.

The best guidance in this situation is to start with parameters from another modeling context and to calibrate the model as well as possible using any local data that are available, including data on work travel from the ACS/CTPP, traffic counts, and any limited survey data that might be available.

Section 4.5.4 (Model Parameters) provides information from two sources. First, sample gamma function parameters for friction factors from seven MPOs, obtained from the MPO Documentation Database, are summarized. Mathematically, it does not make sense to average these parameters, nor can consensus factors be derived. The guidance is to choose a set of parameters as a starting point, perhaps by testing different sets of parameters to see which provide the best results, and adjusting them as needed. This process is described more completely Section 4.5.4.

The second data source is the 2009 NHTS, from which average trip lengths by trip purpose for each urban area size category are presented. This information could be used as a starting point for developing friction factors as well as for reasonableness checks of modeled trip lengths in areas without local survey data. They should not be used as "hard" validation targets for specific urban area models.

4.5.4 Model Parameters

Gravity Model Parameters

Gamma function parameters were available for the classic three trip purposes for seven MPOs from the MPO Documentation Database. Table 4.5 presents the *b* and *c* parameters used by these MPOs. Since friction factors can be scaled without impacting the resulting distribution, the parameters shown in Table 4.5 were scaled to be consistent with one another. The resulting friction factor curves for the home-based work, home-based nonwork, and nonhome-based trip purposes are shown in Figures 4.2 through 4.4.

The MPO size categories for Table 4.5 are:

- Large MPO—Over 1 million population;
- Medium MPO—500,000 to 1 million population;
- Medium (a) MPO—200,000 to 500,000 population; and
- Small MPO—50,000 to 200,000 population.

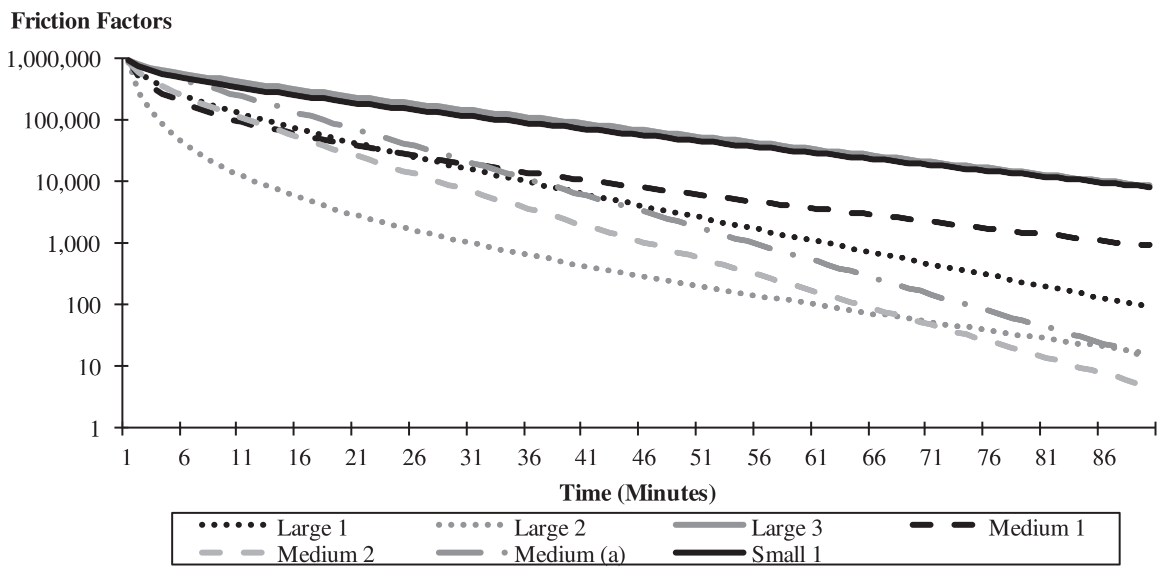
The guidance is to choose one of these seven sets of parameters (the six *b* and *c* parameters from the same model) based

[7]Frequency distributions of trip length as reported from survey respondents are "lumpy" due to rounding of times. One way of resolving this issue is to use only the respondents' reported origins and destinations and to use the travel times from the networks for the corresponding origin-destination zones to create the frequency distributions. This method also has the advantage of using a consistent basis for travel time estimation across all survey observations.

Table 4.5. Trip distribution gamma function parameters for seven MPOs.

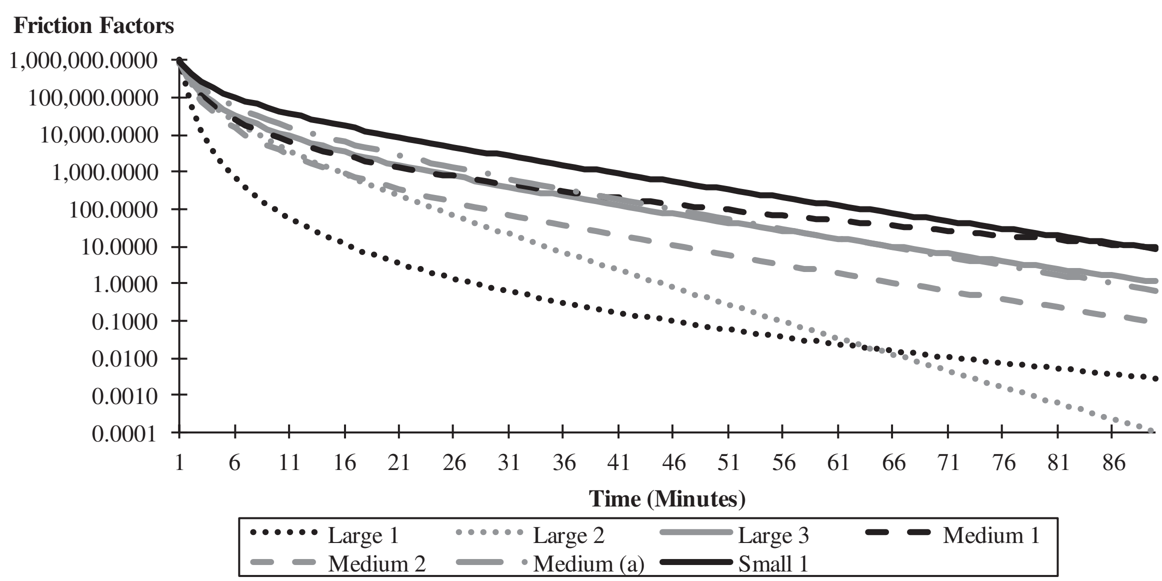
	Home-Based Work		Home-Based Nonwork		Nonhome Based	
	b	*c*	*b*	*c*	*b*	*c*
Large MPO 1	–0.503	–0.078	–3.993	–0.019	–3.345	–0.003
Large MPO 2	–1.65	–0.0398	–1.51	–0.18	–1.94	–0.116
Large MPO 3	–0.156	–0.045	–1.646	–0.07	–2.824	0.033
Medium MPO 1	–0.81203	–0.03715	–1.95417	–0.03135	–1.92283	–0.02228
Medium MPO 2	–0.388	–0.117	–2.1	–0.075	–1.8	–0.16
Medium (a) MPO 1	–0.02	–0.123	–1.285	–0.094	–1.332	–0.1
Small MPO 1	–0.265	–0.04	–1.017	–0.079	–0.791	–0.195

Source: MPO Documentation Database.



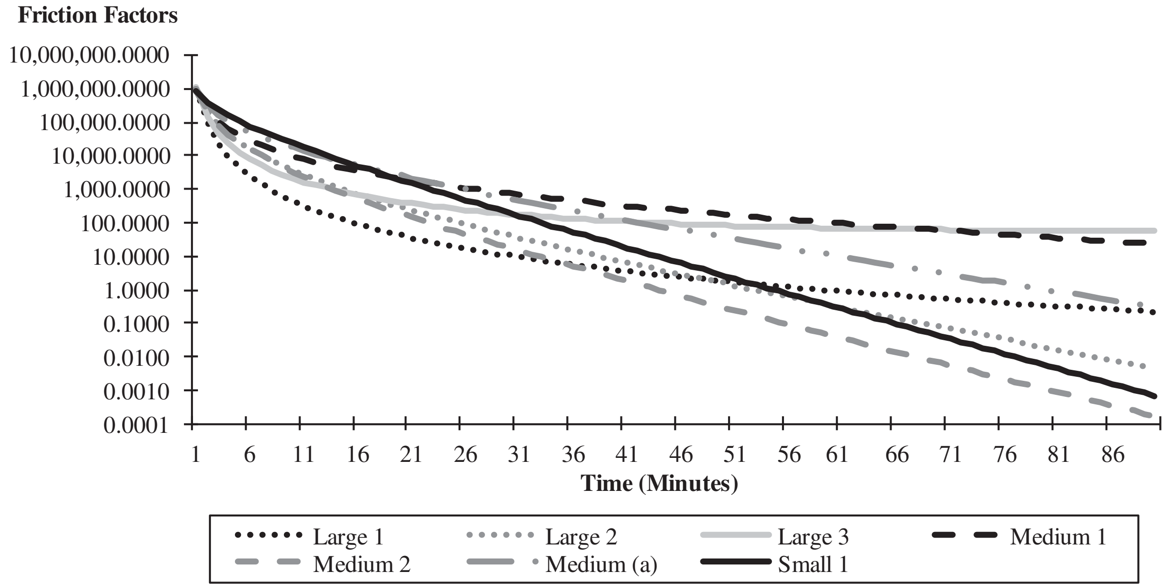
Source: MPO Documentation Database.

Figure 4.2. Home-based work trip distribution gamma functions.



Source: MPO Documentation Database.

Figure 4.3. Home-based nonwork trip distribution gamma functions.



Source: MPO Documentation Database.

Figure 4.4. Nonhome-based trip distribution gamma functions.

on the characteristics of the analyst's model region. The curves shown in Figures 4.2 through 4.4 may be useful in identifying the sensitivity to travel time and the general shape of the friction factors compared to what the analyst knows about travel in his/her region. Note that since *a* is a scaling parameter that does not change the shape of the gamma function curve, it can be set at any value that proves convenient for the modeler to interpret the friction factors.

Whichever model's parameters are chosen, they should serve as a starting point for calibrating the model to local conditions. If the analyst is unsure which set of parameters to choose, multiple sets of parameters could be tested to see which provides the best fit to observed trip length frequencies. Regardless of which set is chosen, the analyst should adjust the parameters as needed to obtain the most reasonable model for the region.

Average Trip Lengths (Times)

Table C.10 presents respondent-reported average trip lengths and standard deviations in minutes from the 2009 NHTS data set. This information can be used to help find starting points for friction factor parameters (for example, as initial values for parameters in exponential friction factor functions) and to test trip length results from trip distribution models for reasonableness. The information is presented for auto, transit, and nonmotorized modes as well as for all modes.

Initially, the trip length data were summarized for the six population ranges available in the NHTS data set. However, the trip lengths do not vary much by urban population for nonwork travel, and many of the differences appear to be small fluctuations between population ranges. The recommendations, therefore, represent mean trip lengths averaged across urban area population ranges in most cases.

It should be noted that the sample sizes for transit trips, especially for urban areas under 1 million in population, were insufficient to estimate separate meaningful average trip lengths by population range. This was true for nonmotorized trips as well in some cases.

Even though average trip lengths are fairly consistent across urban area sizes, this should not be construed to imply that trip lengths are the same among all individual urban areas, even within each population range.

Some patterns can be noted from the data shown in Table C.10:

- Average home-based work trip lengths are longer in larger urban areas, particularly for auto and nonmotorized trips;
- Transit trips are over twice as long as auto trips in terms of travel time; and
- Average trip lengths for nonmotorized trips for all purposes are about 15 minutes and are consistently in the mid-teens. This equates to about 0.75 miles for walking trips.

4.6 External Travel

Travel demand models estimate travel for a specific geographic region. While the trip generation process estimates the number of trips to and from zones within the model region based on socioeconomic data for those zones, not every trip will have both trip ends internal to the boundary of the model. In nearly all models, some trips will have one or both trip ends outside of the geography served by the model. Trips with at least one external trip end, depending on the size of the urban area and its location with respect to other areas, might represent a substantial portion of travel within the region.

By convention, zones located inside the model region are called "internal zones." External zones representing relevant activity locations outside the model region are represented in the model by points at which highway network roadways (and sometimes transit lines) enter and leave the region, often referred to as "external stations." Trips for which both ends are internal to the model region are referred to as "internal–internal" (II). Trips that are produced within the model region and attracted to locations outside the model region are called "internal–external" (IE), while trips produced outside the region and attracted to internal zones are called "external–internal" (EI). Trips that begin and end outside the region but pass through the region are labeled "external–external" (EE). (In some regions, the letter "X" is used rather than the letter "E," as in IX, XI, and XX trips.) Sometimes all trips with one end inside the model region and one end outside are referred to as IE/EI trips. Generally, the terms "external trips" and "external travel" refer to all IE, EI, and EE trips.

4.6.1 Model Function/Best Practices

Usually, external trips are treated as vehicle trips, even if the II trips are treated as person trips. This means that external transit trips are typically ignored as well as changes in vehicle occupancy for external auto trips. In many areas, there is little or no regional transit service that travels outside the model region, or HOV or managed lanes crossing the regional boundary, that might require the ability to analyze mode choice for external travel. Since urban area travel models lack sufficient information to model choices involving interurban travel, it is common practice to treat interurban trips by nonauto modes as having the external trip end at the station or airport, essentially treating these trips as II (with airports usually treated as special generators or airport access/egress treated as a separate trip purpose).

Most of the areas where some treatment of external transit trips is desirable are larger areas, often those close to other urban areas (for example New York and Philadelphia). For the vast majority of urban areas, though, treatment of external vehicle trips is sufficient. Because larger areas tend to have more survey data available, and there are insufficient examples of external transit travel models to evaluate their transferability, the remainder of Section 4.6 concentrates on the modeling of external vehicle trips.

It is important to recognize the relationship between the trip generation and distribution steps for II trips and the external travel modeling process. Two points must be considered in developing modeling procedures for external trips:

- The trip generation models described in Section 4.4 are estimated from household survey data. These surveys include both II and IE trips, and, unless the IE trips were excluded from the model estimation, the resulting trip production models include both II and IE trips. The trip rates presented in Tables C.5 through C.9 based on the NHTS data include all trips generated by the respondent households (II and IE). In most models, the II trips dominate regional travel, and the effect of IE trips is minimal. However, the amount of IE travel generated in zones near the model region boundary can be significant.
- On the other hand, trip attraction models estimated from household survey data include only those trips produced in the model region. So, estimated attraction models include only II trips. Because it is common practice to balance trip attractions to match regional productions and EI trips are modeled using other data sources, the use of only II trips in the models generally does not have the effect of "missing" the EI trips, although the quality of estimates of the split between II and EI attractions depends on the availability and quality of data on external travel, as well as the local household survey data.

Data Sources

Household activity/travel surveys include IE trips, but not EI trips as defined on a production/attraction basis. Furthermore, the information provided on the attraction end of IE trips is based on the ultimate destination and does not specify the external zone that would be the effective destination of a modeled trip. This means that the main information to be obtained on external travel from the household survey would be total numbers of IE trips for different segments of zones and perhaps some rough orientation information regarding the external destinations. Additionally, the number of IE trips reported in household surveys is often low. Thus the household survey cannot serve as the primary source for external model development.

A more complete data source would be an external station survey. In such a survey, drivers of vehicles observed on a roadway crossing the model region boundary are surveyed through vehicle intercept or mailout/mailback surveys, where the license plates are recorded to determine to whom to send the surveys. Ideally, every external station (zone) would be surveyed, although this may be impractical in areas with a large number of external zones, and it may be very inefficient to survey a large number of low-volume roadways.

Data from an external station survey could be used to develop models that estimate the number of IE/EI trips generated by internal zones, by trip purpose if the data have sufficient observations by purpose. Distribution models for IE/EI trips could also be estimated; such models would essentially match the vehicle trip ends between the external and internal zones.

External Productions and Attractions

The definitions of productions and attractions remain the same for external trips as for II trips. That is, the home end of a home-based trip is the production end and the nonhome end is the attraction end; for nonhome-based trips, the origin is the production end and the destination is the attraction end.

For simplicity, some models have treated all IE/EI trips as produced at the external zone (i.e., as if all such trips were EI). In these contexts, this simplification probably is adequate since there are relatively few significant trip attractors outside the urban area for residents of the region, and so the majority of IE/EI trips are, in fact, EI. However, in some regions, especially as areas close to the model region's boundary have become more developed, the share of IE trips has become more significant. So if data are sufficient, it may make sense to model IE and EI trips separately.

External trip generation totals for the **external zones** include EI, IE, and EE trips. The total number of vehicle trips for an external zone for the base year is equal to the observed traffic volume on the corresponding roadway at the regional boundary. For forecast years, most areas must rely on growth factors applied to the base year traffic volumes. Generally, the external zone volume serves as a control total for the sum of EI, IE, and EE trips.

External trip generation totals for the **internal zones** include EI and IE trips. The total number of these trips over all internal zones is controlled by the sum of external trips for the external zones, based on the traffic volumes as described above, and excluding the EE trips. The percentage split between EE and IE/EI trips at each external zone is typically the starting point in estimating external travel components by external zone. Ideally, the percentage split should come from a roadside cordon line survey; however, guidance is provided in the following paragraphs on tendencies that can be used to determine the percentage of EE trips.

External–External Trips

The amount of EE travel may depend on a number of factors, including:

- **Size of the region**—Generally, larger regions have fewer through trips.
- **Presence of major through routes**—Naturally, the presence of these routes, usually Interstate highways, results in higher EE travel.
- **Location of the urban area relative to others**—If other urban areas are located near the boundary of the urban area, this can have significant effects on orientation of travel within the region.
- **Location of physical features and barriers**—If there are any of these in or near the model region, they may affect the amount of through travel.

A fairly complete set of external station surveys for a region would be the best source for estimating EE travel. Such a survey could be used to develop a zone-to-zone trip table of EE trips for the base year. Forecast year tables could be developed by applying growth factors at the zone level, based on projected growth inside and outside the region for areas served by each roadway. A Fratar process is often used for this purpose. This process uses iterative proportional fitting to update a matrix when the marginal (row and column) totals are revised. In this case, the row and column totals are updated to represent the change in EE trips for each external zone between the base and forecast years.

In the absence of such survey data, the true EE trip table will be unknown, as will the error between the modeled and actual EE trips. The validity of transferring EE trip percentages from other regions is unknown; in addition, because the factors listed previously can vary significantly between regions, finding a region similar enough to the application context that has the necessary survey data can be difficult and, even if such a region is found, it is unknown how much the EE travel percentages between the regions would actually vary. Transferring EE trip tables is therefore not recommended.

A suggested method for synthesizing EE trip tables is as follows:

1. Identify which external zone pairs are most likely to be carrying EE trips. These external zone pairs should include any pairs of zones where the corresponding highways are Interstates, freeways, or principal arterials. Figure 4.5 illustrates some examples of external zone pairs that are likely or unlikely to have EE travel. External zone pairs that do not include logical paths within the model region should be excluded. For example, zone 1001 to zone 1002 in Figure 4.5 would be unlikely to include many EE trips as both zones lead to the same general location, meaning that a trip between these two zones would essentially be a "U-turn" movement. Zone pairs with short logical paths through the model region should probably be included even if one or more of the corresponding roadways is of a lower facility type (for example, zone 1002 to zone 1003 in Figure 4.5). While there are undoubtedly a few EE trips that would be made in the model region between external zone pairs that do not meet these criteria, these are probably very small in number and can be ignored without significant impacts on the model results.

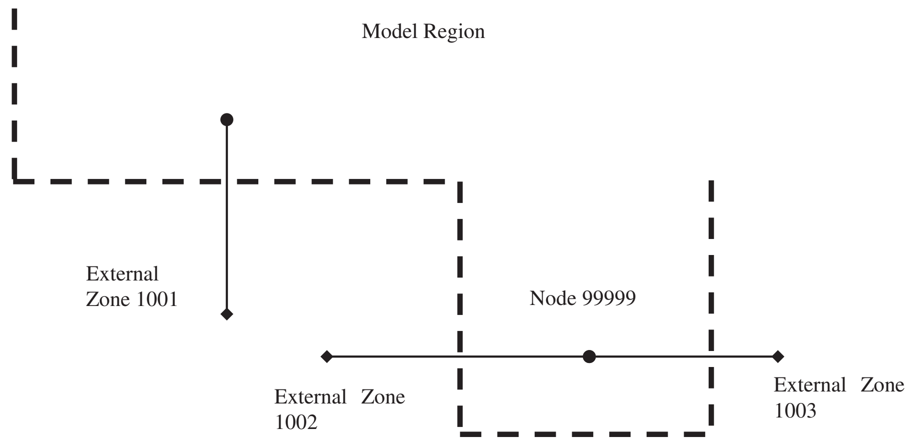


Figure 4.5. Example of external zone pairs with and without EE trips.

2. Estimate the number of EE trips for each zone pair identified in Step 1 that represent reasonable percentages of the total volumes of both highways. It makes sense to focus on the roadway with the lower volume in terms of making sure that the percentages are reasonable. There is little guidance available to estimate percentages. Martin and McGuckin (1998) cites a study by Modlin (1982) that provided a formula, intended to be used in urban areas of less than 100,000 population, that estimates the percentage of total external travel that is EE, based on facility type daily traffic volumes, truck percentages, and model region population. This formula results in EE travel percentages of about 30 percent for principal arterials and 70 percent for Interstates in urban areas of 50,000 population and of about 10 percent and 50 percent, respectively, for urban areas of 100,000 population (note that these figures represent total EE travel on a roadway to all other external zones).
3. During highway assignment, checks on volume-count ratios along "internal" segments of these roadways should help indicate whether or not the EE trips were overestimated or underestimated. For example, a persistent over-assignment along an Interstate passing through a region could indicate that the number and percentage of EE trips might have been overestimated.

While this process is very rough given the lack of data used, the amounts of EE travel are usually fairly small; therefore, the error associated with these estimates, while unknown, is likely small.

Internal–External and External–Internal Trips

The process of modeling IE/EI trips includes the following steps:

1. Identifying the trip purposes to be used for IE/EI trips;
2. Deciding whether to treat all IE/EI trips as EI;
3. Deciding on external zone roadway types to be used;
4. Estimating the number of IE/EI vehicle trips for each external zone by purpose and splitting them into IE and EI trips;
5. Estimating the number of IE/EI vehicle trips for each internal zone by purpose and splitting them into IE and EI trips; and
6. Distributing IE and EI trips between external and internal zones by purpose.

The result of this process is a set of IE and EI vehicle trip tables by trip purpose. These trip tables can be combined into a single trip table, or combined with vehicle trip tables for II trips, for highway assignment. The six steps are described in more detail in the following paragraphs.

Step 1: Identifying the trip purposes to be used for IE/EI trips. Often, the available data are insufficient to model multiple IE/EI trip purposes, and the relatively small number of these trips means that the added cost of separating IE/EI trip purposes does not usually provide a great benefit. Most models, therefore, do not distinguish among trip purposes for IE/EI trips, although some models separate trips into home-based work and all other. Another consideration is that without an external station survey, there may not be enough information to determine the percentage of IE/EI trips by purpose.

Areas that would benefit most from allocating IE/EI trips into multiple purposes are those with an adjacent urban area on the other side of the study area cordon line. In fact, it may become necessary for proper validation of such a model to allow internally generated IE/EI trips such as work to be attracted to external zones, if in fact a large percentage of residents work in the adjacent urban area. Such an adjustment is sometimes made using special generators or by modifying the trip generation program to estimate home-based work attractions to external zones.

Step 2: Deciding whether to treat all IE/EI trips as EI. As mentioned above, some models treat all IE/EI trips as produced at the external zone (i.e., as if all such trips were EI). The analyst must decide whether this distinction is warranted by the volume and orientation of external trips in the model region and the availability of data to distinguish between IE and EI trips. Generally, it is probably not worth modeling IE and EI trips separately in regions with low volumes of external travel and regions with little nonresidential activity located just outside the model area boundary. If data from an external station survey are available, they could be used to determine whether there is a high enough percentage of IE trips to make modeling them separately worthwhile.

Step 3: Deciding on external zone roadway types to be used. Travel characteristics vary significantly depending on the type of highway associated with an external zone. In general, the higher the class of highway at the cordon, the longer its trips are likely to be. For example, some roads, such as Interstate highways, carry large numbers of long-distance trips. On average, a smaller percentage of the total length of trips on these roadways would be expected to occur in the model region, implying that travelers might be willing to travel farther within the region once they cross the regional boundary. Other roads carry predominantly local traffic. Since local trips are generally short, there is a much greater likelihood that the local ends of these trips are near the boundary. The facility type of the external zone highway, therefore, becomes a strong surrogate for other determinants of the types and kind of external travel.

The following stratification scheme for external zones is often used to account for these differences:

- Expressway;
- Arterial near expressway;
- Arterial not near expressway; and
- Collector/local.

These roadway types are, in effect, the trip purposes for the external–internal trips. Other "special" roadway categories that may exist in a region, such as bridge crossings for major bodies of water at the regional boundary, toll roads and turnpikes that carry a large amount of long-distance travel, or international boundary crossings, may warrant separate categories.

Once the roadway types are chosen, each external zone is classified accordingly.

Step 4: Estimating the number of IE/EI vehicle trips for each external zone by purpose and splitting them into IE and EI trips. The control total for IE/EI trips for each external zone is the total volume for the zone minus the EE trips for the zone. If the trips are not separated by purpose or into IE and EI trips, then only total EI trips are needed, and they will be equal to the control total. Otherwise, percentages must be estimated to divide the trips. An external station survey would be the only source for actual percentages. Unfortunately, there is little information available that could be used to develop transferable parameters; even if there were, the substantial differences between urban areas and the influence of areas outside the model region would make transferability questionable in this case.

Step 5: Estimating the number of IE/EI vehicle trips for each internal zone by purpose and splitting them into IE and EI trips. The total IE/EI trips, by purpose and split into IE and EI trips, over all external zones serves as the control total of IE/EI trips for all internal zones. One example of a model used to estimate the IE/EI trips for each zone is discussed below. This example assumes that all IE/EI trips are EI trips, but the same type of model could be used separately for each trip purpose and for IE trips.

The functional form of the external trip generation model for internal zones is presented in Equation 4-11. These trips are treated as being produced at the external station and attracted to the internal zone. The attractions generated by each internal zone are computed as a function of the total trip attractions and the distance from the nearest external zone. The internal trip attraction model generates, for each internal zone, the EI trips as a percentage of the total internal trip attractions. The trip generation model has the form:

$$E_j = AT_jD_j^B \tag{4-11}$$

where:

E_j = EI trips generated in internal zone j;
T_j = Total internal trip attractions generated in internal zone j;
D_j = Distance from zone j to the nearest external station; and
A, B = Estimated parameters.

The EI trip attractions generated by this formula are subtracted from the total internal person trips generated for the zone to produce revised total II trip attractions for the zone. Note that these are person trips that must be converted to vehicle trips, using vehicle occupancy factors (see Section 4.8).

The model parameters A and B are estimated for each roadway type through linear regression based on an external station survey data set. This is done by transforming Equation 4-11 using logarithms:

$$\log(E_j) = \log(A + T_j) + B(\log(D_j)) \tag{4-12}$$

The distance variables D_j are obtained by skimming the highway network and can be expressed in any distance units, although miles are customary. The total trip attractions T_j are determined from the internal trip generation process, as described in Section 4.4. The external trips E_j are obtained directly from the external survey data set. These parameters are calibrated to produce an exact match between the modeled EI vehicle trips and the observed external zone volumes.

Step 6: Distributing IE and EI trips between external and internal zones by purpose. As is the case for the internal trips, the most common approach to distributing IE/EI trips is the gravity model (See Equation 4-9). If external station survey data are available, the friction factors can be estimated in a manner that matches the observed trip length (highway travel time) frequency distribution. K-factors are often used in model calibration to match travel patterns on an aggregate (district) basis. If survey data are unavailable, friction factors from the internal travel model could be used as a starting point for model calibration.

4.6.2 Basis for Data Development

As discussed previously, an external station survey data set is a valuable resource in estimating and calibrating external travel models. If such a survey is unavailable, Section 4.6.3 provides external trip generation parameters from an example urban area.

4.6.3 Model Parameters

Table 4.6 provides sample *A* and *B* parameters for the IE/EI trip generation equation (4-11). These were estimated using external station survey data for a large U.S. urban area.

Example

Consider an internal zone *j* with 100 total attractions, located the following distance from an external station of each facility type:

- Freeway/expressway—10 miles;
- Arterial near expressway—10 miles;
- Arterial not near expressway—5 miles; and
- Collector/local—2 miles.

The number of EI trips attracted to zone *j* for each external station facility type is given by (using the parameters shown in Table 4.6):

- Freeway/expressway: $E_j = (0.071)\ (100)\ (10^{-0.599}) = 1.8$ trips;
- Arterial near expressway: $E_j = (0.118)\ (100)\ (10^{-1.285}) =$ 0.6 trips;
- Arterial not near expressway: $E_j = (0.435)\ (100)\ (5^{-1.517}) =$ 3.8 trips; and
- Collector/local: $E_j = (0.153)\ (100)\ (2^{-1.482}) = 5.5$ trips.

In this example, about 12 of the 100 trip attractions in zone *j* are EI trips.

Table 4.6. Sample trip generation model parameters.

Station Type	*A*	*B*
Freeway/Expressway	0.071	−0.599
Arterial Near Expressway	0.118	−1.285
Arterial Not Near Expressway	0.435	−1.517
Collector/Local	0.153	−1.482

Source: Cambridge Systematics, Inc. (2002).

4.7 Mode Choice

Mode choice is the third step in the four-step modeling process. In models where the unit of travel is vehicle trips, only automobile travel is modeled, and therefore there is no need for a mode choice step. (Hence, these models are sometimes referred to as "three-step models.") The automobile occupancy step, discussed in Section 4.8, is not needed in these models either.

Mode choice is required in models where the unit of travel is person trips by all modes, or by all motorized modes. The mode choice model splits the trip tables developed in trip distribution into trips for each mode analyzed in the model. These tables are segmented by trip purpose and in some cases further segmented by income or number of vehicles, as discussed in Section 4.5.2. If the unit is person trips by motorized modes, these modal alternatives include auto and transit modes. If the unit is person trips by all modes including nonmotorized modes, then the modal alternatives may also include walking and bicycling, although sometimes nonmotorized trips are factored out prior to mode choice.

4.7.1 Model Function

Modal Alternatives

The first step in mode choice is determining which modal alternatives are to be modeled. Generally, alternatives can be classified as auto, transit, and nonmotorized modes. The simplest models may model just these three main modes (or two, if nonmotorized travel is not included in the model).

Auto modes are generally classified by automobile occupancy level (e.g., drive alone, two-person carpool, and three-or-more-person carpool). Sometimes autos using toll roads are modeled as separate alternatives, often also classified by auto occupancy level.

Transit modes apply to complete (linked) trips from origin to destination, including any walk or auto access or egress as well as transfers. These may be classified by access (and sometimes egress) mode and by type of service. Because such variables as walk time and parking cost are important elements in mode choice, walk access and auto access transit modes should be modeled separately, unless there is little demand for transit where people drive or are driven to the transit stop. Service types that may be modeled separately are often defined by local (e.g., local bus) versus premium (e.g., commuter rail) service. Among the modes that have been included in mode choice models in the United States are local bus, express bus, light rail, heavy rail (e.g., subway), and commuter rail. Some models include a generic "premium transit" mode.

There are advantages and disadvantages to having a large number of modal alternatives defined by service type. An advantage is that differences in level of service can be considered more readily, and many travelers view various transit types very differently (for example, some travelers who use commuter rail might not consider using local bus). A disadvantage is that having more modes makes the model more complex, and therefore harder to estimate and more time consuming to apply, and the complexity may result in complicated nesting structures that are hard to estimate and difficult to find transferable parameters for. Another issue is how to classify "mixed mode" trips, for example, a trip where a traveler uses both local bus and heavy rail. There is no ideal method to classify such trips; methods such as classifying trips as the "more premium" of the modes used would be inappropriate for trips that are primarily on a less premium mode, and most modeling software does not provide a way of identifying the percentage of each submode between an origin and destination.

Nonmotorized modes are sometimes separated into two modes, walk and bicycle, but are often treated as a single modal alternative. (Note that a walk or bicycle access segment of a transit trip is not considered a separate trip; it is considered part of the transit trip.)

Mode choice is applied by first estimating the probability of choosing each modal alternative for each traveler or segment of travelers. The probability is based on a set of explanatory variables that include characteristics of the modal level of service, traveler characteristics, and features of the areas where the travel takes place. In four-step models, the probabilities are applied as shares of the market segments to which they apply; that is, if a mode has a 75 percent probability of being chosen by a market segment (e.g., work trips for an origin-destination zone pair), 75 percent of the travelers in that segment are allocated to that mode.

Most mode choice models use the logit formulation. In a logit mode choice model, the alternatives represent the modes. The utility is a function of the explanatory variables. These variables may include the following:

- **Modal level of service—**Auto in-vehicle time, transit in-vehicle time, wait time, walk access/egress time, auto access time, transit fare, parking cost, number of transfers;
- **Traveler characteristics—**Vehicle availability (sometimes relative to other potential drivers), household income, gender, age, worker/student status; and
- **Area characteristics—**Development density, pedestrian environment.

At a minimum, mode choice models need to include level-of-service variables so that the effects of changes in level of service (e.g., run time improvements, fare increases, parking costs) can be analyzed. Transportation investment and policy alternatives usually change the level of service for one or more modes relative to the others, and so the effects on modal usage need to be estimated. The inclusion of traveler characteristics allows the model to be sensitive to changing demographics. Including area characteristics allows the model to consider the effects of land use changes, which may be part of policy alternatives the model is being used to help analyze.

The values for the modal level-of-service variables must be obtained for every origin-destination zone pair. These values are obtained through the process of skimming the networks, as discussed in Section 4.5. A separate skim matrix is needed for each modal alternative (and each time period, if time-of-day modeling, discussed in Section 4.9, is employed). This requirement implies that a network is needed for each mode. These individual modal networks are developed from the basic two networks—highway and transit—and by adjusting parameters to match the assumed use of the mode. For example, skims for a local bus mode could be obtained by allowing travel only on local bus routes in the transit network. For transit auto access modes, provision must be made for allowing auto portions of these trips to be made along the highway network. For nonmotorized modes, the usual practice is to revise the highway network by eliminating links on which only motorized vehicles are allowed (freeways, ramps, etc.) and skimming the network using minimum distance paths.

While the foregoing description of obtaining the mode-specific paths may appear to be relatively simple, great care must be used in the process to ensure that the paths and skims obtained are consistent with the mode choice model. This may be difficult when obtaining paths for "higher-level" modes. For example, while drive-alone paths could be obtained by turning off HOV links in the path-building process, it might be necessary to "encourage" the use of HOV links (or discourage the use of drive-alone links) in order to obtain reasonable HOV paths and skims for the mode choice model. At the same time, this encouragement should be performed in such a way that preserves the relationships between parameters used in the path-building process and mode choice coefficients. This is especially true for transit path-building. If the mode choice model coefficients show that out-of-vehicle time is twice as onerous as in-vehicle travel time (i.e., the ratio of the coefficients is two to one), it is improper to use a different relationship between out-of-vehicle time and in-vehicle time in the path-building process.

4.7.2 Best Practices

As is the case with trip distribution models, mode choice model accuracy can be enhanced by segmenting the model by income or vehicle availability level. When there are more than two modal alternatives, as is common in mode choice models, the multinomial logit model can introduce inaccuracies in the way it estimates how people choose among alternatives. One way of dealing with this issue is the use of a nested logit model (see Section 4.2). A major advantage of nested structures for mode choice is that similar modes, such as transit with auto access and transit with walk access, can be grouped as a subset, all branching from a common "composite mode."

As discussed in Section 4.2, the "nesting coefficient" must be between zero and one and should be statistically significantly different from zero and one. In the literature review of transferability studies (see Appendix B), no research was found into the transferability of nesting coefficients from one area to another. In models around the United States, nesting coefficients are often asserted with values ranging from about 0.2 to 0.8, nearly the entire valid range.

The IIA assumption (discussed in Section 4.2) can be problematic in mode choice models with more than two alternatives. For example, if car, bus, and rail are the alternatives and they all had equal utilities, the probability of choosing a transit mode would be greater than that of choosing the car mode. The modeler would need to decide if this were a correct formulation (i.e., although rail and bus may not be perfect substitutes, such a formulation may still be problematic). A nested logit formulation of this choice set would help address this issue by subordinating the somewhat related bus versus rail choice beneath a car versus transit choice.

4.7.3 Basis for Data Development

Logit mode choice model parameters are estimated using statistical techniques and specialized software designed to estimate this type of model. As in the estimation of a linear regression model, the data required are individual trip observations that include the trip origin and destination, the necessary traveler characteristics, and of course the chosen mode for the trip. Information on the level of service by each available mode can be added to the estimation data set from the network skims; information on area characteristics based on the origin and destination can also be added.

The only data source likely to provide a set of travel observations that include all modal alternatives is a household survey data set. Unfortunately, except in areas with high transit use (or very large survey sample sizes), the number of observations in a household survey for transit modes is likely to be too small to estimate statistically significant model parameters. Therefore, the household survey data set is often supplemented with data from a transit rider survey.

Even with typical household survey sample sizes and large transit rider survey data sets, it is often difficult to estimate mode choice model parameters that are both statistically significant and of reasonable sign and magnitude. As a result, the model development process often includes "constraining" some model parameters (utility coefficients) to specific values, often relative to one another. For example, parameters for transit out-of-vehicle time (wait time, walk time, etc.) might be constrained to be a multiple of the coefficient for in-vehicle time, say two or three, to reflect the fact that travelers find walking or waiting more onerous than riding.

Because of the difficulty in model estimation and in obtaining sufficient estimation data sets, mode choice is the model component most often characterized by parameters that are not estimated from local data, even in urban areas where parameters for other model components are estimated in that way. This practice of transferring parameters from other models has resulted, ironically, in a relative lack of recent models available for consideration as the estimation context. Many recently estimated models include at least some constrained coefficients.

The MPO Documentation Database includes mode choice model parameters for a limited number of models. These are presented in Section 4.7.4.

4.7.4 Model Parameters

Even for applications with similar circumstances, unless models have identical specifications, the values for specific coefficients may differ significantly between models. The alternative definitions, nesting structures, and presence or absence of other variables in a model can affect the coefficients of any variable. So it is much more valid to transfer individual models rather than composites of models with different variables or structures.

With that in mind, the best guidance for an MPO without sufficient local data for model estimation (the application context) is to transfer a complete model from another area (the estimation context), preferably from an area of similar demographic, geographic, and transportation system characteristics.

Model parameters can then be calibrated to ensure reasonable results in the application context, preferably retaining the relationships (i.e., ratios) between coefficients that have been estimated elsewhere. Care should be taken to note whether any of the model parameters in the estimation context were transferred themselves from elsewhere or otherwise constrained.

It is, of course, impractical to present in this report every mode choice model that might be considered in the estimation context. Analysts are encouraged to research specific models from likely estimation contexts and obtain information from sources such as direct contact of MPOs or on-line model documentation. If this is not feasible, information is presented in Tables 4.7 through 4.15 in simplified form for some of the models in the MPO Documentation Database for the classic three trip purposes.

The information from the MPO Documentation Database includes parameters for the level-of-service variables likely to be used in mode choice models in areas to which mode choice models are likely to be transferred. The MPO Documentation Database includes mode choice model parameters for about 30 MPO models. All of these models are located in urban areas with populations over 500,000 and most are in areas with populations over 1 million. For some of the models in the MPO Documentation Database, information on the mode choice models is incomplete, and some models have unusual or complex variable or modal alternative definitions that would make transferring parameters difficult. These models were excluded from the tables below, and so the number of models for which information on transferable parameters is available is less than 30.

Table 4.7 presents the characteristics of nine mode choice models for home-based work trips from the MPO Documentation Database. These models can be summarized as follows:

- Eight models from areas with populations over 1 million, and one model from the 500,000 to 1 million population range;
- Six nested logit and three multinomial logit models;
- Two models that include nonmotorized trip modes, and seven that do not; and
- Two models that have transit modes separated into local and premium submodes; one that separates transit into local, premium (e.g., express bus), and rail submodes; and six that use generic modes representing all transit. All nine models have separate modes for walk and auto access to each transit submode.

The nesting structures for the nested models in this group include separate nests for auto, transit, and nonmotorized modes.

Table 4.8 presents the coefficients of the variables in the nine models described in Table 4.7. Note that six models use a generic out-of-vehicle time variable while the others have separate components for some types of out-of-vehicle time. All of these coefficients are "generic," meaning they do not differ by modal alternative although some of the variables do not pertain to all modes (for example, wait time is not included in the utilities for auto modes). Table 4.9 presents some of the relationships between pairs of coefficients for these models.

There are some notable similarities among the parameters shown in Table 4.8 and the relationships shown in Table 4.9. The in-vehicle time coefficients range from –0.019 to –0.044, indicating similar sensitivity to travel time. It should be noted that the FTA guidance for New Starts forecasts indicates that compelling evidence is needed if the in-vehicle time coefficient does not fall between –0.020 and –0.030 (Federal Transit Administration, 2006), and most are close to this range. All of the models have out-of-vehicle time coefficients that are greater in absolute value than the in-vehicle time coefficients, with the ratios ranging from 1.5 to 4.7. FTA guidance for New Starts forecasts also indicates that compelling evidence is needed if the ratio does not fall between 2.0 and 3.0, and most are within this range.

Table 4.7. Characteristics of home-based work mode choice models from the MPO Documentation Database.

Model	Population Range	Nested Logit?	Include Nonmotorized?	Auto Submodes	Transit Submodes
A	< 1 million	Yes	No	DA/SR	Local/Premium
B	> 1 million	No	No	DA/SR	None
C	> 1 million	No	No	DA/SR	None
D	> 1 million	No	No	None	None
E	> 1 million	Yes	No	DA/SR	Local/Premium
F	> 1 million	Yes	No	DA/SR	Local/Premium/Rail
G	> 1 million	Yes	No	DA/SR	None
H	> 1 million	Yes	Yes	DA/SR	None
I	> 1 million	Yes	Yes	DA/SR	None

DA = drive alone, SR = shared ride.

Table 4.8. Coefficients from home-based work mode choice models in the MPO Documentation Database.

Model	In-Vehicle Time	Out-of-Vehicle Time	Walk Time	First Wait Time	Transfer Wait Time	Cost
A	–0.021		–0.054	–0.098[a]	–0.098	–0.0031
B	–0.030	–0.075				–0.0043
C	–0.036	–0.053				–0.0077
D	–0.019		–0.058	–0.081	–0.040	–0.0072
E	–0.025	–0.050				–0.0025
F	–0.044	–0.088				–0.0067
G	–0.028	–0.065				–0.0055
H	–0.033		–0.093	–0.038	–0.038	–0.0021
I	–0.025	–0.050				–0.0050[b]

The units of time variables are in minutes; cost variables are cents.

[a] Model A uses a first wait time stratified by the first 7 minutes and beyond. The coefficient shown is for the first 7 minutes; the coefficient for beyond 7 minutes is –0.023.

[b] Model I has a separate coefficient for auto parking cost, which is –0.0025; the coefficient shown is for all other auto operating and transit costs.

Table 4.9. Relationships between coefficients from home-based work mode choice models in the MPO Documentation Database.

Model	Out-of-Vehicle Time/ In-Vehicle Time	Walk/ In-Vehicle Time	First Wait/ In-Vehicle Time	Value of In-Vehicle Time
A		2.6	4.7	\$4.06 per hour
B	2.5			\$4.19 per hour
C	1.5			\$2.81 per hour
D		3.1	4.3	\$1.58 per hour
E	2.0			\$6.00 per hour
F	2.0			\$3.94 per hour
G	2.3			\$3.05 per hour
H		2.8	1.2	\$9.43 per hour
I	2.0			\$3.00 per hour

The value of time is computed as the ratio of the in-vehicle time and cost coefficients, converted to dollars per hour. It represents the tradeoff in utility between in-vehicle time and cost; for example, in Model E an average traveler would be indifferent between a travel time increase of 6 minutes and a transit fare increase of 60 cents. There is some variability in the implied values of time, with model D on the low end.[8]

[8]Note that these values of time are implied to be constant for all persons making home-based work trips. This is, of course, a substantial simplification, as people value time differently. In some models where segmentation of travel by income level occurs, as discussed in Section 4.5.2, the cost coefficients, as shown in the last column of Table 4.8, may vary by income level. However, even this is a simplification, as varying income levels are not the only reasons why individuals value time differently. Further segmentation is difficult, however, since data for segmentation and estimation of different values of time are not readily available, and the time and resources required for model application increase with additional segmentation.

The guidance for choosing a model from Tables 4.7 through 4.9 is to look for a model with similar modal alternatives to those that the analyst wishes to model in the application context. For example, if nonmotorized modes are to be included, Models H and I can be considered. Other considerations include whether a nested logit model is desired or required (A, E, F, G, H, or I), perhaps the population of the area (although most of the models in the tables are for large urban areas), the variables the analyst wishes to include, the prevalence of existing transportation modes, and the analyst's assessment of the reasonableness of the parameters and relationships given his or her knowledge of the region.

Tables 4.10, 4.11, and 4.12 show the model characteristics, parameters, and relationships, respectively, for eight models from the MPO Documentation Database for home-based nonwork trips. Tables 4.13, 4.14, and 4.15 show the model characteristics, parameters, and relationships, respectively, for 11 models from the MPO Documentation Database for nonhome-based trips. The information in these tables is presented and used the same way as the information in Tables 4.7, 4.8, and 4.9 for home-based work trips. Note that most of the models are simpler than for work trips, with fewer submode alternatives and fewer nested logit models. Note that the parameters are a bit more variable for nonwork trips than for work trips, and the values of time are lower for nonwork travel, as expected.

The coefficients shown in Tables 4.8, 4.11, and 4.14 are used in the utility function for each mode (see Equation 4-1). For example, the utility for transit with auto access for Model B in Table 4.8 is given by:

$$V_{tw} = \beta_{tw0} - 0.030\,(\text{in-vehicle time}) \\ - 0.075\,(\text{out-of-vehicle time}) - 0.0043\,(\text{cost})$$

The utilities are then used to compute the choice probabilities using Equation 4-2. The logit model utility and probability computations are performed the same way as in the vehicle availability logit model example presented in Section 4.3.4. Note that values for the alternative-specific constants (β_{n0} in Equation 4-1) are not provided in Tables 4.8, 4.11, and 4.14. These constants are not considered transferable, and their values are determined during mode choice model calibration or transfer scaling.

4.8 Automobile Occupancy

The highway assignment step, discussed in Section 4.11, requires tables of vehicle trips while the output of early model steps is in person trips. (As mentioned earlier, some models use auto vehicle trips as the unit of travel. Since such models

Table 4.10. Characteristics of home-based nonwork mode choice models from the MPO Documentation Database.

Model	Population Range	Nested Logit?	Include Nonmotorized?	Auto Submodes	Transit Submodes
A	< 1 million	No	No	None	None
D	> 1 million	No	No	None	None
E	> 1 million	Yes	No	DA/SR	Local/Premium
G	> 1 million	No	No	DA/SR	None
I	> 1 million	Yes	Yes	DA/SR	None
J	> 1 million	No	No	None	None
K	> 1 million	Yes	No	DA/SR	Local/Premium
L	< 1 million	No	Yes	DA/SR	None

DA = drive alone, SR = shared ride.

Table 4.11. Coefficients from home-based nonwork mode choice models in the MPO Documentation Database.

Model	In-Vehicle Time	Out-of Vehicle Time	Walk Time	First Wait Time	Transfer Wait Time	Cost	Auto Operating Cost	Parking Cost	Transit Cost (Fare)
A	−0.007	−0.017[a]				−0.005			
D	−0.011		−0.066	−0.061	−0.059	−0.033			
E	−0.020	−0.060				−0.003			
G	−0.010	−0.046				−0.029			
I	−0.008	−0.025					−0.010	−0.025	−0.010
J	−0.025		−0.075	−0.050[a]	−0.050		−0.170	−0.085	−0.250
K[b]	−0.022	−0.066				−0.009			
L	−0.007	−0.017[a]				−0.009			

The units of time variables are minutes, cost variables are cents.

[a] Models A, J, and L use a first wait time stratified by the first 7 minutes and beyond. The coefficient shown is for the first 7 minutes; the coefficient for beyond 7 minutes is –0.007 for Model A, –0.025 for Model J, and –0.007 for Model L.

[b] Model K has an additional variable for "transfer penalty," which has a coefficient of –0.154. This coefficient is seven times the in-vehicle time coefficient, which implies that a transit transfer has the same effect on utility as an increase in travel time of 7 minutes.

Table 4.12. Relationships between coefficients from home-based nonwork mode choice models in the MPO Documentation Database.

Model	Out-of-Vehicle Time/ In-Vehicle Time	Walk/ In-Vehicle Time	First Wait/ In-Vehicle Time	Value of In-Vehicle Time
A	2.4			$0.48 per hour
D		6.0	5.6	$0.21 per hour
E	3.0			$3.69 per hour
G	4.6			$0.21 per hour
I	3.1			$0.48 per hour
J		3.0	2.0	$0.09 per hour
K	3.0			$1.40 per hour
L	2.4			$0.80 per hour

Table 4.13. Characteristics of nonhome-based mode choice models from the MPO Documentation Database.

Model	Population Range	Nested Logit?	Include Nonmotorized?	Auto Submodes	Transit Submodes
A	< 1 million	No	No	DA/SR	None
D	> 1 million	No	No	DA/SR	None
E	> 1 million	Yes	No	DA/SR	Local/Premium
F	> 1 million	Yes	No	DA/SR	Local/Premium/Rail
G	> 1 million	No	No	DA/SR	None
I	> 1 million	Yes	No	None	None
J	> 1 million	No	No	None	None
L	< 1 million	No	No	None	None
M	> 1 million	No	Yes	DA/SR	None
N	> 1 million	Yes	No	DA/SR	None
O	< 1 million	No	Yes	DA/SR	None

DA = drive alone, SR = shared ride.

Table 4.14. Coefficients from nonhome-based mode choice models in the MPO Documentation Database.

Model	In-Vehicle Time	Out-of-Vehicle Time	Walk Time	First Wait Time	Transfer Wait Time	Cost	Auto Operating Cost	Parking Cost	Transit Cost (Fare)
A	–0.026		–0.065	–0.065[a]	–0.065	–0.008			
D	–0.011		–0.066	–0.061	–0.059	–0.033			
E	–0.020	–0.060				–0.002			
F	–0.022	–0.044				–0.003			
G	–0.006	–0.068				–0.008			
I	–0.020	–0.050					–0.006	–0.016	–0.006
J	–0.025		–0.075	–0.050[a]	–0.050		–0.179	–0.090	–0.250
L	–0.026		–0.065	–0.065[a]	–0.065	–0.013			
M[b]	–0.013		–0.032	–0.032[a]	–0.050	–0.002			
N[b]	–0.030		–0.053	–0.083	–0.083	–0.182			
O	–0.035	–0.082				–0.011			

The units of time variables are minutes, cost variables are cents.

[a] Models A, J, L, and M use a first wait time stratified by the first 7 minutes and beyond. The coefficient shown is for the first 7 minutes; the coefficient for beyond 7 minutes is –0.026 for Model A, –0.025 for Model J, –0.026 for Model L, and –0.025 for Model M.

[b] Models M and N have an additional variable for "transfer penalty," which has a coefficient of –0.306 in Model M and –0.030 in Model N.

Table 4.15. Relationships between coefficients from nonhome-based mode choice models in MPO Documentation Database.

Model	Out-of-Vehicle Time/ In-Vehicle Time	Walk/ In-Vehicle Time	First Wait/ In-Vehicle Time	Value of In-Vehicle Time
A	2.5			$2.01 per hour
D		5.8	5.4	$0.21 per hour
E	3.0			$5.45 per hour
F	2.0			$4.04 per hour
G	11.3			$0.46 per hour
I	2.5			$2.00 per hour
J		3.0	2.0	$0.08 per hour
L	2.5			$1.20 per hour
M	2.5			$5.08 per hour
N		1.7	2.8	$0.10 per hour
O	2.3			$1.86 per hour

have no mode choice step, and the outputs of trip distribution will already be in vehicle trips, the auto occupancy step is not needed in these models.) A process to convert person trips made by auto to vehicle trips is therefore required. This conversion typically is based on a set of factors, called auto occupancy factors, which are applied to the various automobile passenger trip tables produced by the mode choice step described in Section 4.7. Because the auto occupancy factors vary considerably by trip purpose, it is recommended that the categorization of passenger trips by purpose used through the preceding steps be retained.

Sometimes mode choice models include multiple auto modes that are defined based on automobile occupancy levels (e.g., drive alone, two-person carpool, and three-or-more-person carpool). In such models, much of the conversion process from auto person trips to auto vehicle trips takes place in the mode choice model: There is one vehicle trip per drive-alone auto person trip and one vehicle trip per two-person carpool person trip (i.e., the conversion factors for these modes are 1.0 and 2.0, respectively). For three-or-more-person carpool trips, a conversion factor equivalent to the average vehicle occupancy for vehicles with three or more occupants is used. These factors, which may vary by trip purposes, are generally derived from local household survey data or transferred from comparable MPO models.

4.8.1 Model Function

Auto occupancy factors are scalar factors which are applied to the passenger automobile tables. In some cases the auto occupancy factor is adjusted based on Travel Demand Management policies, but the choice to ride in a shared-ride automobile mode is more properly a mode choice decision as presented in Section 4.7. It has already been stated that the automobile occupancy is expected to vary based on trip purpose; for example, the auto occupancy of a work trip is typically much lower than the automobile occupancy for a recreational trip. Other considerations that may affect automobile occupancy are metropolitan size and density, transit availability, automobile ownership, and income.

There is also support to suggest that automobile occupancy may vary by time of day. For example, work trips with lower auto occupancy may predominate during the peak hours. This possibility suggests that disaggregating passenger trips by time of day, which is discussed in Section 4.9, might be more appropriately done before applying auto occupancy factors. When the calculations are done in this order, the time-of-day effect on trip purpose and the associated auto occupancies by purpose will result in lower auto occupancies during peak hours.

The scalar formula for converting auto passenger trips into auto vehicle trips is:

$$Auto_{ij}^{p} = T_{ijauto}^{p} * AOC^{p} \tag{4-13}$$

where:

Auto_{ij}^{p} = Auto vehicle trips between zone i and zone j for purpose p;

$\mathrm{T}_{ij\mathrm{auto}}^{p}$ = Auto person trips between zone i and zone j for purpose p; and

AOC^p = Auto occupancy factor (persons, including driver, per auto) for purpose *p*.

Typical values for the auto occupancy factors are presented in Section 4.8.4.

4.8.2 Best Practices

If the model will be used to analyze changes in auto occupancy levels due to changes in transportation level of service, policy changes, or specific implementations designed to affect carpooling (such as HOV lanes), then it is necessary to include in the mode choice model separate modal alternatives related to auto occupancy levels (i.e., drive alone, shared ride with two occupants, etc.) with level-of-service variables that are specific to the various alternatives.

If the model is not to be used for these types of analyses, and person trips are the unit of travel, then using auto occupancy factors by trip purpose to convert auto vehicle trips to auto person trips using Equation 4-13 may be considered best practice.

4.8.3 Basis for Data Development

When sufficient local data are available, best practice for obtaining automobile occupancy rates is to estimate them by trip purpose from household activity/travel survey data. This type of data source would also be used in estimating the parameters of mode choice models related to the choice between auto modes defined by occupancy level.

To provide information for areas without local data, the 2009 NHTS data set was used to develop vehicle occupancy factors by trip purpose and urban area population shown in Table 4.16.

4.8.4 Model Parameters

Table 4.16 shows the average daily vehicle occupancy levels by trip purpose from the 2009 NHTS. These factors are presented for average weekday, morning peak period (7:00 to 9:00 a.m.), and afternoon peak period (3:00 to 6:00 p.m.) trips. Because there is no clear correlation between urban area population and vehicle occupancy, rates are not presented by urban area population range. This finding is consistent with the information presented in *NCHRP Reports 365* and *187* (Martin and McGuckin, 1998; Sosslau et al., 1978).

Table 4.16 presents occupancy rates for three groups: all auto trips, carpools with two or more persons, and carpools with three or more persons. If a mode choice model has three auto modes—drive alone, two-person carpool, and three-or-more-person carpool—then the rates for carpools with three or more persons can be applied to the three-or-more-person carpool person trips from the mode choice model to obtain vehicle trips. If a mode choice model has two auto modes—drive alone and two-person carpool—then the rates for carpools with two or more persons can be applied to the two-or-more-person carpool person trips from the mode choice model to obtain vehicle trips.

Example

Consider an urban area where the outputs of the mode choice model with the classic three trip purposes include morning peak period person trip tables for the drive-alone, two-person

Table 4.16. Average daily vehicle occupancy by trip purpose by time period.

	Trip Purpose					
Vehicle Occupancy—Time Period	Home-Based Work	Home-Based Nonwork	Home-Based School	Home-Based Other (Excluding School)	Nonhome Based	All Trips
All Auto Modes—daily	1.10	1.72	1.14	1.75	1.66	1.55
Carpool 2 Plus Only—daily	2.42	2.71	2.35	2.71	2.75	2.72
Carpool 3 Plus Only—daily	3.60	3.81	3.46	3.81	3.79	3.80
All Auto Modes—a.m. peak	1.09	1.66	[a]	[a]	1.43	1.34
Carpool 2 Plus Only—a.m. peak	2.36	2.65	[a]	[a]	2.65	2.61
Carpool 3 Plus Only—a.m. peak	3.42	3.57	[a]	[a]	3.68	3.64
All Auto Modes—p.m. peak	1.11	1.66	[a]	[a]	1.65	1.50
Carpool 2 Plus Only—p.m. peak	2.45	2.62	[a]	[a]	2.72	2.65
Carpool 3 Plus Only—p.m. peak	3.63	3.66	[a]	[a]	3.75	3.70

[a] Use daily parameters; NHTS data insufficient to estimate.
Source: 2009 NHTS.

carpool, and three-or-more-person carpool modes. Say that one origin-destination zone pair has the following values in these trip tables:

- Home-based work: Drive alone—50, two-person carpool—10, three-or-more-person carpool—2
- Home-based nonwork: Drive alone—40, two-person carpool—50, three-or-more-person carpool—20
- Nonhome based: Drive alone—30, two-person carpool—30, three-or-more-person carpool—10

The person trips for the morning peak period can be converted to vehicle trips using the values in Table 4.16:

- Home-based work: Vehicle trips = 50/(1) + 10/(2) + 2/(3.42) = 55.58.
- Home-based nonwork: Vehicle trips = 40/(1) +50/(2) + 20/(3.57) = 70.60.
- Nonhome based: Vehicle trips = 30/(1) + 30/(2) + 10/(3.68) = 47.72.

This zone pair would have a total of 55.58 + 70.60 + 47.72 = 173.90 vehicle trips.

4.9 Time of Day

It is desirable for many reasons to estimate travel by time of day, including the need for temporally varying model outputs (for example, speeds by time of day for air quality conformity analysis) and to enhance model accuracy (levels of congestion and transit service may vary significantly between peak and off-peak periods). To do this, daily travel measures are converted to measures by time of day at some point in the modeling process using a discrete number of time periods. Typically, a four-step model with time-of-day modeling uses three to five periods (for example, morning peak, mid-day, afternoon peak, night).

In urban areas that experience significant congestion, it has become standard modeling practice to perform highway assignment separately for different time periods while smaller urban areas often continue to use daily assignment procedures. The MPO Documentation Database indicates the following percentages of MPOs using time period rather than daily highway assignment:

- MPO population greater than 1 million: 88 percent;
- MPO population between 500,000 and 1 million: 64 percent;
- MPO population between 200,000 and 500,000: 45 percent; and
- MPO population between 50,000 and 200,000: 30 percent.

4.9.1 Model Function

It is typical for models to start by estimating daily travel in the trip generation step. In a four-step model, the trip generation model is typically applied to estimate average weekday trips.

It is important to consider how to determine the period in which a trip occurs, especially if it begins in one period and ends in another. Trips can be assigned to a time period based on:

- The departure time;
- The arrival time; and
- The temporal midpoint of the trip.

In an aggregately applied model such as a four-step model, the midpoint would be the most logical way to define a trip's time period, since the majority of the trip would occur during that period. Some models use the concepts of "trips in motion," essentially splitting trips into components to determine percentages of travel by time period. The specific definition usually makes little difference in aggregately applied models in the percentages of trips occurring in each period, but the definition must be known in order to estimate and validate the model.

The most common method of time-of-day modeling in four-step models is simple factoring. At some point in the modeling process, fixed factors specific to trip purpose and direction are applied to daily trips to obtain trips for each time period. (Sometimes, this factoring is done in two steps, with daily trips split into peak and off-peak trips, and later the peak trips split into morning peak and afternoon peak, and perhaps off-peak trips split into additional periods.) While this method is relatively easy to implement and to apply, it is not sensitive to varying transportation levels of service, limiting its usefulness in analyzing policy changes or congestion management activities.

The ways in which fixed time-of-day factors may be applied within the four-step process are as follows (Cambridge Systematics, Inc., 1997a):

- In **pre-distribution** applications, the daily trips are factored between the trip generation and trip distribution steps of the modeling process. The data required include factors representing the percentage of trips by purpose during each hour and for each direction, production-to-attraction or attraction-to-production as well as directional split factors. It should be noted, however, that the directional split factors cannot be applied until after both ends of trips have been determined (i.e., after trip distribution). An advantage of this method is that differences in travel characteristics by time of day can be considered in both trip distribution and mode choice. In models with feedback loops, this method can provide a "clean" way to feed back travel times from one iteration to the next; trip distribution, mode choice, and trip assignment can be run separately for each time period, since the factors are applied prior to these steps.

- In **post-distribution** applications, the factors are applied between the trip distribution and mode choice steps. The data required for this approach to splitting includes factors representing the percentage of trips by purpose during each period and for each direction, production-to-attraction or attraction-to-production. This process also provides an opportunity to consider that some trips are in the attraction-to-production direction and to use skims that reflect correct directionality. However, the modeler should decide whether the additional complexity introduced by doing so is worthwhile.
- In **post-mode choice** applications, the factors are applied to daily trips between mode choice and the assignment steps. The data required include factors representing the percentage of the trips by purpose and mode during each time period and for each direction, production-to-attraction or attraction-to-production. An issue with this approach is that transit path-building procedures may not be consistent between mode choice and transit assignment, since mode choice would be done on a daily basis while transit assignment would be done by time period.
- In **post-assignment** applications, the factors are applied to loaded trips after the assignment step is complete. The data required include factors that represent the percentage of daily traffic or transit ridership for each time period on a link and can also include directional split factors depending on how the link-level factor is represented. The main limitation of this type of procedure is that equilibrium highway assignment on a daily basis is much less meaningful than assignment for shorter, more homogeneous periods. Also, changes in land use that could affect temporal distribution of traffic are not considered when using fixed link-based factors.

4.9.2 Best Practices

While activity-based models are beginning to consider the time of day at which trips will occur based on the sequence of travel activities from a household, in four-step models the usual practice is to allocate the daily trips that are calculated from trip distribution and mode choice to time period during the day based on a fixed set of factors. These factors typically are developed from the temporal patterns of trips reported in household surveys or, for auto or transit passenger trip tables, from reported demand, such as vehicle counts for autos or ridership for transit, by time period. The typical application is:

$$T^{p}_{ijmTOD} = T^{p}_{ijm} * F^{p}_{mTOD} \qquad (4\text{-}14)$$

where:

$T^{p}_{ijm\mathrm{TOD}}$ = Trips between zone i and zone j by mode m for purpose p during the period TOD;
T^{p}_{ijm} = Daily trips between zone i and zone j by mode m for purpose p; and
$F^{p}_{m\mathrm{TOD}}$ = Percentage of daily trips by mode m for purpose p that occur during period TOD.

While there is no consensus on the best point in the modeling process where daily trips should be converted to peak and off-peak period trips, based on the points in the previous discussion, many analysts prefer to perform the conversion prior to mode choice (in models that include a mode choice step). This could mean applying factors after trip generation (to productions and attractions) or after trip distribution (to person trip tables in production-attraction format). If peak hour trips are desired, a two-step process may be used, where factors to convert peak period to peak hour trips are applied to the peak period trips.

Nevertheless, the information in the MPO Documentation Database indicates that the majority of MPOs currently apply time-of-day factors after mode choice, due to the method's simplicity. However, using different sets of parameters for auto and transit travel may lead to inconsistencies between the transit path-building for mode choice and transit assignment. For example, say there is a corridor whose only available transit service is express bus that operates only during peak periods. The mode choice model, applied to daily trips, would estimate some transit trips for the corridor based on the presence of the express bus service. If, say, a fixed set of factors converting daily trips to trips by time period is used, the application of the factors will result in some off-peak trips in the corridor, which the transit assignment process will be unable to assign since there is no off-peak transit service. This problem would occur even if there were separate time-of-day factors for auto and transit trips.

The definition of the time periods used should depend on the analysis needs of the region, characteristics of congestion, and differences in transportation service (for example, frequency of transit service). In larger, more congested urban areas, travel conditions typically vary significantly between peak and off-peak periods, and so treating them separately would produce more accurate results. If the situations in the morning and afternoon peak periods, or between mid-day and night off-peak periods, are substantially different, then it would be preferable to separate those periods in the model.

It is important to recognize, however, the more periods, the greater the cost in terms of model estimation, validation, programming, and run time; therefore, there are good reasons to limit the number of periods used. The most common number of time periods in models that perform assignments by time of day is four, with morning peak, mid-day, afternoon peak, and night periods. Models that separate the night period into evening and overnight (with the dividing point reflecting the time when transit service ceases or is greatly reduced), and models that combine the mid-day and night periods into a single off-peak period, are also used.

The lengths of the peak periods depend on the extent of congestion in the region. Household survey data can be examined to determine the extent of the peak periods. In areas where such survey data are unavailable, traffic count data can be used.

4.9.3 Basis for Data Development

The basic data required for estimating time-of-day models of any type are household survey data, specifically the reported beginning and ending times of activities, tours, or trips. The survey data are processed for the specific type of model being estimated (fixed factor, logit, etc.) and are used separately by trip/tour purpose. These survey data (in expanded form) are also valuable for time-of-day model validation, although, as is the case anytime when the estimation data set is used for validation, the data must be used with caution.

For areas without local household survey data, factors from other sources, such as the NHTS, may be transferred. However, as discussed below, time-of-day distributions vary significantly among urban areas, and so significant model validation is required when using transferred time-of-day data.

Time-of-day distributions for truck and freight travel usually differ from those for passenger travel and can vary among urban areas. The best sources of data for these distributions are local vehicle classification counts by time of day.

4.9.4 Model Parameters

This section presents the time-of-day distributions by hour for each trip purpose, by direction for home-based trips derived from 2009 NHTS data for weekdays. Table C.11 in Appendix C shows these time-of-day distributions—for all modes[9] and individually for auto, transit, and nonmotorized modes—for use in areas where time-of-day factors are applied after mode choice. There does not seem to be a relationship between time of day and urban area population, and so the results are not stratified by population range.

The numbers shown in Table C.11 can be used to develop factors by trip purpose for any time periods defined as beginning and ending on the hour. However, while the factors are fairly consistent across urban area size categories, there can be considerable variation between different urban areas. Peaking conditions can vary greatly based on many factors. The type of economic activity that predominates in an area can affect peaking—for example, an area with large manufacturing plants might have peaks defined mainly by shift change times while an area with a large tourism industry may see later peaks. Another factor has to do with regional geography and dispersion of residential and commercial activities. Areas where commuters may travel long distances may see earlier starts and later ends to peak periods. Levels of congestion can also affect peaking, as peak spreading may cause travel to increase in "shoulder periods."

The last two rows of each section of Table C.11 show the combined factors for a typical morning peak period (7:00 to 9:00 a.m.) and a typical afternoon peak period (3:00 to 6:00 p.m.). If factors for a period defined differently are desired, then the appropriate rows from Table C.11 can be summed. For example, if factors for all modes for an afternoon peak period defined from 4:00 p.m. to 6:00 p.m. for the classic three trip purposes are desired, the factors for the rows labeled with hours ending at 5:00 and 6:00 p.m. in the all modes section of the table are added together. This would result in the following factors:

- Home-based work: From home—1.5 percent, To home—19.5 percent.
- Home-based nonwork: From home—6.9 percent, To home—9.5 percent.
- Nonhome based: 15.5 percent.

The factors are applied to daily trips by purpose, as illustrated by the following example. Say that afternoon peak period auto vehicle trips are desired for a period defined as 3:00 to 6:00 p.m. The factors from the auto modes section of Table C.11 are:

- Home-based work: From home—2.6 percent, To home—25.7 percent.
- Home-based nonwork: From home—9.5 percent, To home—15.3 percent.
- Nonhome based: 25.0 percent.

These factors are applied to the daily auto vehicle trip table. Say that the daily home-based work production-attraction

[9]Distributions by mode are presented for models where time-of-day factors are applied after mode choice. However, it should be noted that the NHTS sample sizes for transit and nonmotorized trips are much lower than those for auto trips, and so the transit and nonmotorized factors have more error associated with them, and the trips in the sample are concentrated in larger urban areas.

trip table has 100 trips from zone 1 to zone 2 and 50 trips from zone 2 to zone 1. Applying these factors results in the following origin-destination trips (recall that the home end is the production end for home-based trips):

- 2.6 home to work trips from zone 1 to zone 2.
- 25.7 work to home trips from zone 2 to zone 1.
- 1.3 home to work trips from zone 2 to zone 1.
- 12.9 work to home trips from zone 1 to zone 2.

This means that there are 15.5 home-based work trips traveling from zone 1 to zone 2 and 27.0 home-based work trips traveling from zone 2 to zone 1 in the afternoon peak period. As expected for the afternoon peak, most of these trips are returning home from work. This process would be repeated for the other two trip purposes. Since nonhome-based trips are already on an origin-destination basis, only a single factor is applied to this trip table.

As noted previously, the information provided in Table C.11 represents average national factors from the NHTS, but peaking can vary greatly from one area to another, regardless of urban area size. To illustrate this point, Table 4.17 shows the percentage of daily travel by purpose occurring during two periods—7:00 to 9:00 a.m. and 3:00 to 6:00 p.m.—for nine urban areas with populations of approximately 1 million according to the 2000 U.S. Census. While the averages presented in this table, based on data from the 2001 NHTS, have associated statistical error ranges not presented here, it is clear that the percentages for some areas differ significantly from those for other areas. For example, the reported percentage of daily home-based work travel between 3:00 and 6:00 p.m. was nearly twice as high in Providence as in Memphis. This variation indicates that when default parameters such as those in Table C.11 are used in lieu of local data, calibration may be required to obtain model results that are consistent with local conditions.

4.10 Freight/Truck Modeling

Truck models and **freight models** are different, although the terms are often used interchangeably. Freight models are multimodal and consider freight activities based, generally, on commodity flows. Truck models consider trucks regardless of whether they serve freight. Although most urban area freight is carried in trucks, it is also true that truck travel serves purposes other than just carrying freight. Trucks carrying commodities are referred to as “freight trucks”; nonfreight trucks are also referred to as service trucks. This section discusses freight and truck modeling functions, practices, and parameters and points the reader to appropriate resources for additional information.

4.10.1 Model Function

Freight and truck models enhance the overall travel demand forecasting framework and support additional decision making and alternatives evaluation. Modeling of freight/truck traffic can be important for a variety of reasons. One reason is that it typically makes a disproportionately high contribution to mobile source emission inventories in urban areas, especially for nitrogen oxide and fine particulate matter. Another reason is that in many areas and Interstate highway corridors, truck traffic is a significant component of travel demand, and the magnitude of truck traffic influences the available road capacity for passenger car movements. A third reason is that many regions have placed increased emphasis on goods

Table 4.17. Time-of-day percentages for urban areas of approximately 1 million in population.

	Home-Based Work		Home-Based Nonwork		Nonhome Based		All Trips	
Urban Area	**7–9 a.m.**	**3–6 p.m.**	**7–9 a.m.**	**3–6 p.m.**	**7–9 a.m.**	**3–6 p.m.**	**7–9 a.m.**	**3–6 p.m.**
Austin	32.3%	20.8%	12.5%	23.8%	6.9%	24.6%	13.6%	23.7%
Buffalo	23.7%	26.7%	9.3%	23.6%	5.9%	23.6%	9.7%	23.8%
Greensboro	30.3%	24.0%	12.2%	25.6%	8.1%	26.7%	12.7%	25.8%
Jacksonville	29.6%	24.7%	10.4%	24.4%	9.1%	27.1%	11.6%	25.3%
Hartford	26.0%	29.5%	9.2%	25.3%	7.2%	20.5%	10.4%	24.3%
Memphis	35.0%	18.2%	13.6%	25.6%	6.9%	27.2%	13.5%	25.4%
Nashville	32.7%	23.8%	10.1%	24.9%	7.5%	24.7%	10.4%	24.7%
Providence	28.9%	33.7%	11.8%	24.9%	7.9%	16.3%	11.8%	22.4%
Raleigh	32.4%	26.3%	12.0%	26.5%	8.0%	19.1%	12.2%	24.0%
Average	**30.1%**	**25.3%**	**11.2%**	**25.0%**	**7.5%**	**23.3%**	**11.8%**	**24.4%**

Source: 2001 NHTS.

movement and the role of the transportation system in facilitating economic activity. Having freight or truck models can help enable the evaluation of alternative strategies influencing freight or truck levels.

NCFRP Report 8: Freight-Demand Modeling to Support Public-Sector Decision Making (Cambridge Systematics, Inc. and Geostats, LLP, 2010) includes a discussion on classifying freight models and provides an overall forecasting framework, which includes nonfreight/service trucks. Adapted from this presentation, the basic freight/truck model types are as follows:

- **Trend analysis**—Trend analysis directly forecasts freight activity using, at most, historical or economic trends. It does not provide a trip table that could be used in travel demand models but can be used to calculate the background truck traffic on highway links which automobiles must consider. When used in this way, truck traffic cannot be rerouted in response to congestion.
- **Commodity forecasting**
  - **Synthetic modeling of commodity flows**—This model type develops modal commodity flow origin-destination tables using commodity generation, distribution, and mode choice models and then uses payload and temporal factors (1) to convert those commodity tables to a suitable format for assignment to modal networks and (2) to evaluate the flows on those networks.
  - **Direct acquisitions of commodity flows**—This model type directly acquires a commodity flow table instead of following the synthetic process. If the acquired table includes modal flows that are directly used, use of these mode-specific tables may replace mode choice, otherwise a mode choice model is required. After the modal commodity table is obtained, payload and temporal factors are used to convert those commodity trip tables to a suitable format for assignment to modal networks and then to evaluate the flows on those networks as is done in the synthetic model.
- **Nonfreight trucks—synthetic modeling**—Generation of information for nonfreight trucks is necessary to determine correct multiclass highway performance for freight trucks. If not, freight performance will not consider the interaction with what may be a majority of trucks on the road. The creation of nonfreight trip tables will often follow the traditional trip generation and trip distribution steps. It will not include a mode choice step because by definition only one mode, that of trucks, is being considered, and these truck trips would be generated and distributed in vehicle equivalents.
- **All trucks—synthetic modeling**—Synthetic modeling as described for nonfreight trucks can also be used to produce estimates of all trucks. If it is, the performance of freight trucks cannot be separated from the performance of all trucks. However, it is also possible to employ a hybrid approach where freight models are developed for some segments of truck travel (e.g., for trucks with an external trip end).

With the commodity forecasting methods in particular, freight demand forecasting can be thought of as a series of steps similar to those described in previous sections for passenger modeling, in which a trip table of transportation demand is created and then assigned to a modal network. Thus, freight generation is similar to the steps described in Section 4.4 for passenger trip generation; freight distribution is similar to the steps described in Section 4.5; freight mode choice is similar to the steps described in Section 4.7 for passenger mode choice; and the estimation of freight vehicles from tons and the temporal distribution is similar to the time-of-day process described in Section 4.9.

4.10.2 Best Practices

At the time of a national survey of practice conducted in 2005 (Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting, 2007), truck trips were modeled in some fashion by about half of small and medium MPOs and almost 80 percent of large MPOs, although few MPOs reported the ability to model all freight movement. However, as freight and nonfreight truck movement volumes have increased and communities have become more concerned with infrastructure needs and investments, more interest in including freight or truck treatment in models has developed.

Two standard sources that comprehensively discuss methods for developing freight and truck models are the original Quick Response Freight Manual (QRFM 1) (Cambridge Systematics, Inc. et al., 1996) and its update, Quick Response Freight Manual II (QRFM 2) (Cambridge Systematics, 2007b), both prepared for FHWA. The interested reader can refer to these manuals to obtain more information about freight and truck modeling. The manuals discuss growth factor methods, incorporating freight into four-step travel forecasting, commodity models, hybrid approaches, and economic activity models. Several case studies are included as well.

NCHRP Synthesis of Highway Practice 384: Forecasting Metropolitan Commercial and Freight Travel (Kuzmyak, 2008) identifies methods of freight and commercial vehicle forecasting currently used in professional practice, with a primary focus on MPO forecasting, although some consideration is given to statewide freight models. The report finds that metropolitan freight and commercial vehicle forecasting is performed primarily through the use of traditional four-step models but acknowledges inherent limitations for this purpose and notes the desirability to collect data from shippers or carriers that are reluctant to divulge confidential business information. Four case studies are presented along with nine profiles of MPO freight modeling practice, covering Atlanta, Baltimore, Chicago, Detroit, Los Angeles, New York, Philadelphia, Phoenix, and Portland (Oregon).

Since the publication of the QRFM 2, the FHWA has also released the Freight Analysis Framework, Version 3 (FAF3), which includes several data products. The 2007 U.S. Commodity Flow Survey forms the core data for the FAF3, but several additional data sources were employed in developing the products. Among the data products are origin-destination-commodity-mode flow matrices and GIS link files that contain FAF3 estimates of commodity movements by truck and the volume of long-distance trucks over specific highways (Oak Ridge National Laboratory, 2010).

The GIS link files were developed through the use of models to disaggregate interregional flows from the Commodity Origin-Destination Database into flows among localities and assign the detailed flows to individual highways. These models are based on geographic distributions of economic activity rather than a detailed understanding of local conditions. The developers of the FAF3 data caution that while FAF provides reasonable estimates for national and multistate corridor analyses, FAF estimates are not a substitute for local data to support local planning and project development (Oak Ridge National Laboratory, 2011).

4.10.3 Basis for Data Development

A variety of data sources can inform freight/truck model development, including:

- Socioeconomic, demographic, and employment data from public or commercial data sources;
- Locally sourced and FHWA HPMS vehicle classification counts, separating trucks by type;
- Commercial vehicle travel surveys, bearing in mind that such surveys are generally difficult to conduct and that response rates can prove particularly challenging;
- FAF3 data products, understanding that care must be taken to understand the associated limitations and error potential; and
- Commodity flow surveys, public or commercial.

This list of potential data sources is not exhaustive, and not all sources are required for every application. (Note that the first two items refer to information that is also used for passenger travel demand modeling and is likely available to MPO modelers in some form.) The interested reader may refer to the QRFM 2 or *NCHRP Synthesis 384,* which provide more detailed discussion about freight and truck model data sources and uses.

4.10.4 Model Parameters

Freight models typically include many of the same steps as do passenger models. The difference is in the travel purposes considered and the decision variables used. Also, in freight models, cargo must be converted into modal vehicles, and these vehicles, primarily trucks, are modeled directly.

The following discussion describes steps in the freight/truck modeling process: (1) freight trip generation, (2) freight trip distribution, (3) freight mode choice, (4) application of payload and temporal factors, and (5) creation of vehicle trip tables. These steps cover the freight/truck demand modeling process prior to vehicle assignment. Steps 1 through 4 pertain to commodity-based freight modeling only, while Step 5 pertains to both freight and truck modeling. In fact, in some cases, Step 5, creation of vehicle trip tables, comprises the entire truck modeling process prior to highway assignment. All steps are summarized herein to give the reader a broad overview to potential methods.

Step 1—Freight Trip Generation: Productions and Attractions by Commodity in Tons

This step estimates cargo freight productions and attractions. To be consistent with the modeling of passenger travel, these productions and attractions are estimated for an average weekday (if a source is used that presents information for another temporal level, such as annual, a conversion is needed). The volumes of commodity flows that begin in a zone (called "productions") and end in a zone (called "attractions") must be determined for each zone. If freight mode choice is included, the freight flows must be expressed in units that are common to all modes. In the United States, tons are commonly used although other multimodal units, such as value, can be used. As described for passenger trips in Section 4.4, the productions and attractions of freight are calculated by applying trip rates to explanatory variables. Commodity cargo trips are one-way trips, not round-trips, and so the production rates and explanatory variables are different than those used for attractions. The production and attraction rates vary by commodity type, which is analogous to trip purpose in passenger models. The explanatory variables are typically measures of the activity in economic sectors, such as employment, which produce or consume (attract) freight cargo.

Public agencies generally develop equations for their own study area from a commodity flow survey of their area. For an FHWA project (not yet published as of this writing), some general linear equations have been developed to disaggregate FAF data from regions to counties. A sample of coefficients for these equations is shown in Table 4.18. In this table, the variables represent employment by type, except for farm acres (in thousands). For example, the equation for the "other agricultural products" commodity type is:

$$\begin{aligned} \textit{Tons produced} &= 0.188 * \textit{food manufacturing employment} \\ &\quad + 0.051 * \textit{farm acres}(\textit{in thousands}) \end{aligned}$$

Average equations should be used with caution, since the economies of each state and region are so different that equations developed for average economic conditions cannot be expected to apply in all cases.

Step 2—Freight Trip Distribution: Trip Table Origins and Destinations

This step estimates freight trips between origins and destinations. As is the case for passenger trip distribution, described earlier in Section 4.5, the most common means to distribute freight trips between zones is through the use of a gravity model. For freight models, the impedance variable in the gravity model for the large geographies considered by freight is most often distance. In the most common freight distribution models, an exponential function is used (see the discussion of friction factors in Section 4.5.1) to compute the friction factors, where the parameter is the inverse of the mean value of the impedance.

By examining commodity flow survey data, it is possible to determine those parameters, such as the average trip length by commodity, that are used to vary the accessibility in response to changes in the impedance variable. Using locally derived

Table 4.18. Tonnage production equations for selected commodities (*2002 Kilotons*).

Commodities (SCTG[a])	NAICS	Variables	Coefficient	T-Stat	R^2
Cereal Grains (2)	311	Food Manufacturing	0.407	5.11	0.48
		Farm Acres (in thousands)	0.441	4.20	
Other Agriculture Products (3)	311	Food Manufacturing	0.188	10.43	0.65
		Farm Acres (in thousands)	0.051	2.14	
Meat/Seafood (5)	311	Food Manufacturing	0.053	25.94	0.86
Milled Grain Products (6)	311	Food Manufacturing	0.053	13.64	0.62
Logs (25)	113	Forestry and Logging	0.323	4.02	0.70
	115	Support Activities for Agriculture and Forestry	0.843	3.91	
	321	Wood Product Manufacturing	0.465	6.48	
Wood Products (26)	321	Wood Product Manufacturing	0.625	18.37	0.75
Newsprint/Paper (27)	113	Forestry and Logging	0.887	13.59	0.73
	323	Printing and Related Activities	0.086	7.38	
Paper Articles (28)	322	Paper Manufacturing	0.101	10.76	0.81
	323	Printing and Related Activities	0.038	4.82	
Base Metals (32)	331	Primary Metal Manufacturing	0.424	8.69	0.75
	333	Machinery Manufacturing	0.085	3.24	
Articles of Base Metals (33)	332	Fabricated Metal Product Manufacturing	0.115	14.51	0.65
Machinery (34)	332	Fabricated Metal Product Manufacturing	0.085	2.92	0.63
	333	Machinery Manufacturing	0.081	2.01	
Electronic and Electrical (35)	333	Machinery Manufacturing	0.02	3.00	
	334	Computer and Electronic Product Manufacturing	0.012	4.35	0.70
	335	Electrical Equipment, Appliance, and Component Manufacturing	0.029	2.44	

[a]Standard Classification of Transported Goods

Source: Federal Highway Administration (2009a).

Table 4.19. Average trip lengths by commodity group.

Commodity Group		Average Trip Length (Miles)
Code	**Name**	
1	Agriculture	845.30
2	Mining	593.58
3	Coal	946.86
4	Nonmetallic Minerals	141.13
5	Food	826.70
6	Consumer Manufacturing	1,071.04
7	Nondurable Manufacturing	1,020.29
8	Lumber	548.44
9	Durable Manufacturing	980.87
10	Paper	845.99
11	Chemicals	666.41
12	Petroleum	510.47
13	Clay, Concrete, Glass	359.77
14	Primary Metal	945.74
15	Secondary and Miscellaneous Mixed	586.47

Source: Alliance Transportation Group, Inc. and Cambridge Systematics, Inc. (2010).

data is encouraged, as economic conditions and geographic locations of model regions vary to such an extent that the average trip lengths for one model may not be applicable for another region. Table 4.19 presents average trip lengths from a statewide model for Texas.

Step 3—Freight Mode Choice: Trip Table Origins and Destinations by Mode

This step estimates cargo freight between origins and destinations by mode. As was discussed in Section 4.7 for passenger trips, the choice of mode used by freight is a complicated process. For freight, the choice will be based on many considerations, including characteristics of the mode, characteristics of the goods, and characteristics of the production and attraction zones. Typically, insufficient detail exists to properly model this choice, because either the format and parameters of the choice equations or the data on the characteristics are not known for the base or forecast year. Frequently, the future choice of mode is assumed to be the same as the existing choice of mode.

Table 4.20 shows tonnages and mode shares for freight in California from the FAF2. This information can be obtained from the FAF for any state.

Table 4.20. FAF freight shipments from California shipments by weight, 2002 and 2035 (millions of tons).

	2002 From State		2035 From State	
Mode	**Number**	**Percentage**	**Number**	**Percentage**
Truck	92.8	73	366.0	77
Rail	11.7	9	35.4	7
Water	1.2	1	2.2	< 1
Air and Truck	0.4	< 1	2.6	< 1
Truck and Rail	4.0	3	14.3	3
Other Intermodal	5.0	4	29.5	6
Pipeline and Unknown	12.4	10	26.7	6
Total	**127.4**	**100**	**476.9**	**100**

Source: http://www.ops.fhwa.dot.gov/freight/freight_analysis/faf/state_info/faf2/ca.htm.

Step 4—Freight Payload and Temporal Factors: Trip Table Origins and Destinations by Mode by Vehicle

This step converts the estimates of cargo freight flow by mode in tons per year into vehicle flows. For the purposes of this report, the vehicle flows of concern are freight trucks. The conversion of truck tons into truck vehicles is similar to the auto occupancy step described for passenger travel in Section 4.8. The tons in the commodity origin-destination tables are divided by the payload factor for the commodity type. The payload factors, in tons per truck, must match the behavioral commodity classification system used by the model. These payload factors should always vary by commodity. They may also vary by distance traveled. These factors may also consider the empty mileage, the class of the vehicles, etc.

A conversion is also necessary to correct the time period from annual to daily. If the average weekday in the forecasting model should be for midweek truck flows, it may be appropriate to divide annual flows by 295 days, which reflects observations of midweek truck traffic at continuous counting stations compared to annual truck counts at those same locations. To adjust the daily flows to hourly flows *NCFRP Report 8* recommends that the hourly flows for trucks should be considered to be 6 percent of daily flow for each of the hours from 11:00 a.m. to 7:00 p.m.

Table 4.21 shows payload factors used by Tennessee in freight forecasting.

Step 5—Create Vehicle Origin-Destination Tables

The transportation of freight is not the only reason for truck travel. Nonfreight trucks, which provide services, move construction materials and equipment, and are used in maintenance activities as well as the local movement of goods, are not included in the commodity flow table methodology. Freight trucks may constitute the majority of trucks on the road on rural principal highways, but in urban areas, nonfreight trucks can represent from 50 to 70 percent of the trucks on major highways, according to calculations from FAF highway assignments. In addition, the scale of the distances traveled by freight and nonfreight trucks is much different. Freight truck trips tend to average distances of hundreds of miles, much longer than the tens of miles typically traveled on individual trips by service trucks.

The differences in impact level and travel behavior of freight versus nonfreight trucks have a major bearing on the types of truck trips that are included in travel demand models. Freight may move over national distances, and the model area used in forecasting freight flows may not be the same as the model area needed to address nonfreight trucks, which have primarily a local area of operation. Thus, MPO models may primarily include nonfreight trucks and only include freight trucks as external trips. State or multistate models, which have zone systems and networks that cover larger areas, are more likely to need to include freight truck trips with two internal trip ends.

Models typically calculate trip tables for nonfreight trucks separately from freight trucks. Sometimes these are distinguished as heavy trucks and medium trucks. The forecasts of nonfreight trucks will most often be through a synthetic process of trip generation and trip distribution, similar to the steps for freight described in Steps 1 and 2 above. Although the trip generation rates and the trip distribution factors should be developed through the use of commercial vehicle surveys, the next three subsections discuss sample parameters for total truck trip generation, nonfreight truck trip generation, and truck trip distribu-

Table 4.21. Freight model truck payload after adjustment.

Commodity	Pounds per Truck	Tons per Truck
Agriculture	48,500	24
Chemicals	48,500	24
Construction and mining	50,500	25
Food and kindred products	48,500	24
Household goods and other manufactures	38,500	19
Machinery	36,500	18
Mixed miscellaneous shipments, warehouse and rail intermodal drayage, secondary traffic	36,500	18
Paper products	46,500	23
Primary metal	51,500	26
Timber and lumber	53,000	27

Source: PBS&J (2005).

tion. However, the interested reader is encouraged to consult *NCHRP Synthesis 384* for a broader array of sample parameters.

As noted in the introduction to this section, the freight commodity flow framework is but one method used by modelers to address truck trip making in models. Where the concerns are concentrated on representing truck flows within an area largely to support more accurate passenger car assignment or where truck survey data are not available, areas often use simplified approaches. Several areas use vehicle classification counts, specifically truck counts by truck type, to calibrate input origin-destination trip tables of regional truck models using an Origin-Destination Matrix Estimation (ODME) process. The ODME process iteratively updates the input origin-destination trip table of the model so that model truck volume results match with observed truck counts. A base year ODME matrix can be factored to place future-year truck demand on the network as well. The user of such methods should take care to recognize the limitations inherent in both ODME and growth factor techniques.

Total truck trip rates. Table 4.22 presents truck daily vehicle trip generation rates from two sources: a survey done by Northwest Research Group (NWRG) for southern California and the Puget Sound Regional Council (PSRC) truck model. These rates are linear equations where the dependent variables are the number of truck vehicle trip ends and the independent variables are the number of households and employment by type. They can be applied at the zone level to estimate the total number of truck trip ends per zone.

Note that the two sources have different definitions of trucks for which rates are provided. NWRG defines rates for trucks of 14,000–28,000 pounds while PSRC defines rates for single-unit trucks of two to four axles, six or more tires, and 16,000–52,000 pounds. Both of these definitions exclude smaller trucks and commercial vehicles that may not be included directly in passenger travel models.

Nonfreight truck trip rates. An example of daily trip rates for nonfreight trucks only (as opposed to all trucks, as shown in Table 4.22) is shown in Table 4.23. This table shows rates from *NCHRP Synthesis of Highway Practice 298: Truck Trip Generation Data* (Fischer and Han, 2001).

A nonfreight truck trip table may be developed by adapting an existing total truck table. If this is the case, care must be taken to avoid double counting the trucks that carry freight. It will be necessary to adjust the total truck trip rates and distributions to account for freight trucks, which are handled separately.

Truck trip distribution. As is the case with freight modeling as discussed previously, the most common procedure for distributing truck trips uses the gravity model. The calibration of friction factors should be consistent with observed truck travel. As examples, *NCHRP Synthesis 384* presents friction factor curves for the Atlanta and Baltimore truck models, adjusted to provide the best fit with the known

Table 4.22. Sample total truck trip rates by truck type and land use.

	Truck Type			
	14,000–28,000 Pounds NWRG Survey		2–4 Axles, 6+ Tire, Single Unit, 16,000–52,000 Pounds PSRC Truck Model	
Land Use	**Production**	**Attraction**	**Production**	**Attraction**
Households	0.011	0.011	0.0163	0.0283
Employment				
Agriculture/Mining/Construction	0.040	0.044		
Agriculture			0.0404	0.2081
Mining			0.0404	10.8831
Construction			0.0453	0.0644
Retail	0.032	0.035	0.0744	0.0090
Education/Government	0.037	0.038	0.0135	0.0118
Finance, Insurance, Real Estate	0.008	0.008	0.0197	0.0276
Manufacturing Products	0.050	0.050	0.0390	0.0396
Equipment			0.0390	0.0396
Transportation/Utility	0.168	0.170	0.0944	0.0733
Wholesale	0.192	0.190	0.1159	0.0258

Source: Cambridge Systematics, Inc. (2008a).

Table 4.23. Sample nonfreight truck trip rates by land use.

Land Use	Maricopa Association of Governments	Southern California Association of Governments
Households	0.069	0.0087
Employment		
Agriculture/Mining/Construction	0.106	0.0836
Retail	0.132	0.0962
Education/Government	0.006	0.0022
Financial, Insurance, Real Estate	0.021	–
Manufacturing Products	0.100	0.0575
Transportation/Utility	0.106	0.4570
Wholesale	0.106	0.0650
Other	0.106	0.0141

Note: Truck definition for Maricopa Association of Governments data is 8,000 to 28,000 pounds, while for Southern California Association of Governments it is 14,000 to 28,000 pounds.

Source: Rates are from *NCHRP Synthesis 298* (Fischer and Han, 2001) as cited in Cambridge Systematics, Inc. (2008a).

Table 4.24. Sample average truck trip lengths or travel times.

Truck Type	Atlanta (1996)	Baltimore (1996)	Detroit (1999)	Los Angeles (2000)
Heavy	22.8 min.	34.0 min.	20.1 min.	24.1 miles
Medium	19.9 min.	17.5 min.	20.5 min.	13.1 miles
Light		16.2 min.	18.3 min.	5.9 miles

Source: *NCHRP Synthesis 384* (Kuzmyak, 2008).

average trip lengths of trucks. Table 4.24 provides a summary of average trip lengths or travel times (if known), and date of origin, used by a sample of MPOs.

4.11 Highway Assignment

All of the preceding sections have dealt with the development of trip tables. Assignment is the fourth step in a four-step travel demand model. This section deals with highway assignment while Section 4.12 deals with transit assignment.

Highway assignment is the process by which vehicle trips for each origin-destination interchange included in the vehicle trip tables are allocated to the roadway network. The allocation process is based on the identification of paths through the network for each origin-destination interchange. The assignment process may be mode-specific with, for example, paths for single occupant vehicles being determined using different criteria than paths for multi-occupant vehicles or trucks.

4.11.1 Model Function

There are a number of methods by which a trip table can be assigned to a network. All of these methods are basically variations of the formula:

$$V_a = \sum_{ij} t_{ij} * P_{ija} \qquad (4\text{-}15)$$

where:

t_{ij} = The number of vehicle trips from origin *i* to destination *j*;

P_{ija} = The probability of using link *a* on the path from origin *i* to destination *j*; and

V_a = The volume of vehicles on link *a*.

While the algorithms and computer code required to efficiently solve the assignment problem, as well as the requirements for storing the probability matrix, do not often lead to the assignment problem being defined in this way, describing the process in this manner does allow for the identification of features that distinguish the various assignment methods.

When the probability matrix is predetermined in some manner that cannot be changed, the method is called **a fixed path assignment**.

When the probability matrix takes on the value of one when the link is used and zero when the link is not used it is said to be an **all or nothing (AON) assignment**.

When the cells of the probability matrix are calculated from a stochastic formula that calculates the percentage of trips to be assigned to a set of links contained in reasonable paths, the method is called a **stochastic assignment.**

When the probability matrix takes on discrete values associated with the percentages of the trip table which are assigned in successive AON assignments, where between iterations the congested time is updated based on a comparison of the assigned volume on a link to its capacity, new AON paths are then calculated, and those percentages are applied to each of the successive AON probabilities (i.e., one or zero), the method is called **incremental capacity-restrained assignment**.

When the cells of the probability matrix are calculated from the percentage of the trip table assigned to successive applications of AON as in the incremental capacity-restrained assignment, but those percentages are selected through an iterative process that will result in satisfying Wardrop's first principle, which states that "the journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route" (Wardrop, 1952), the method is said to be a **user equilibrium assignment**. A variant of this method, called stochastic user equilibrium, uses stochastic assignment rather than AON assignment in successive steps to arrive at equal journeys on used paths, in which case the perceived times are said to be reasonably equal. A common method to determine the allocation of a trip table to successive iterations is the Frank-Wolfe algorithm (Frank and Wolfe, 1956).

An additional consideration in assignment is the number of trip tables that will be assigned and the manner in which the trip tables are assigned. If the trip table is assigned to the network links prior to a user equilibrium assignment, for example by assigning that trip table to fixed or AON paths that do not consider congestion, that trip table is said to be preloaded. Those trip tables (i.e., classified by vehicle and/or purpose) that are assigned jointly in a user equilibrium assignment are said to be a multimodal multiclass assignment.

The first three assignment processes previously described—fixed path, AON, and stochastic—are insensitive to congestion impacts that occur when demand for a network link approaches the capacity of the link. The last two assignment methods—capacity restrained and user equilibrium—explicitly attempt to account for congestion impacts in the traffic assignment process. The last two procedures are typically preferred for future forecasts because they inject a level of realism into the assignment process through reductions of travel speeds as traffic volumes on links increase. In addition, the last two procedures are required if air quality impacts of various alternatives or land use scenarios need to be estimated from traffic assignment results.

While the first three assignment procedures are insensitive to congestion impacts, these can provide important analysis capabilities. For example, AON assignments are useful for determining travel desires in the absence of congestion impacts and are commonly used to preload truck trips and other external through-trip movements in regional models. Such information can also be useful in targeting transportation improvements. In uncongested networks, stochastic assignment may be the only method available to represent user choices of similar alternative paths.

In all capacity-restrained and user equilibrium assignments, link travel times are adjusted between iterations using a vehicle-delay function (sometimes referred to as a "volume-delay," "link performance," or "volume-time" function). These functions are based on the principle that as volumes increase relative to capacity, speeds decrease and link travel times increase.

One of the most common of these vehicle-delay functions was developed by the BPR, the predecessor agency of the FHWA. The BPR equation is:

$$t_i = t0_i * \left(1 + \alpha * \left(\frac{v_i}{c_i}\right)^{\beta}\right) \tag{4-16}$$

where:

t_i = Congested flow travel time on link *i*;
$t0_i$ = Free-flow travel time on link *i*;
v_i = Volume of traffic on link *i* per unit of time (somewhat more accurately defined as flow attempting to use link *i*);
c_i = Capacity of link *i* per unit of time (see below);
α = Alpha coefficient, which was assigned a value of 0.15 in the original BPR curve; and
β = Beta coefficient, the exponent of the power function, which was assigned a value of 4 in the original BPR curve.

While t_i represents the link *i* travel time and is expressed in units of time (usually minutes), it may also reflect other costs associated with travel, especially tolls and auto operating costs such as fuel costs. The value t_i (and $t0_i$) may therefore be represented by something like Equation 4-17:

$$t_i = tt_i + \mathrm{K1} * d_i + \mathrm{K2} * \mathrm{toll}_i \tag{4-17}$$

where:

tt_i = Actual travel time on link *i*;
d_i = Length of link *i* in units of distance (e.g., miles);
toll_i = Per vehicle toll on link *i* in monetary units;
K1 = Parameter reflecting marginal per-mile auto operating cost and conversion from monetary to time units; and
K2 = Parameter reflecting conversion from monetary units to time units.

Parameter K2, therefore, represents the inverse of the value of time. Note that the value of time is also an implied parameter in mode choice (see Section 4.7.4). However, the values of time implied by mode choice model parameters are often lower than those used in highway assignment, especially those used in toll road planning studies. This reflects, in part, the different market segments analyzed in each model component (travelers by all modes for mode choice, highway users in potential toll corridors in assignment), but also the artificial separation of mode and route choices in a four-step model. A 2003 memorandum (U.S. Department of Transportation, 2003) indicated a "plausible range" for the value of time in year 2000 dollars for local travel to be $7.90 to $13.40 per hour, with a recommended value of $11.20 for autos (the value for trucks was $18.10). These values are substantially higher than the values of time implied by the mode choice parameters presented in Section 4.7.4.

It is customary to express capacity in vehicles per hour. In models where daily (weekday) highway assignment is used (and therefore the volume variable is expressed in vehicles per day), the hourly capacity estimates must be converted to daily representations. This conversion is most commonly done using factors that can be applied to convert the hourly capacity to effective daily capacity (or, conversely, to convert daily trips to hourly trips, which is equivalent mathematically). These factors consider that travel is not uniformly distributed throughout the day and that overnight travel demand is low. The conversion factors are therefore often in the range of 8 to 12, as opposed to 24, which would be the theoretical maximum for an hourly-to-daily factor. [These factors are sometimes referred to as "CONFAC," the variable name in the Urban Transportation Planning System (UTPS) legacy software on which many aspects of modern modeling software are still based.]

These types of conversion factors continue to be needed in models where time periods for assignment greater than 1 hour in length are used. In such cases, the factors convert the hourly capacity to the capacity for the appropriate time period. For example, if a morning peak period is defined as 6:00 to 9:00 a.m., the conversion factor will convert hourly capacity to capacity for the 3-hour period. It is important to consider that travel is not uniformly distributed throughout the 3-hour period, although it is likely to be more evenly distributed over a shorter time period, especially a peak period that is likely to be relatively congested throughout. The theoretical maximum for the factor is the number of hours in the period (three, in this example), and in a period where there is roughly uniform congestion throughout the peak period, the factor could be close to three. Typical factors for a 3-hour peak would range from two to three. The factors for longer off-peak periods would likely be well lower than the theoretical maximum.

Depending on the application, the value of c_i (Equation 4-16) may not represent the true capacity of the link in a traffic operations sense (see Section 3.3). In the original BPR function, c_i represented the limit of the service volume for LOS C, which is often approximately 70 percent of the "ultimate" capacity (at LOS E), although the conversion between these two values is not simple. Current best practice is to use the LOS E capacity for the following reasons (Horowitz, 1991):

1. Ultimate capacity has a consistent meaning across all facility types while design capacity does not. For example, it is a relatively simple matter to relate the capacity of an intersection to the capacity of the street approaching that intersection.
2. Ultimate capacity is always easier to compute than design capacity. Finding the design capacity of a signalized intersection is especially difficult.
3. Ultimate capacity can be more easily related to traffic counts than design capacity, which would also require estimates of density, percent time delay, and reserve capacity or stopped delay.
4. Ultimate capacity is the maximum volume that should be assigned to a link by the forecasting model. Design capacity does not give such firm guidance during calibration and forecasting.

For these reasons, ultimate capacity (LOS E) is assumed to be used for capacity in the remainder of this chapter. As noted in Section 3.3.1 of this report, detailed capacity calculations as presented in the *Highway Capacity Manual* may not be possible in travel model networks as some of the variables used in the manual are not available in these networks.

4.11.2 Best Practices

While there is much ongoing research into the use of dynamic assignment and traffic simulation procedures, the state of the practice for regional travel models remains static equilibrium assignment. There has been some recent research into more efficient algorithms to achieve equilibrium than Frank-Wolfe, and some modeling software has implemented these algorithms. Since most urban areas are dependent on the major proprietary software packages for their model applications, static equilibrium procedures will continue to be used for regional modeling for the time being.

There have been some highway assignment implementations that incorporate node delay as a better way of identifying intersections that may cause congestion on multiple links, sometimes referred to as junction modeling. Some modeling software has incorporated methods to consider node delay.

For project planning and design applications to determine link volumes, the use of post-processing techniques such as those discussed in *NCHRP Report 255: Highway Traffic Data for Urbanized Area Project Planning and Design* (Pedersen and Samdahl, 1982) are recommended rather than reliance on raw

Table 4.25. BPR coefficients estimated using the 1985 *Highway Capacity Manual.*

	Freeways			Multilane Highways		
Coefficient	**70 mph**	**60 mph**	**50 mph**	**70 mph**	**60 mph**	**50 mph**
α	0.88	0.83	0.56	1.00	0.83	0.71
β	9.8	5.5	3.6	5.4	2.7	2.1

Source: Horowitz (1991). While the terms "freeways" and "multilane highways" are not defined, it can be assumed that the term "freeways" refers to modern "Interstate standard" limited access highways and "multilane highways" includes lower design roadways, including those without access control.

model output. Post-processing techniques are recommended because the assigned volumes on individual links can have substantial error, as noted when comparing highway assignment outputs to traffic counts (although count data are often sampled and also have associated error).

4.11.3 Basis for Data Development

Horowitz (1991) fit the BPR formula (among others) to the speed/volume relationships contained in the Highway Capacity Software, Version 1.5, based on the 1985 *Highway Capacity Manual* (Transportation Research Board, 1985). The results of this work are presented in Section 4.11.4. These values were also presented in *NCHRP Report 365.* There is a wealth of literature on volume-delay function form and parameters, including the 2010 *Highway Capacity Manual,* that the analyst may wish to consult.

The MPO Documentation Database provided BPR function parameters from 18 MPOs for freeways and arterials. These also are presented in Section 4.11.4.

4.11.4 Model Parameters

The BPR formula parameters estimated by Horowitz are presented in Table 4.25. The speeds shown in this table represent facility design speeds, not model free-flow speeds.

According to the information in the MPO Documentation Database, the BPR formula is the most commonly used volume-delay function. MPOs use a variety of values for the α and β parameters, and most use different parameters for freeways and arterials. Table 4.26 presents BPR function parameters used by 18 MPOs for which data were available from the database.

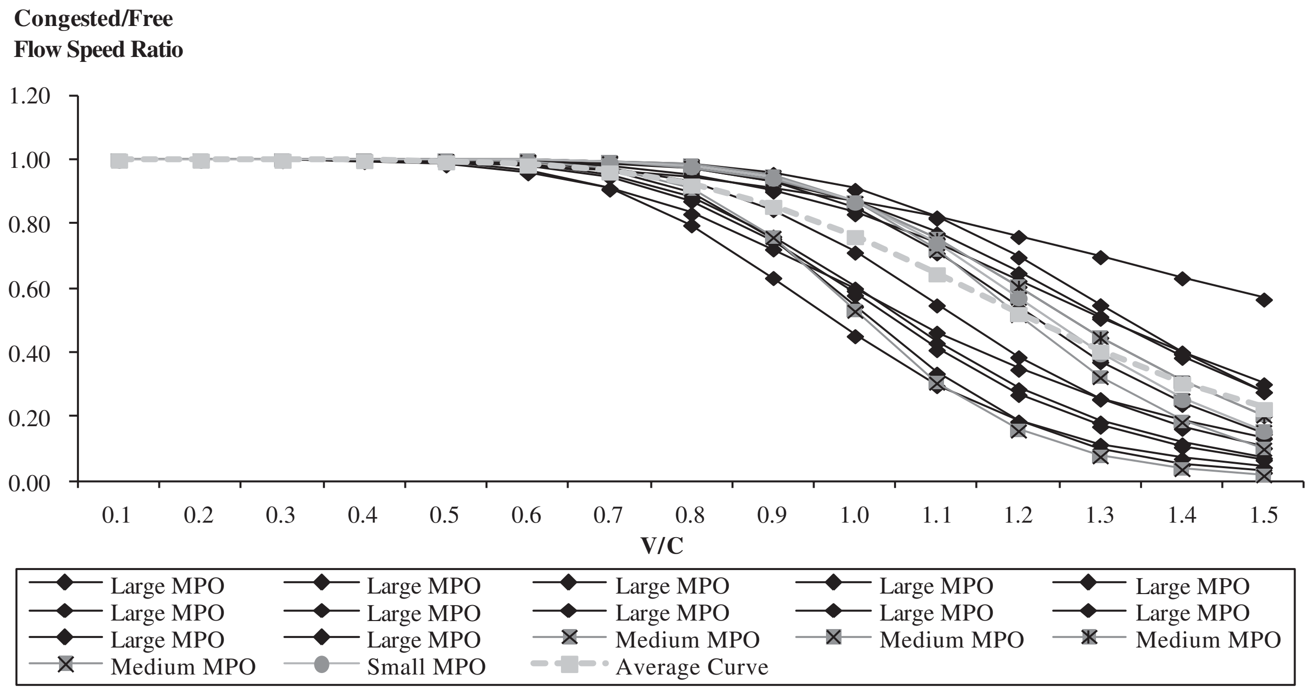
Figures 4.6 and 4.7 graph the ratios of the congested speeds to free-flow speeds on facilities at different volume/capacity

Table 4.26. BPR function parameters (morning peak period).

		Average		Minimum		Maximum		Standard Deviation	
	n	**α**	**β**	**α**	**β**	**α**	**β**	**α**	**β**
Freeways									
MPO population greater than 1,000,000	13	0.48	6.95	0.10	4.00	1.20	9.00	0.36	1.39
MPO population between 500,000 and 1,000,000	5	0.43	8.82	0.15	5.50	0.88	10.00	0.39	1.92
MPO population between 200,000 and 500,000	1	0.15	8.00	0.15	8.00	0.15	8.00	–	–
MPO population between 50,000 and 200,000	1	0.15	8.80	0.15	8.80	0.15	8.80	–	–
Arterials									
MPO population greater than 1,000,000	11	0.53	4.40	0.15	2.00	1.00	6.00	0.29	1.66
MPO population between 500,000 and 1,000,000	4	0.42	5.20	0.15	3.20	0.75	10.00	0.29	3.22
MPO population between 200,000 and 500,000	1	0.50	4.00	0.50	4.00	0.50	4.00	–	–
MPO population between 50,000 and 200,000	2	0.45	5.60	0.15	3.20	0.75	8.00	0.42	3.39

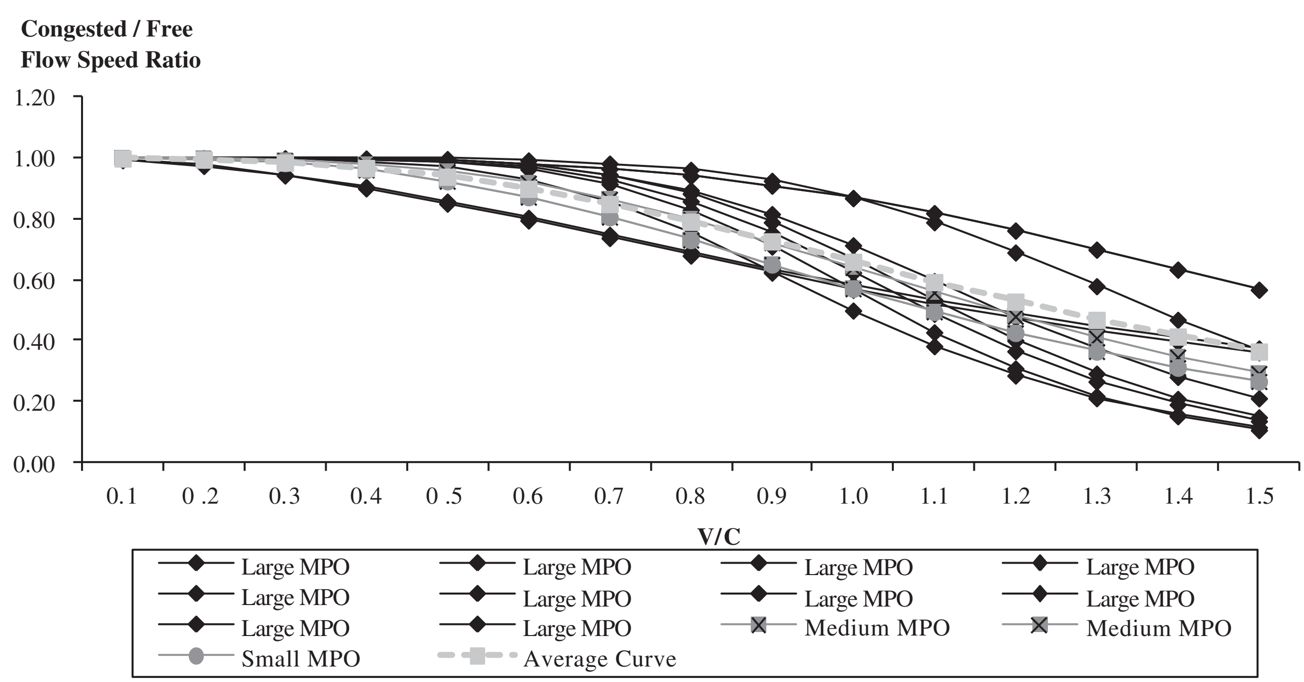
n = number of models in MPO Documentation Database

Source: MPO Documentation Database.



Source: MPO Documentation Database.

Figure 4.6. Freeway congested/free-flow speed ratios based on BPR functions.



Source: MPO Documentation Database.

Figure 4.7. Arterial congested/free-flow speed ratios based on BPR functions.

ratios using the BPR functions from the 18 MPOs. In addition, each graph includes an "average" BPR function based on the curves shown in Figures 4.6 and 4.7. The average BPR functions differ from the parameter averages shown in Table 4.26 in that the functions were derived via linear regressions to match the averages of the congested/free-flow speed ratios for the different volume/capacity ratios.[10] The resulting average BPR functions are:

- **Freeways:**
  - Alpha = 0.312.
  - Beta = 5.883.
- **Arterials:**
  - Alpha = 0.514.
  - Beta = 3.001.

4.12 Transit Assignment

While highway assignment deals with the routing of automobiles over a highway network, transit assignment deals with the routing of linked passenger trips (including walk and auto access and egress) over the available public transportation network. Differences from highway assignment include the following:

- The transit network includes not only links but also routes comprising the links, which represent the different transit services running between stops or stations;
- The flow unit in the trip table which is being assigned is passengers, not vehicles;
- The impedance functions include a larger number of level-of-service variables, including in-vehicle time, wait time, walk access and egress time, auto access and egress time, fare, and transfer activity; and
- Some paths offer more than one parallel service, sometimes with complex associated choices (e.g., express bus versus local bus service).

4.12.1 Model Function

Transit assignment is closely tied to transit path building. Typically, person trips estimated using a mode choice model are assigned to the transit paths built as input to the mode choice model. The typical transit assignment process is different from traffic assignment processes, where auto paths based on estimated congested travel times are input to a mode choice model and the output vehicle trips are assigned to the roadway network using an equilibrium or other capacity-restrained assignment method. The mode choice-traffic assignment process may require a feedback or iterative process to ensure that estimated roadway speeds used for mode choice (as well as for trip distribution) match the roadway speeds resulting from the traffic assignment process. Speeds on the transit network may also be affected by the roadway speeds, depending on the software and network coding methodologies.[11] The transit speeds used to develop the transit paths used to construct the travel time and cost skims for input to mode choice and the resulting transit assignment should match.

In the past, transit path-building and assignment were generally performed in production-attraction format with the production zone being defined as the home zone for home-based trips and the attraction zone being defined by the nonhome location. This procedure can be used to determine boardings by line, revenues, and maximum load points. It has often been performed by time of day with transit paths and assignments being performed for morning peak and mid-day periods. Such an approach accounts for time-of-day differences in transit services with the afternoon peak period being assumed to be symmetrical to the morning peak period (which is an oversimplification). In regions offering nighttime transit service, the night service may either be modeled as a separate time period or aggregated with the mid-day service for assignment purposes. Finally, some areas provide the same basic levels of transit service throughout the day and, as a result, perform nontime-specific, or daily, transit path-building and assignments.

More recently, some regions have started building transit paths in origin-destination format. This approach has been used to account for directional differences in service by time of day. Service differences may be due to different frequencies of service, different service periods, or different transit speeds due to different levels of traffic congestion. The information is particularly important for tour-based and activity-based modeling procedures, although it can also be used with trip-based modeling procedures.

4.12.2 Best Practices

Table 4.27 summarizes the time-of-day directional assignment procedures for 23 MPOs. Of the 20 MPOs reporting the use of time-of-day transit paths, 17 indicated the trip purposes assigned to each time-of-day network. Four of the 17 MPOs assigned home-based work trips to the peak period

[10]Note that volume/capacity ratios over 1.0 are shown in Figures 4.6 and 4.7. In effect, what is really being shown are the modeled demand/capacity ratios. In the real-world situations, traffic volumes cannot exceed roadway link capacities.

[11]In many models, run times are hard coded on transit lines resulting in no direct sensitivity to highway speed changes. However, good practice still dictates reviewing transit speeds for general consistency with the underlying highway speeds.

Table 4.27. MPOs using transit assignment procedures.

	Number of MPOs									
	Production-to-Attraction					Origin-to-Destination				
MPO Regional Population	A.M. Peak[a]	Mid-Day	P.M. Peak	Night	Daily	A.M. Peak	Mid-Day	P.M. Peak	Night	Daily
More than 1,000,000	12	11	3	3	0	3	3	3	1	0
200,000 to 1,000,000	3	3	1	0	3	1	1	1	0	0
50,000 to 200,000	1	1	0	0	0	0	0	0	0	0

[a] Includes MPOs assigning both morning and afternoon trips to the morning peak network in production-to-attraction format.
Source: MPO Documentation Database.

network and the remaining 13 estimated transit trips for each trip purpose by time of day and assigned the trips using time-of-day transit paths.

Transit path-builders can be characterized into two basic groups: shortest path and multipath. Shortest path methods find the shortest path through the network, based on a specified linear combination of impedance components including items such as walk or drive access time, wait time, in-vehicle time, transfer time, additional transfer penalties, walk egress time, and fare. The coefficients of the linear combination are usually based on the relative coefficients of these variables in the mode choice model.[12] Multipath procedures find multiple "efficient" paths through the transit network based on similar criteria. The multipath methods may include multiple paths for each interchange even if the alternate paths do not minimize total travel impedance. The inclusion or exclusion of alternate paths is based on a specified set of decision rules.

The use of shortest path or multipath methods should be coordinated with the type of mode choice model used. Some mode choice models incorporate path choice in the mode choice structure. For example, in regions with both bus and rail service, the mode choice model might include walk to bus only, walk to rail only, and walk to bus/rail as separate modes. If the mode choice model is structured to include path choice, the use of a shortest path procedure is reasonable although careful use of a multipath method is also appropriate.

Alternatively, some regions simply model transit use for all combined transit modes in the mode choice model. In these regions, use of a multipath method can be used to determine path choice. Of the 22 MPOs reporting their transit path-building procedures, 17 used shortest path for their peak period and off-peak period walk-to-transit paths and five used multipath procedures. For drive access to transit paths, 20 of the 22 MPOs used shortest path for their peak period and off-peak period drive-to-transit paths and two used multipath procedures.

FTA has developed a number of guidelines for transit path-building and mode choice for Section 5309 New Starts applications. The FTA guidelines have influenced path-building procedures and parameters and should be reviewed prior to model development, especially if a New Starts application is being considered for a region.

Two issues for transit path-building and the transit assignment process are:

- **Source of bus speeds**—Are bus speeds related to auto speeds in a reasonable manner, and do they reflect observed speeds?
- **Consistency with mode choice parameters**—Are transit path-building and assignment parameters consistent with the relationships used in the mode choice model?

Table 4.28 summarizes the sources of bus speeds and the consistency of the path-building parameters with mode choice parameters for the 21 MPOs reporting the information. Information is reported for only the morning peak and mid-day networks since all of the MPOs had those two networks.

4.12.3 Basis for Data Development

The basis for data development for the model parameters described below is the information obtained from 23 MPO models in the MPO Documentation Database, as discussed in the previous section.

4.12.4 Model Parameters

The main model parameters for transit path-building are the relationships between the components of transit travel impedance. Common parameters, which are usually expressed in terms of their relationship to in-vehicle time, include:

- Monetary cost/fare (value of time) including transfer costs;
- Initial wait time;

[12]As discussed in Section 4.7, there is usually a different mode choice model for each trip purpose, with different coefficients. While development of a separate set of transit paths for each trip purpose would be possible, transit trips are usually not assigned by purpose, and so a single set of paths is used. This is usually based on the home-based work mode choice model.

Table 4.28. Transit assignment consistency reported by MPOs.

	Bus Speeds Related to Auto Speeds (Yes/Total Reporting)		Path-Building Parameters Consistent with Mode Choice (Yes/Total Reporting)	
Regional Population	**Morning Peak**	**Mid-Day**	**Morning Peak**	**Mid-Day**
More than 1,000,000	14/17	13/17	13/17	12/17
200,000 to 1,000,000	2/4	2/4	2/5	2/4
50,000 to 200,000	0/0	0/0	0/0	0/0

Source: MPO Documentation Database. Numbers refer to number of agencies in the database for each item.

Table 4.29. Ratios of walk time to in-vehicle time reported by MPOs.

	Peak Period						Off-Peak Period					
	Walk Access			Drive Access			Walk Access			Drive Access		
Regional Population	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
More than 1,000,000	2.2	1.5	3.0	2.2	1.5	3.0	2.4	1.5	3.0	2.3	1.5	3.0
200,000 to 1,000,000	2.4	1.5	3.0	2.0	1.0	3.0	2.4	1.5	3.0	2.0	1.0	3.0
50,000 to 200,000	–	–	–	–	–		–	–	–	–	–	–

Source: MPO Documentation Database.

Table 4.30. Ratios of wait time to in-vehicle time reported by MPOs.

	Peak Period						Off-Peak Period					
	Walk Access			Drive Access			Walk Access			Drive Access		
Regional Population	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
More than 1,000,000	2.1	1.5	2.6	2.1	1.5	2.6	2.1	1.5	3.0	2.2	1.5	3.0
200,000 to 1,000,000	2.9	1.5	4.5	3.0	1.5	4.5	2.9	1.5	4.5	3.0	1.5	4.5
50,000 to 200,000	–	–	–	–	–		–	–	–	–	–	–

Source: MPO Documentation Database.

- Transfer wait time;
- Transfer penalty time;
- Dwell time;
- Walk time; and
- Auto time.

Typically, the auto time and dwell time parameters are set to 1.0, as both are actually in-vehicle time. While some MPOs consider fares in their transit path-building and assignment procedures, there is little variation in fares in some locations, and so fare is often excluded from the path-building impedance.

Two of the main parameter relationships that affect transit path-building and transit assignment are the ratio of walk time to in-vehicle travel time and ratio of wait time to in-vehicle travel time. Table 4.29 summarizes the ratios of walk time to in-vehicle travel time, and Table 4.30 summarizes the ratios of wait time to in-vehicle travel time, from models included in the MPO Documentation Database. As can be seen in the tables, there is little variation in the mean values of ratios, with all of the means falling in the range 2.0 to 3.0. Detailed inspection of the reported ratios shows that most of the ratios are 2.0, 2.5, or 3.0. This result is not surprising since FTA New Starts guidelines ask applicants to "provide compelling evidence" if the ratio of out-of-vehicle time to in-vehicle time in a mode choice model is outside of the range of 2.0 to 3.0 and the guidelines also encourage consistency between transit path-building and mode choice model parameter relationships.

CHAPTER 5

Model Validation and Reasonableness Checking

5.1 Introduction

Much has been written and presented recently regarding model validation and reasonableness checking, including the FHWA *Travel Model Validation and Reasonableness Checking Manual, Second Edition* (Cambridge Systematics, Inc., 2010b); the Florida Department of Transportation (FDOT) *FSUTMS-Cube Framework Phase II, Model Calibration and Validation Standards: Model Validation Guidelines and Standards* (Cambridge Systematics, Inc., 2007a); the final report for NCHRP Project 8-36B, Task 91, "Validation and Sensitivity Considerations for Statewide Models" (Cambridge Systematics, Inc., 2010a); and the FHWA's Shining a Light Inside the Black Box webinar series (Ducca et al., 2008).

This chapter demonstrates how the information from Chapters 3 and 4 of this report can support the model validation and reasonableness checking concepts and procedures presented in the aforementioned documents. **It is intended to complement, not duplicate, other reference material on validation and reasonableness checking**. The reader should review the references listed in the previous paragraph for more complete information on model validation and reasonableness checking. There are two primary uses for the data provided in this report:

- Developing travel model components when no local data suitable for model development are available; and
- Checking the reasonableness of model components developed using local data.

In the first case, local data should be collected to validate the models or model components developed based on this report. In the second case, the data in this report can be used to supplement and support the validation and reasonableness checking process.

5.2 Model Validation Overview

5.2.1 Definitions

It is important to provide clear definitions for the terms "validation" and "reasonableness checking" as used in this report. Different references may provide different definitions or emphasize different aspects of model validation. The following definitions of validation are used in the four references noted in Section 5.1:

- **Validation** is the application of the calibrated models and comparison of the results against observed data. Ideally, the observed data are data *not* used for the model estimation or calibration but, practically, this is not always feasible. Validation data may include additional data collected for the same year as the estimation or calibration of the model or data collected for an alternative year. Validation also should include sensitivity testing. (*Travel Model Validation and Reasonableness Checking Manual, Second Edition*)
- **Validation** is the procedure used to adjust models to simulate base year traffic counts and transit ridership figures. Validation also consists of reasonableness and sensitivity checks beyond matching base year travel conditions. (FDOT *FSUTMS-Cube Framework Phase II Model Calibration and Validation Standards: Model Validation Guidelines and Standards*)
- **Validation** is the process that determines whether or not a model is reasonably accurate and reliable while sensitivity assesses the ability of the model to forecast changes in travel demand based on changes in assumptions. ("Validation and Sensitivity Considerations for Statewide Models")
- **Validation** is "forecasting" current travel patterns to demonstrate sufficient ability to reproduce highway counts and transit line volumes. (Shining a Light Inside the Black Box)

A common theme in all of the above definitions is a comparison against observed data, especially against locally collected travel data, traffic counts, and transit boardings. The data summarized in this report provide independently collected observed travel data. Of course, the data summarized in this report are not specific to any single location and, thus, do not fully satisfy the intent of model validation as defined above. The best use of the data in this report is to supplement local data.

In areas with existing travel models, the data included in this report may be used for **reasonableness checking**. The observed travel data summaries and model parameters contained herein provide an independent source of data for comparing travel models estimated and calibrated using locally collected data to travel characteristics from other areas.

5.2.2 Model Validation and Reasonableness Checking Considerations

The validation documents referenced in Section 5.1 present a number of considerations that should guide model validation and reasonableness checking:

- Model validation and reasonableness checking should encompass the entire modeling process from the development of input data required for model development and application to model results.
- Matching a specified standard such as "the coefficient of determination for modeled to observed traffic volumes should be 0.89 or greater" is **not** sufficient to prove the validity or reasonability of a model.
- The intended model use affects model validation and reasonableness checking:
  - For models that will be used to assess short-term infrastructure improvements or design, validation efforts may focus on the ability of the model to reproduce existing travel.
  - For models that will be used for planning and policy analyses, validation efforts may focus on the reasonableness of model parameters and sensitivities to changes in input assumptions.
- Planning for model validation and reasonableness checking is important to ensure that this important step is not overlooked and that data required to validate the models are collected.
- Variability and error are inherent in the travel modeling process. Variability and error occur in the input data used to estimate and apply travel models, in estimated or specified model parameters, and in the data used to validate the models.

5.2.3 Uses of Data in This Report for Validation and Reasonableness Checking

If the data and parameters included in Chapter 4 of this report are used to specify or enhance travel models for an area, the specification and collection of independent validation data such as traffic counts, transit boardings, travel time studies, and special generator cordon counts (see Chapter 3) are required for model validation. Those data may be supplemented with data from other sources such as the U.S. Census, ACS, LEHD, locally collected travel surveys, or other sources. The locally collected data may be used to perform traditional model validation tests such as comparisons of modeled to observed vehicle miles of travel, screenline crossings, traffic volumes on roadways, and transit boardings.

If areas have existing travel models estimated from locally collected data, the data contained in Chapter 4 may be used for reasonableness checking of model parameters and rates for trip-based travel models. The information contained in Chapter 4 also can be used to check the reasonableness of more advanced modeling techniques such as activity-based travel models, provided the results from those models can be converted to the trips resulting from the tours and activities.

5.2.4 Layout of Chapter

The remainder of this chapter provides an overview of the use of information contained in this report for model validation and reasonableness checking. Section 5.3 focuses on validation and reasonableness checking of existing travel models. Section 5.4 provides an example of model reasonableness checking of model components and overall validation of a travel model specified using information from Chapter 4.

Section 5.5 provides cautions and caveats to using the data contained in this report for model validation and reasonableness checking. Although these data can provide useful information regarding the reasonableness of travel models, this information cannot be used to validate travel models.

5.3 Model Validation and Reasonableness Checking Procedures for Existing Models

The general approach to model validation and reasonableness checking of existing models using information provided in this report focuses on answering the following questions:

- Are the rates and parameters developed for a specific model component for the region reasonable?

- If the rates or parameters for a specific model component are different from what would be expected, are there other characteristics of the model being considered that would "explain" the differences?

As discussed in Section 1.1, this report is the third of a series of NCHRP reports that summarize typical model rates and parameters. Thus, in some cases, results summarized in this report can be compared to those summarized in *NCHRP Report 187* (Sosslau et al., 1978) and *NCHRP Report 365* (Martin and McGuckin, 1998). Such comparisons might provide an idea of the stability or trends of specific model rates and parameters over time that may help identify the reasonableness of estimated or calibrated model parameters for a region.

5.3.1 Are the Estimated Model Rates for the Region Reasonable?

Chapter 4 provides some aggregate summaries of travel data. The summaries are averages of individuals' travel behaviors summarized over different groupings of individuals, market segments, and regions. It should be possible to compare information reported in Chapter 4 to results from a travel model estimated for a region at some level of aggregation even if the underlying travel model for the region is unique.

For example, suppose a region uses an activity-based travel model. Since the information reported in Chapter 4 is trip based, no direct comparison of model parameters is possible. However, many activity-based travel models produce travel forecasts for individuals that mimic typical travel surveys. Thus, it should be possible to summarize the results of the activity-based models to produce "trip-based" summaries for statistics such as trip rates, average trip lengths, time of day of travel, mode shares, and so forth.

Example—Reasonableness of Trip Generation—A "Success" Story

Tables 5.1 through 5.3 show a typical trip generation model estimated for an example large urban area with a population between 1 and 3 million people. Table 5.4 shows the total trip rates resulting from Tables 5.1 through 5.3.

Tables 5.5 and 5.6 provide comparisons of the average trip rates by household size and by income group for the example

Table 5.1. Modeled home-based work trip production rates for example urban area.

	Household Size					
Income Group	**1**	**2**	**3**	**4**	**5+**	**Average**
Low (Less than $25,000)	0.5	1.4	1.4	1.4	2.7	*0.8*
Middle ($25,000–$99,999)	1.3	1.9	2.1	2.3	2.7	*1.9*
High ($100,000 or more)	1.0	1.9	2.6	2.5	2.1	*2.2*
Average	*1.1*	*1.9*	*2.2*	*2.4*	*2.5*	*1.8*

Table 5.2. Modeled home-based nonwork trip production rates for example urban area.

	Household Size					
Income Group	**1**	**2**	**3**	**4**	**5+**	**Average**
Low (Less than $25,000)	1.5	2.6	5.4	5.5	5.6	*2.2*
Middle ($25,000–$99,999)	1.7	3.6	5.3	8.3	11.6	*4.9*
High ($100,000 or more)	1.9	3.2	5.3	10.5	11.6	*6.2*
Average	*1.6*	*3.4*	*5.3*	*9.2*	*11.5*	*4.9*

Table 5.3. Modeled nonhome-based trip production rates for example urban area.

	Household Size					
Income Group	**1**	**2**	**3**	**4**	**5+**	**Average**
Low (Less than $25,000)	0.9	0.9	3.3	3.1	3.1	*1.1*
Middle ($25,000–$99,999)	1.5	2.8	3.3	4.0	3.8	*2.8*
High ($100,000 or more)	2.5	3.5	4.7	5.1	6.3	*4.4*
Average	*1.4*	*2.9*	*3.7*	*4.5*	*4.6*	*3.0*

Table 5.4. Total trip production rates—HBW + HBNW + NHB for example urban area.

	Household Size					
Income Group	**1**	**2**	**3**	**4**	**5+**	**Average**
Low (Less than $25,000)	2.9	4.9	10.1	10.0	11.4	*4.1*
Middle ($25,000–$99,999)	4.5	8.3	10.7	14.6	18.1	*9.6*
High ($100,000 or more)	5.4	8.6	12.6	18.1	20.0	*12.8*
Average	*4.1*	*8.2*	*11.2*	*16.1*	*18.6*	9.7

HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

Table 5.5. Comparison of example region to NHTS trip production rates by household size.

Trip Purpose and Data Source	Household Size				
	1	**2**	**3**	**4**	**5+**
Home-Based Work					
Hypothetical Region	*1.1*	*1.9*	*2.2*	*2.4*	*2.5*
NHTS	0.5	1.2	2.0	2.3	2.4
Home-Based Nonwork					
Hypothetical Region	*1.6*	*3.4*	*5.3*	*9.2*	*11.5*
NHTS	1.8	4.0	6.7	10.6	13.4
Nonhome based					
Hypothetical Region	*1.4*	*2.9*	*3.7*	*4.5*	*4.6*
NHTS	1.3	2.5	3.8	5.3	5.7
Total					
Hypothetical Region	*4.1*	*8.2*	*11.2*	*16.1*	*18.6*
NHTS	3.6	7.7	12.5	18.2	21.5

Source: 2009 NHTS.

Table 5.6. Comparison of example region to NHTS trip production rates by income group.

<table>
<tr><th rowspan="2">Trip Purpose and Data Source</th><th colspan="5">Income Range</th></tr>
<tr><th>Less than $10,000</th><th>$10,000–$24,999</th><th>$25,000–$49,999</th><th>$50,000–$99,999</th><th>$100,000 or More</th></tr>
<tr><td>Home-Based Work</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Hypothetical Region</td><td colspan="2">0.8</td><td colspan="2">1.9</td><td>2.2</td></tr>
<tr><td>NHTS</td><td>0.6</td><td>0.8</td><td>1.3</td><td>1.9</td><td>2.0</td></tr>
<tr><td>Home-Based Nonwork</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Hypothetical Region</td><td colspan="2">2.2</td><td colspan="2">4.9</td><td>6.2</td></tr>
<tr><td>NHTS</td><td>4.1</td><td>4.7</td><td>5.0</td><td>6.2</td><td>7.6</td></tr>
<tr><td>Nonhome based</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Hypothetical Region</td><td colspan="2">1.1</td><td colspan="2">2.8</td><td>4.4</td></tr>
<tr><td>NHTS</td><td>1.6</td><td>1.9</td><td>2.7</td><td>3.8</td><td>4.7</td></tr>
<tr><td>Total</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Hypothetical Region</td><td colspan="2">4.1</td><td colspan="2">9.6</td><td>12.8</td></tr>
<tr><td>NHTS</td><td>6.3</td><td>7.4</td><td>9.0</td><td>11.9</td><td>14.3</td></tr>
</table>

Source: 2009 NHTS.

urban area with the comparable rates from the NHTS as summarized in Section 4.4.4. For the example urban area, the home-based work average household trip rates are higher than the averages shown by the NHTS for all household sizes although they are close for households of three or more persons. For the home-based nonwork trip purpose, the trip rates by household size for the example urban area are all lower than the NHTS trip rates. For the nonhome-based trip purpose and for all trip purposes combined, the results were mixed with example urban area rates being higher than NHTS rates for the lowest two household sizes and lower for the top three household sizes.

The comparison of trip production rates by income group shown in Table 5.6 is not quite as straightforward as the comparison of trips by household size as shown in Table 5.5. Unlike household sizes, income groups are affected by the year for which the incomes were reported, the income group breakpoints used in the survey and, possibly, by the region of the country for which the incomes were reported. For the 2009 NHTS data, the incomes were reported in 2008 dollars. Thus, for the example urban area, Consumer Price Index information was used to convert the income group dollar ranges from 1998 dollars to 2008 dollars. After the conversion, the income group breakpoints for the example urban area were reasonably close to the $25,000 and $100,000 breakpoints in the NHTS data. After the conversion of the income group breakpoint for the example area, the lowest-income group for the example area spanned two income groups for the NHTS data, as did the middle-income group.

After the adjustments of the income groupings, the home-based work trip rates for the example urban area were higher than the comparable income groups in the NHTS data. The trip rates for the example urban area were at the low end or lower than the comparable income groups in the NHTS data for both the home-based nonwork and nonhome-based trip purposes. Results for total trip rates were mixed.

Since the NHTS provides an agglomeration of trip rates for many urban areas throughout the country, there would be no reason to expect the trip rates from the example region to precisely match those obtained from the NHTS data. Nevertheless, it would be reasonable for the estimated trip rates for the region to reflect similar patterns to those shown in the NHTS data. The marginal trip rates for the example urban area by household size and by income group shown in Tables 5.5 and 5.6 reflect the NHTS trip rate patterns. While there are differences between the marginal trip rates for the example region and the NHTS data, the rates from the two sources reflect similar trends. Thus, while the NHTS data cannot be used to validate the trip rates for the example region, the comparison demonstrates an overall reasonableness of the trip generation model for the example region.

> Other sources might be considered for checking the reasonableness of home-based work trip rates. Specifically, CTPP/ACS data may provide alternative sources for determining HBW trip rates.

Example—Reasonableness of Trip Distribution—A "Nonsuccess" Story

The preceding example regarding trip generation rates provided a "success" story where the model in question was supported as being reasonable even though the trip generation rates did not precisely match the rates summarized from NHTS data. The following example describes a situation where simple comparisons to the summaries included in this report would have suggested that a regional model might not be reasonable. Additional analyses would be required to determine the reasonableness of the model.

Trip-based travel models were developed for a midsized urban area (population between 500,000 and 1 million). The observed average trip duration for home-based work trips was summarized from the household survey as 35.4 minutes for all person trips by auto. This average was based on congested auto travel times. Based on data from the 2009 NHTS, as reported in Table C.10 in Appendix C, the average home-based work trip duration for an urban area with 500,000 to 1 million people was 22 minutes. Thus, the observed average home-based work trip duration for the region appeared to be too high.

Such a conclusion led to additional analysis. The initial checks of the processing of the observed data, the modeled congested travel speeds used in conjunction with the reported trip interchanges to estimate the average trip duration, and the trip durations reported by the travelers in the household survey confirmed the 35-minute average for the home-based work trip duration. The analyses also showed that the average trip durations for home-based nonwork and nonhome-based trips were within reasonable ranges based on summaries of NHTS data.

Further investigation focused on the share of home-based work trips as a proportion of total trips. Reported home-based work, home-based nonwork, and nonhome-based trip shares were 11 percent, 54 percent, and 35 percent, respectively. For urban areas with 500,000 to 1 million people, the NHTS data showed these shares as 14 percent, 56 percent, and 30 percent. The low home-based work share coupled with the long average trip duration suggested that the region was different from other similar-sized urban areas.

Anecdotal information from local planners provided a plausible explanation for the differences. Specifically, due to the state of the public school system at the time, many residents enrolled their children in private and parochial schools. Since the private and parochial schools were often beyond walking distance, school children were driven to and from school by parents as part of the parents' work journeys. This anecdotal information was supported by the reported travel patterns in the regional travel survey. The local planners also were unconcerned regarding the 35-minute average trip duration for direct home-to-work trips due to general roadway congestion levels.

The result of the analyses led to modifications in the design of the trip-based travel models for the region. The models were designed to explicitly account for the increased serve passenger trips made by parents to serve the school trips of their children.

Example—Model Parameters (Trip Distribution)

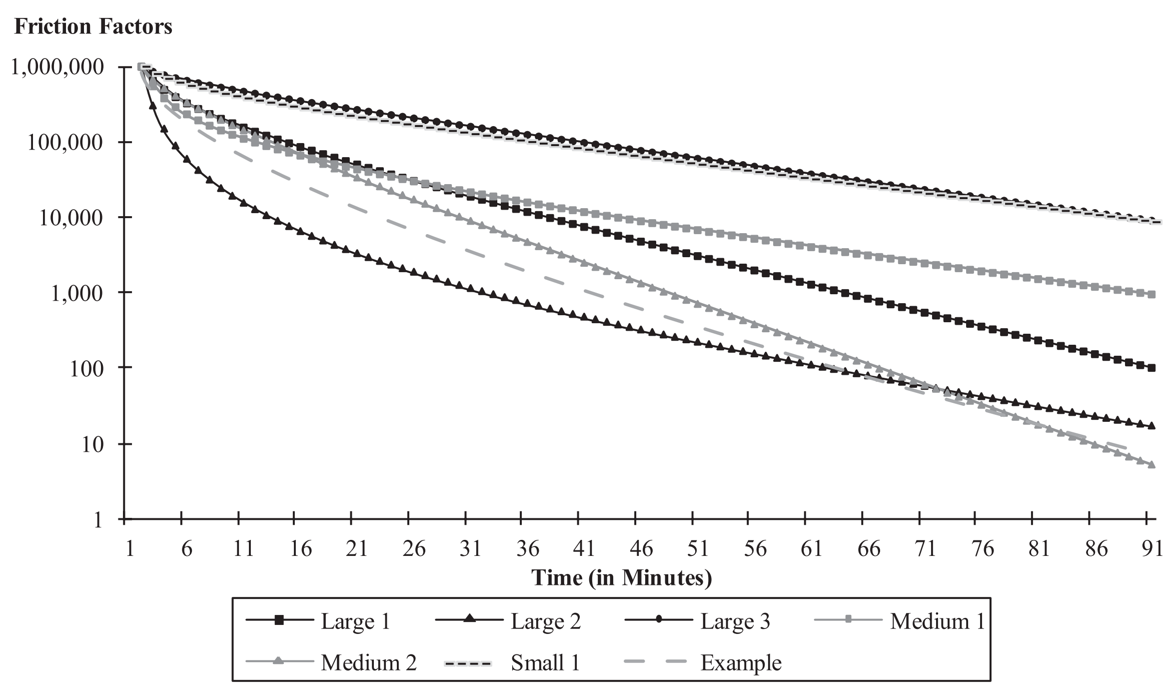
It can be useful to compare estimated model parameters to those developed in other regions as a reasonableness check. This is, quite often, a step used in the estimation of discrete choice models such as mode choice models. However, it also can be performed using more aggregate models. Suppose a region estimated the following gamma function parameters for a home-based work trip distribution model implemented using the gravity model:

$a = 5{,}280$
$b = -0.926$
$c = -0.087$

A review of Table 4.5 contained in Chapter 4 does not provide any clear indication regarding the reasonableness of the parameters. However, since the *a* parameter is simply a scale value, it can be modified to plot the various gamma functions over the same range of values. Figure 5.1 shows the resulting plot of the various functions. Again, while the data in Chapter 4 cannot validate the parameters estimated for the regional model, the information shown in Figure 5.1 suggests that the estimated function may be reasonable. However, some caution might be warranted if the example region was medium sized. The example function is generally steeper at low travel times and produces friction factors that are lower than the other medium-sized region friction factors over most of the range of travel times.

Example—Temporal Validation

Some of the summaries contained in Chapter 4 can be compared to similar summaries contained in its predecessors, *NCHRP Reports 187* and *365*. For example, Table 5.7 compares average household trip rates from those two reports and summaries of 2009 NHTS data, while Table 5.8 compares shares of total trips by trip purpose. For urban areas with populations greater than 500,000, household-based average trip rates appear to be generally increasing over time. The rates appear to be generally decreasing for areas with populations less than 500,000. For shares of trips by trip purpose, home-based work shares are decreasing over time while nonhome-based shares



Source: MPO Documentation Database.

Figure 5.1. Comparison of trip distribution gamma functions.

Table 5.7. Comparison of household trip rates.

Urban Area Population	Daily Person Trips per Household: *NCHRP Report 187*[a,c] (Published 1978)	*NCHRP Report 365*[a,c] (Published 1998)	2009 NHTS Data[b]
50,000 to 100,000	14.1	9.2	9.1
100,000 to 200,000	14.5	9.2	9.1
200,000 to 500,000	11.8	9.0	9.1
500,000 to 1,000,000	7.6	8.6	9.6
1,000,000 to 3,000,000	7.6	8.5	9.6
More than 3,000,000	7.6	8.5	9.6

[a] Trip rates are total person trips in motorized vehicles.

[b] Trip rates are total person trips by all modes.

[c] Because of differences between urban area categories in the three reports, the rates shown were chosen from the closest matching category.

Source: Sosslau et al. (1978), Martin and McGuckin (1998), 2009 NHTS.

Table 5.8. Comparison of shares of trips by trip purpose.

Urbanized Area Population	Percentage of Daily Person Trips by Trip Purpose: *NCHRP Report 187*[a] (Published 1978)			*NCHRP Report 365*[a] (Published 1998)			2009 NHTS Data[b]		
	HBW	HBNW	NHB	HBW	HBNW	NHB	HBW	HBNW	NHB
50,000 to 100,000	16	61	23[c]	20[c]	57[c]	23[c]	15	54	31
100,000 to 200,000	20	57	23[c]	20[c]	57[c]	23[c]	15	54	31
200,000 to 500,000	20	55	25[c]	21[c]	56[c]	23[c]	15	54	31
500,000 to 1,000,000	25	54	21[c]	22	56[c]	22[c]	14	56	30
1,000,000 to 3,000,000	25	54	21[c]	22[c]	56[c]	22[c]	14	56	30
More than 3,000,000	25	54	21[c]	22[c]	56[c]	22[c]	14	56	30

[a] Shares by purpose are based on person trips in motorized vehicles.

[b] Shares by purpose are based on person trips by all modes.

[c] Because of differences between urban area categories in the three reports, the rates shown were chosen from the closest matching category.

HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

Source: Sosslau et al. (1978), Martin and McGuckin (1998), 2009 NHTS.

are increasing. For regions that are updating or redeveloping models, comparing aggregate results to trends that can be drawn from this report and its predecessors can be useful for checking model reasonableness.

5.4 Model Validation and Reasonableness Checking Procedures for Models or Model Components Developed from Information Contained in Chapter 4

The *Travel Model Validation and Reasonableness Checking Manual, Second Edition* recommends the development of a model validation plan when a model is developed or updated. The validation plan should outline model validation and reasonableness checks that will be performed along with the validation data that will be used as the bases for comparison for the model results. This recommendation holds true for models developed from locally collected travel survey data or models specified using rates borrowed from other regions or provided in Chapter 4.

As an example, suppose an MPO for a region of 250,000 people was updating its travel model based on rates provided in Chapter 4 and Appendix C. The existing travel model had been specified using data from *NCHRP Report 365*, and no travel survey data were available. A validation plan was developed and, based on that plan, available resources were focused on the collection of traffic counts (daily and by time of day). In addition, staff from the MPO and their families were asked to record travel times on their trips to and from work.

Since the travel model being updated was based on *NCHRP Report 365* rates, the MPO had developed a procedure to esti-

Table 5.9. Initial trip production rates for example urban area.

	Household Size				
Trip Purpose	**1**	**2**	**3**	**4**	**5+**
HBW	0.5	1.2	2.0	2.3	2.4
HBNW	1.8	3.6	6.7	9.5	12.9
NHB	1.3	2.5	3.8	5.3	5.7

HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

Table 5.10. Initial trip production reasonableness check for example urban area.

Measure	HBW	HBNW	NHB	Total
Trip Rates				
Original Model[a]	1.8	4.8	2.0	8.6
Updated Model	1.6	5.4	3.1	10.1
MPO Averages	1.4	5.1	3.0	9.6
Distribution of Trips by Purpose				
Original Model[a]	21%	56%	23%	100%
Updated Model[b]	15%	53%	32%	100%
MPO Averages[c]	15%	53%	32%	100%

[a] Based on Martin and McGuckin (1998), Table 9.

[b] Based on model shown in Table 5.9.

[c] Tables C.5 through C.7.

HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

mate households by household size. Average trip production rates from Tables C.5 through C.7 were used to specify the trip rates shown in Table 5.9 for the example MPO model.

Table 5.10 shows the trips per household resulting from the applications of the original model based on *NCHRP Report 365* rates along with results from the application of the model summarized in Table 5.9 using the MPO's socio-economic distributions of households by household size. Table 5.10 also shows the average trip rates for MPOs from Tables C.5 through C.7. The table also shows the modeled distributions of trips by trip purpose resulting from the original and updated models. Based on the information shown in Table 5.10, MPO modeling staff suspected that the model would result in more travel in the region than would be shown by the observed traffic counts.

Trips were distributed using the friction factors for "Medium (A)" MPOs shown in Table 4.5. The informal travel time survey of MPO staff did not suggest any substantial issues with the coded network speeds. Most staff reported observed travel times within ±10 percent of the modeled travel times for their trips from home to work. The modeled average trip durations are shown in Table 5.11 along with the average trip durations for urban areas of less than 500,000 population from Table C.10. The results shown in Table 5.11 also suggested that the model would show less travel in the region than would be shown by the observed traffic counts.

When the modeled vehicle trips were assigned (after applying mode split, auto occupancy, and time-of-travel model components), the resulting vehicle miles of travel were close to the vehicle miles of travel estimated from the traffic counts

Table 5.11. Initial trip distribution reasonableness check for example urban area.

	Trip Durations in Minutes			
Measure	**HBW**	**HBNW**	**NHB**	**Total**
Implied by Table C.10	20	18	18	18
Based on Model Application	18	16	18	17
Percentage Difference	–10%	–11%	0%	–4%

HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

collected for the model validation. Modeled screenline crossings were within 10 to 15 percent of the observed screenline crossings. Based on the information provided by the reasonableness checks for the trip production and trip distribution models and the model validation results, both the trip production and trip distribution models were deemed to produce reasonable results.

5.5 Cautions Regarding Use of This Report for Validation

The examples shown in this chapter illustrate both the risk and value of using information contained in this report for model validation and reasonableness checking. Since the data contained in Chapter 4 are highly aggregated from nationally collected data, they can be used only for general reasonableness checking. As stated previously, agreement between modeled information for a specific region and the general information in this report for any single measure is insufficient to demonstrate that a model for the region is valid. Likewise, failure to reasonably match the general summaries contained in this report does not invalidate a regional travel model. However, failure to reasonably match a general summary contained in this report should lead to further investigation of a regional travel model to explain the difference from the general travel patterns resulting from typical traveler behavior.

It also is important to verify that the data being compared are, in fact, comparable. A prime example of this issue is trip generation. Many regions summarize and forecast all person travel made in motorized vehicles, while others summarize and forecast all person travel. Efforts have been made in Chapter 4 to clearly identify whether all travel or only travel in motorized vehicles has been included in the summaries.

Finally, differences in data collection and processing techniques can introduce variation in the summarized data. There is a high level of consistency in the collection and processing of the NHTS data summaries contained in Chapter 4. However, since different MPOs have collected data for their own regions and developed their own models from those data, summaries of MPO-reported data and parameters are subject to variation from the data collection and processing procedures.

CHAPTER 6

Emerging Modeling Practices

Over the past few decades, because of escalating capital costs of new infrastructure and increasing concerns regarding traffic congestion, energy dependence, greenhouse gas emissions, and air quality, the originally supply-oriented focus of transportation planning has expanded to include the objective of addressing accessibility needs and problems by managing travel demand within the available transportation supply. Consequently, there has been an increasing interest in travel demand management strategies, such as mixed land use development, parking pricing, and congestion pricing, all of which attempt to change land use and transportation service characteristics to influence individual travel behavior and control aggregate travel demand. The evaluation of such demand management strategies using travel demand models places more emphasis on the realistic representation of behavior to accurately reflect traveler responses to management policies.

This realization has led to the consideration of the following issues, all of which have the potential to improve upon travel demand forecasts and enable more informed policy making:

- Time-space constraints and interactions in the activity-travel decisions of an individual;
- The accommodation of interindividual interactions in activity-travel decision making across individuals (such as joint participation in activities and travel, serve passenger trips, and allocation of responsibilities among individuals in a household);
- The recognition of the linkages across trips within the same "tour" (i.e., chain of trips beginning and ending at a same location) of an individual and across activities/tours of the individual over the day; and
- The explicit consideration of time as an all-encompassing continuous entity within which individuals make activity/travel participation decisions.

The result has been the increasing consideration of a fundamental behavioral paradigm referred to as an activity-based approach to travel demand modeling.

TRB Special Report 288: Metropolitan Travel Forecasting—Current Practice and Future Direction (SR 288) is the product of a TRB study, funded by FHWA, FTA, and the Office of the Secretary of Transportation, to determine the national state of practice in metropolitan area travel demand forecasting and to recommend improvements (Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting, 2007). SR 288 recommends that the federal government "support and provide funding for the continued development, demonstration, and implementation of advanced modeling approaches, including activity-based models" and "continue support for the implementation of activity-based modeling and other advanced practices; considerably expand this support through deployment efforts in multiple urban areas." Chapter 6 of SR 288 is devoted to advancing the state of the practice.

The purpose of this chapter is to introduce the concepts of advanced modeling procedures such as activity-based models, dynamic traffic assignment models, and traffic simulation models. It is not intended to provide comprehensive documentation of these advanced models, but rather to describe how they work and how they differ from the conventional models discussed in the rest of the report.

This discussion should not be construed as a recommendation that all urban areas should be planning to switch to these types of modeling approaches in the near future, nor should it be viewed as a statement that such advanced modeling approaches address all of the problems associated with conventional modeling approaches. However, with these advanced approaches becoming more prevalent, and the likelihood that more areas will continue to switch to using them, it is desirable for the travel modeling community to become more familiar with them.

6.1 The Activity-Based Approach

The fundamental difference between the trip- and activity-based approaches is that the former approach directly focuses on "travel participation behavior" as the decision entity of interest, while the activity-based approach views travel as a demand derived from the need to pursue activities and focuses on "activity participation behavior." The underlying philosophy of the activity-based approach is to better understand the behavioral basis for individual decisions regarding participation in activities in certain places at given times, and hence the resulting travel needs. This behavioral basis includes all the factors that influence the why, how, when, and where of performed activities and resulting travel. Among these factors are the needs, preferences, prejudices, and habits of individuals (and households), the cultural/social norms of the community, and the travel service characteristics of the surrounding environment.

At a fundamental level, therefore, the activity-based approach emphasizes the point that the needs of the households are likely to be translated into a certain number of total activity stops by purpose followed by (or jointly with) decisions regarding how the stops are best organized. For example, consider a congestion pricing policy during the evening commute period along a corridor. Also, consider an individual who has the daily pattern shown in the top pattern of Figure 6.1, where the shopping stop during the evening commute is at a location that entails travel along the "to-be-priced" corridor (but assume that the person would not be traveling the "to-be-priced" corridor if she went directly home from work). In response to the pricing policy, the individual may now stop making the shopping stop during the evening commute but may generate another stop in the evening after returning home from work (see bottom pattern of Figure 6.1). If some of these post-home arrival stops are undertaken in the peak period, congestion may be simply transferred to other locations in the network. The activity-based approach explicitly acknowledges the possibility of such temporal redistributions in activity participation (and hence travel) by focusing on sequences or patterns of activity participation (using the whole day or longer periods of time as the unit of analysis), and thus is able to provide a holistic picture of policy effects.

A second defining aspect of the activity-based approach is its use of "tours" as the basic element to represent and model travel patterns. Tours are chains of trips beginning and ending at a same location, say, home or work. The tour-based representation helps maintain consistency across, and capture the interdependency (and consistency) of the modeled choice attributes among, the activity episodes (and related travel characteristics) undertaken in the same tour. This approach contrasts with the trip-based approach that considers travel as a collection of "trips," each trip being considered independent of other trips.

The activity-based approach can lead to improved evaluations of the impact of policy actions because of the explicit consideration of the interrelationship in the choice attributes (such as time of participation, location of participation, and mode of travel) of different activity episodes within a tour and, therefore, the recognition of the temporal, spatial, and modal linkages among activity episodes within a tour. Take, for example, an individual who drives alone to work and makes a shopping stop on the way back home from work (see Figure 6.2). The home-work and work-home trips in this scenario are not independent.

Now consider an improvement in transit between the home and the work place. The activity-based approach would recognize that the individual needs to make a stop on the return home from work and so may not predict a shift to transit for the work tour (including the home-work, work-shop, and shop-home trips), while a trip-based model would break the tour into three separate and independent trips—a home-based work trip, a nonhome-based nonwork trip, and a home-based nonwork trip—and would be more likely (and inaccurately so) to shift the morning home-based work trip contribution of the individual to transit.

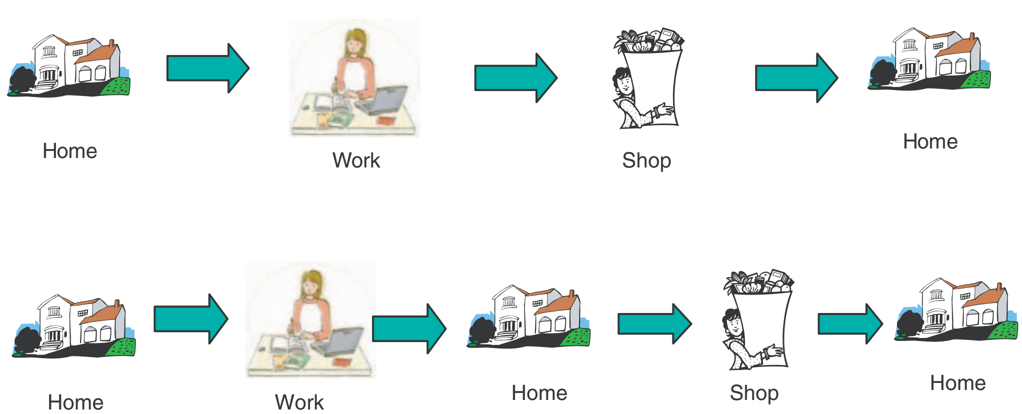


Figure 6.1. Temporal substitution of trips.

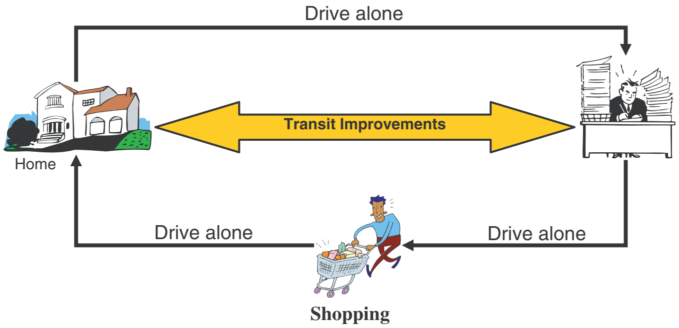


Figure 6.2. Trip sequencing and interrelationship in attributes of linked trips.

In fact, the close association between mode choice for the work commute and stop making along the way is now well established. For instance, a study of Austin area workers (Bhat, 2004) found that the drive-alone mode share was 70 percent for commuters who never stopped on the way to or from work, compared to 87 percent for commuters who sometimes made a stop. Correspondingly, the share of commuters who used transit or a nonmotorized mode was higher for individuals who did not make a commute stop.

A third defining feature of the activity-based approach relates to the way the time dimension of activities and travel is considered. In the trip-based approach, time is included as a "cost" of making a trip and a day is viewed as a combination of broadly defined peak and off-peak time periods (see, for example, the time-of-day modeling discussion in Section 4.9). On the other hand, the activity-based approach views individuals' activity-travel patterns as a result of their time use decisions within a continuous time domain. Individuals have 24 hours in a day (or multiples of 24 hours for longer periods of time) and decide how to use that time among (or allocate that time to) activities and travel (and with whom), subject to their sociodemographic, spatial, temporal, transportation system, and other contextual constraints. These decisions determine the generation and scheduling of trips. Hence, determining the impact of travel demand management policies on time use behavior is an important precursor step to assessing the impact of such policies on individual travel behavior.

Take the example of a worker who typically leaves work at 5:00 p.m. (say, the start of the afternoon peak period), drives to a grocery 15 minutes away, spends about 25 minutes shopping, and then gets back home by 6:00 p.m. (Figure 6.3). In response to an early release from work policy designed by the employer that lets the employee off from work at 4:00 p.m. instead of 5:00 p.m., a naïve model system may predict that the person would be off the road and back home by 5:00 p.m. (i.e., before the peak period begins; see the middle pattern in Figure 6.3). But the individual, now released from work earlier and having more time on his hands after work, may decide to drive a longer distance to a preferred grocery where he spends more time shopping (70 minutes rather than 25 minutes) and may eventually return home only at 6:00 p.m. (see the bottom pattern of Figure 6.3). So, in the case of this individual, not only would the policy be ineffective in keeping the person off the road during the peak period, but also the longer time spent at the grocery (in emissions analysis terms, the "soak duration," the period between successive trips when the vehicle is not operational) would have adverse air quality implications. The activity-based model is able to consider such interactions in space and time due to its emphasis on time use and thus can produce more informed evaluations of policy actions.

Another feature of the activity-based approach is the recognition of interactions among household members, which leads to the accommodation of linkages among trips of household members. As a result, policy actions could have complex

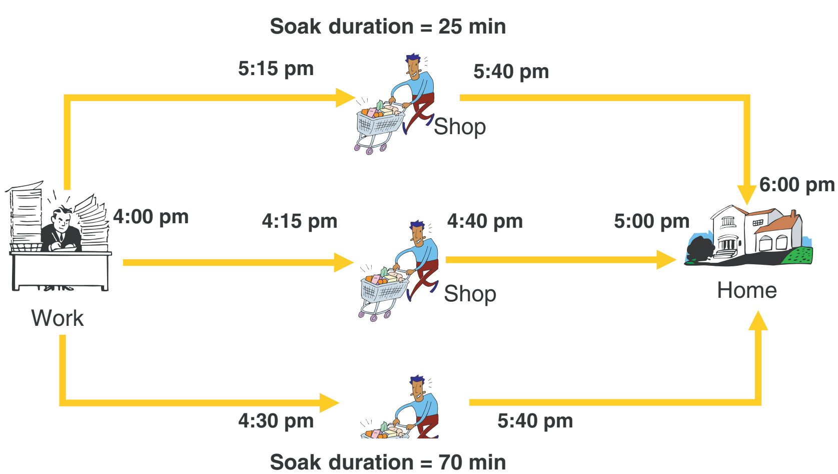


Figure 6.3. Duration and timing of activities and trips.

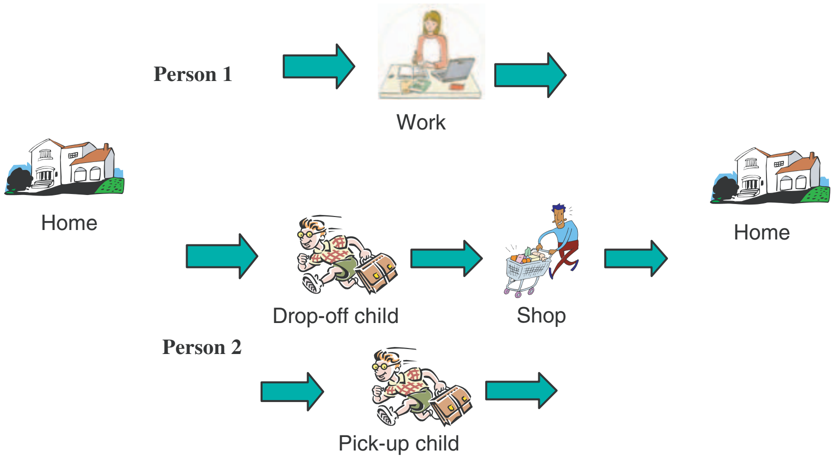


Figure 6.4. Resource sharing—linkages among trips of household members.

responses, as shown in Figure 6.4. Consider that Person 1 (the worker) was originally dropping off the child at school in the mornings and picking up the child from school in the evenings, as part of the commute. Assume a pricing strategy on a corridor that connects the school location and the worker's work location. Because of this pricing policy, the worker may not pursue the drop-off/pick-up tasks himself and has a simple home-work-home pattern (top pattern of Figure 6.4). But now Person 2 (the nonworker) generates drop-off and pick-up trips, perhaps supplemented with shopping stops during his drop-off/pick-up trips.

Such an explicit modeling of interindividual interactions and the resulting joint travel is particularly important to examine the effects of occupancy-specific tolling strategies such as HOV and HOT lanes (Davidson et al., 2007). Another way that household linkages in activities can have an effect on responses to policies is through a reluctance to change the spatial and temporal attributes of joint activity episode participations. For instance, serve passenger trips (such as dropping off/picking up children from daycare/school or other extracurricular activities) and joint social/recreational out-of-home activities of household members may not be moved around much because of schedule constraints. Acknowledging such joint interactions can, therefore, potentially lead to a more accurate evaluation of policy actions.

A final important feature of activity-based approaches relates to the level of aggregation of decision makers used in the estimation and application of the models. In the trip-based approach, several aspects of travel (number of trips produced and attracted from each zone, trip interchanges, and mode split) are usually (though not always) estimated and/or applied at a relatively aggregate level of decision makers (such as at the spatial level of travel analysis zones). The activity-based models, on the other hand, have the ability to relatively easily accommodate virtually any number of decision factors related to the sociodemographic characteristics of the individuals who actually make the activity-travel choices. Using micro-simulation techniques, activity-based models predict the entire activity-travel patterns at the level of individuals (while recognizing temporal/spatial constraints across individuals of a household due to joint activity participations and serve passenger activities). Such a methodology ensures a realistic, consistent, and integral prediction of activity-travel patterns, which should lead to the better aggregate prediction of travel flows on the network in response to demographic changes or policy scenarios. Thus the activity-based models are well equipped to forecast the longer-term changes in travel demand in response to the changes in the sociodemographic composition and the activity-travel environment of urban areas, as well as in response to land use and transportation policies.

6.2 Activity-Based Travel Model Systems in Practice

6.2.1 Overall Process for Activity-Based Model Systems

The overall process used in the implementation of an activity-based model system comprises a sequence of three broad steps:

1. Population synthesis;
2. Long-term choice models; and
3. Activity-based travel models.

Activity-based model systems require as inputs the information on each (and every) individual and household of the population of the study area, because the systems simulate the activity-travel patterns of each individual in the study area. Such disaggregate-level sociodemographic inputs are generated by synthesizing (i.e., simulating) the population of the study area. This synthesis is achieved by using zonal-level (or other levels of geography such as the block level or parcel level) forecasts of sociodemographic variables (such as household size, structure, and income) as controls for sampling households using data from sources such as the ACS PUMS. At the end, the population synthesis procedure provides a synthetic sample of all households and individuals in the study area with information on household residential locations and all control variables used in the synthesis procedure.

Several other socioeconomic attributes (which are not used as control variables) required by the activity-travel models are either directly borrowed from the households drawn from the PUMS data, or generated by a separate set of disaggregate models. The use of separate disaggregate models has the advantage that it provides natural variation in the predicted socioeconomic attributes, rather than "replicating" PUMS individuals and households. Some activity-based systems generate the synthetic population based on a two-way control mechanism for both household-level attributes as well as individual-level attributes.

After the population synthesis, the longer-term decisions such as auto ownership, work locations, and school locations are determined to recognize that such decisions are longer-term decisions that are not adjusted on a daily basis. Subsequent to the determination of long-term choices, the synthetic population of households and individuals is "processed" through the activity-based travel model system, as discussed in more detail in the following sections.

6.2.2 Generic Structure of Activity-Based Systems

Activity-based model systems used in practice typically consist of a series of utility maximization-based discrete choice models (i.e., multinomial logit and nested logit models) that are used to predict several components of individuals' activity-travel decisions. In addition to such utility maximization-based model components, some model systems employ other econometric structures, including hazard-based duration structures and ordered response structures to model various activity-travel decisions. In effect, these model systems employ econometric systems of equations to capture relationships between individual-level sociodemographics and activity-travel environment attributes on the one hand and the observed activity-travel decision outcomes on the other. As of 2011, MPOs within the United States that have developed an activity-based travel model include Portland, Oregon; San Francisco, Sacramento, and Los Angeles, California; New York, New York; Columbus, Ohio; Denver, Colorado; and Atlanta, Georgia. Several other urban areas have activity-based models under development.

While there are quite substantial variations among the many activity-based modeling systems in the precise sequence and methods used to predict the entire activity-travel pattern of each individual, all of these systems essentially include a three-tier hierarchy of (1) day-level activity pattern choice models (or, simply, pattern-level choice models); (2) tour-level choice models; and (3) trip/stop-level choice models. The choice outcomes from models higher in the hierarchy (assumed to be of higher priority to the decision maker) are treated as known in the lower-level models. The pattern-level models typically provide a skeletal daily pattern for each individual, including whether the individual goes to work (or school, if the person is a student), whether the individual takes any children to/from school, any joint activities (and their purposes) among individuals in a household and the individuals involved, individual participations in activities by purpose, and number of total tours (home- and work-based) in the day.

The tour-level models typically determine the number of stops in a tour by purpose and their sequence, the travel mode for the tour, and the time of day and duration of the tour. For workers, tours are constructed based on focusing on the home-work and work-home commutes first, along with the number of stops, sequence, and travel mode during the commutes. Next, other tours during the day are constructed; those with joint activities are usually given scheduling precedence. For nonworkers, tours relating to serve passenger stops (including dropping off/picking up children from school/day care) and tours with joint activities may get scheduling precedence. Finally, the stop-level models predict the stop location, mode choice, and time of day of travel for each of the stops in each tour.

6.2.3 Data Needs for Estimation of Activity-Based Systems

The primary sources of data for the estimation of tour- and activity-based models are household activity and/or travel surveys. As the term "household activity and/or travel surveys" suggests, the surveys can be either travel surveys (that collect information on out-of-home travel undertaken by the household members) or activity-travel surveys (that collect information on out-of-home activities and associated travel). Both the surveys implicitly or explicitly collect information on (1) household-level characteristics, (2) individual-level characteristics, and (3) information on the activity/travel episodes undertaken by the individuals. Activity surveys, however, also may collect additional information on individuals' activities, specifically the participation in, timing, and duration of in-home and joint activities.

It should be noted that the development of several activity-based models to date has involved the use of household travel survey data that are not any different from those collected and used by regional MPOs for their trip-based model development and calibration. Thus, the notion that activity-based models are data hungry is not necessarily accurate, at least at the estimation stage (though, activity-based models would perhaps benefit more from larger sample sizes than would trip-based models, especially from the standpoint of estimating models of joint activity participation). The estimation of activity-based models does require more extensive efforts (relative to a trip-based approach) in preparing the data to construct the entire sequence of activities and travel, but such intense scrutiny of data also helps identify data inconsistencies that might go unchecked in the trip-based approach. For example, there might be "gaps" in an individual's travel diary because of non-reporting of several trips; these will be identified during data preparation for activity analysis but may not be identified in the trip-based approach because it highlights individual trips and not the sequence between trips and activities.

Data on regional land use and transportation system networks also are typically used in model estimation. Land use data include information on the spatial residential characteristics of households, employment locations, and school and other locations at the level of spatial resolution (for example, zones or parcels) used in the models. The typical land use information includes size and density measures, such as number of households, population, area (or size), employment by each category of employment, household density, population density, and employment density for each category of employment. In addition, one or more of the following land use data also are used by some activity modeling systems: (1) land use structure information, such as the percentage of commercial, residential, other developed, and open areas; percentage of water coverage; and the land use mix; (2) sociodemographic characteristics, such as average household size, median household income, ethnic composition, housing characteristics such as median housing value, and housing type measures (single- and multiple-family dwelling units); and (3) activity opportunity measures such as activity center intensity (i.e., the number of business establishments within a fixed network distance) and density (i.e., the number of business establishments per square mile) for each of several activity purposes.

Transportation network data needed in activity models are similar to data used in trip-based models and typically include highway network data, transit network data, and nonmotorized mode data. The transportation system performance data should be of high quality, with time-varying LOS characteristics (in-vehicle, out-of-vehicle, access, egress, and wait times) across different time periods, as well as across different location pairs.

6.2.4 Data Needs for Application of Activity-Based Systems

Once the activity-based modeling system has been estimated using the data sources discussed in the previous section, the application of these activity-based models for a study area for a base year requires as inputs the information on all individuals and households of the study area for the base year. Synthetic population generation techniques are used for this purpose, sometimes supplemented with a series of other demographic models (see Section 6.2.1). For a future-year forecasting exercise, the inputs should consist of the future-year synthetic population and land use and LOS data. Thus, activity-based model development should be supported with the development of detailed input data (i.e., the synthetic population and LOS and land use data) for future years. This can be done either by using aggregate demographic and land use projections for future years and applying a synthetic population generator (just as in the base year) or "evolving" the base-year synthetic population (see Eluru et al., 2008). More details on this are provided in Section 6.3.1.

6.2.5 Data Needs for Calibration and Validation of Activity-Based Systems

The following data sources can be used to calibrate and validate activity-based model systems:

- Validation of input data
  - The base-year synthetic population inputs can be validated against census data.
  - To validate the input work locations, the home-work trip lengths and patterns can be matched against those in observed data sources such as CTPP.
  - To validate the vehicle ownership inputs, census data and perhaps other sources such as motor vehicle department estimates of auto registrations can be used.
- Calibration and validation of activity-travel outputs
  - Each component of the activity-travel model system can be validated by comparing its predictions to the observed activity-travel patterns in the household activity-travel survey.
  - The commute mode choice model can be validated using data such as CTPP.
  - The entire model system can be validated by comparing the traffic assignment outputs with the observed traffic volumes in the study area.
  - Highway traffic assignment validation can be undertaken by using observed traffic volumes by time of day, while transit traffic assignment validation can be pursued by using transit boarding/alighting data by route and stop by time of day from an on-board transit survey/count.

Along with the above-identified base-year calibrations and validations, it is essential to understand the forecasting ability and the policy sensitivity of activity-based models for nonbase-year conditions.

To test the forecasting ability, the model performance for past years (for example, year 1990) and for existing "future" years relative to the base year for the travel modeling effort (for example, year 2010) can be compared with the observed patterns in those years. For this purpose, complete input data (including the aggregate sociodemographic variable distributions for synthetic population generation, and the land use and LOS data), observed traffic volumes, household activity-travel survey data, and the census data (if available) are required for past years and existing "future" years. In this regard, it is important that the regional planning agencies store and document the land use data and transportation network data of past and existing "future" years.

An examination of the policy sensitivity of activity-based models for nonbase-year conditions can be undertaken by assessing the impact on activity-travel patterns of changes in transportation system and land use patterns. To this end, in the recent past, several tests have been undertaken to assess the sensitivities of specific components of activity-based models to policy scenarios. Examples include (1) an analysis of the impact of LOS changes (systemwide and localized); (2) analyses of capacity expansion and centralized employment scenarios; (3) analysis of area pricing schemes; (4) assessment of the effect of shortened work days; (5) analyses of cordon pricing and increased transportation network connectivity scenarios; (6) user-benefit forecasts of light rail transit projects; (7) equity analysis of transportation investment impacts; (8) examination of the impacts of land use and urban form on area travel patterns; (9) analysis of congestion pricing policies; (10) analysis of FTA New Starts projects; and (11) analysis of transit investments. Such an examination of the response to several policy scenarios can be a useful assessment of the abilities of the activity-based model system (especially when compared with the outputs from a trip-based model system).

The scenario approach discussed above to assessing the policy sensitivity of activity-based models, however, may not completely represent the complexity of real-life projects and policies. Furthermore, sensitivity testing using test scenarios serves only as a broad qualitative reasonableness assessment of performance, rather than a quantitative performance measurement against observed data. A more robust way to quantify and assess the predicted policy sensitivity from activity-based models is to compare the model predictions with real-world data before—and after—real-life transportation infrastructure investments or policy actions. Hence, it is important to collect traffic counts and other travel pattern data before—and after—any major transportation infrastructure investments or policy actions.

6.2.6 Software for Activity-Based Modeling

At present, there are no readily available standard software packages to apply activity-based models. The model systems developed for various MPOs have been developed and implemented as customized stand-alone software, and then integrated with standard proprietary modeling software for such purposes as network skimming, matrix manipulation, and highway and transit assignment. Most activity model systems are coded using C++, C#, Python, or Java and make use of an object-oriented approach, which offers the advantages of code reuse, software extensibility, and rapid implementation of system variants.

6.2.7 Challenges of Developing and Applying Activity-Based Modeling Systems

The development of activity-based models requires careful and extensive data preparation procedures to construct entire "sequences" of activities and "tours" of travel. The data preparation process for the activity-based modeling is involved and requires skilled and experienced personnel. Furthermore, as mentioned previously, activity-based model development is associated with an initial overhead of data preparation, model estimation, calibration and validation, and the process of "putting it all together" into customized software. However, once the model system is developed, the system can be packaged as user-friendly travel demand modeling and policy analysis software. Further, the software can be sufficiently generic to allow its use in any study area, provided the model parameters for that area are available.

The implementation of activity-based models (for either the base year or for future years) requires the end user to be well aware of the details of the system. Another implementation challenge is the significant amount of run time, because activity-based models simulate the activity-travel patterns of each (and every) individual of a study area. However, it appears that the run times can be significantly reduced by one or more of the following techniques:

- Simulation of the activity-travel patterns of a sample of the population without substantially compromising the accuracy of the aggregate-level outputs;
- Efficient computing strategies such as data caching and multi-threading;
- "Clever" methods of model specification where dummy exogenous variables are used so that a substantial part of the computations in the application context can be undertaken for market segments (defined by combinations of dummy exogenous variables) rather than for each individual in the population; and
- Use of cloud (or cluster) computing approaches that use several parallel processors at the same time.

The implementation challenges associated with activity-based models appear to be higher for the forecast-year implementation rather than for the base-year implementation, primarily because of the need to generate detailed socioeconomic input data for the forecast years. Also, the development of future-year parcel-level land use data is a challenge associated with the implementation of models that use parcel-level data. And in rapidly growing areas, there may be many more synthetic persons and households to simulate than in the base year.

Finally, while the required technical background, resource requirements for development and maintenance, implementation challenges, and institutional issues associated with ownership of activity-based models are immediately evident, the need remains to assess, document, and demonstrate the potential practical benefits of these models.

6.3 Integration with Other Model Systems

The recognition of the linkages among sociodemographics, land use, and transportation is important for realistic forecasts of travel demand, which has led practitioners and researchers to develop approaches that capture sociodemographic, land use, and travel behavior processes in an integrated manner. Such behavioral approaches emphasize the interactions among population socioeconomic processes; the households' long-term choice behaviors; and the employment, housing, and transportation markets within which individuals and households act (see Waddell, 2001). From an activity-travel forecasting perspective, these integrated urban modeling systems need to consider several important issues that are outlined in this section. Some elements of this integration with activity-based models already have been introduced at several MPOs.

6.3.1 Generation of Disaggregate Sociodemographic Inputs for Forecast Years

As indicated in Section 6.2.3, activity-based travel forecasting systems require highly disaggregate sociodemographics as inputs, including data records of each and every individual and household in the study area. Hence, disaggregate population generation procedures are used to create synthetic records of each and every individual and household for activity-travel microsimulation purposes. However, to be able to forecast the individual activity-travel patterns and aggregate transportation demand at a future point in time, activity-based travel demand models require, as inputs, the disaggregate sociodemographics, and the land use and transportation system characteristics of that future point in time.

While synthetic population generator (SPG) procedures can be used for this purpose as a first step operationalization strategy, these procedures work off aggregate demographic and land use projections for future years rather than the more desirable route of evolving the base-year population. Specifically, individuals and households evolve through a sociodemographic process over time. As the sociodemographic process unfolds, individuals may move into or out of life-cycle stages such as schooling, the labor market, and different jobs. Similarly, households may decide to own a house as opposed to rent, move to another location, and acquire/dispose of a vehicle. Such sociodemographic processes need to be modeled explicitly to ensure that the distribution of population attributes (personal and household) and land use characteristics are representative at each point of time and are sufficiently detailed to support the activity-travel forecasting models.

There have been relatively limited attempts to build models of sociodemographic evolution for the purpose of travel forecasting. Examples in the transportation field include the CEMSELTS system by Bhat and colleagues (Eluru et al., 2008), the DEMOgraphic (Micro) Simulation (DEMOS) system by Sundararajan and Goulias (2003), and the Microanalytic Integrated Demographic Accounting System (MIDAS) by Goulias and Kitamura (1996). Examples from the non-transportation field include DYNACAN (Morrison, 1998), and LIFEPATHS (Gribble, 2000).

6.3.2 Connecting Long- and Short-Term Choices

Many (but not all) operational activity-based travel demand models treat the longer-term choices concerning the housing (such as residential tenure, housing type, and residential location), vehicle ownership, and employment choices (such as enter/exit labor market and employment type) as exogenous inputs. Consequently, the land use (in and around which the individuals live, work, and travel) is treated as exogenous. In such cases, the possibility that households can adjust with combinations of short- and long-term behavioral responses to land use and transportation policies is systematically ignored (see Waddell, 2001). A significant increase in transportation costs, for example, could result in a household adapting with any combination of daily activity and travel pattern changes, vehicle ownership changes, job location changes, and residential location changes.

While many travel forecasting models treat the long-term choices and hence the land use as exogenous to travel behavior, there have been recent attempts to model the longer- and shorter-term choices in an integrated manner. These include OPUS/UrbanSim (Waddell et al., 2006), CEMUS (Eluru et al., 2008), ILUTE (Salvini and Miller, 2005), and ILUMASS (Strauch et al., 2003). There also have been models studying the relationships between individual elements of land use-related choices and travel behavior choices. However, most of these models and model systems are trip based. That is, although these models attempt to study the land use and travel behavior processes in an integrated manner, the travel behavior aspect of these models is based on a trip-based approach.

6.3.3 Demand-Supply Interactions

The end use of travel forecasting models is, in general, the prediction of traffic flow conditions under alternative sociodemographic, land use, and transportation LOS scenarios. The traffic flow conditions, which are usually predicted after a traffic assignment procedure, are a result of the interactions between the individual-level demand for travel and the travel options and LOS (or the capacity) supplied by the transportation system. At the same time, the activity-travel patterns predicted by an activity-based modeling system (that are input into traffic assignment) are themselves based on specified LOS values. Thus, as in a traditional trip-based model, one needs to ensure that the LOS values obtained from the traffic assignment procedure are consistent with those used in the activity-based model for activity-travel pattern prediction. This is usually achieved through an iterative feedback process (see Section 1.3) between the traffic assignment stage that outputs link flows/LOS and the activity-based travel model that outputs activity-travel patterns. It is important to consider such demand-supply interactions for accurate predictions of activity-travel behavior, and the resulting traffic flow conditions. Further, since the travel LOS varies with the temporal variation in travel demand, and the demand for travel is, in turn, dependent on the transportation level of service, the interactions may be time-dependent and dynamic in nature. Thus, it is important to consider the dynamics of the interactions between travel demand and the supply of transportation capacity (see next section for additional details).

Similar to how transportation market processes (i.e., the interactions between individual-level travel demand and the transportation supply) influence the individual-level activity-travel patterns, the housing and labor market processes influence the residential and employment choices of individuals. In fact, individuals act within the context of, and interact with, housing, labor, and transportation markets to make their residential, employment, and activity-travel choices. While the transportation market process may occur over shorter timeframes (such as days or weeks), the employment and housing market processes are likely to occur over longer periods of time. That is, in the short term, the daily activity-travel patterns are directly influenced by the dynamics of the interaction between travel demand and supply; while in the long term, the activity-travel behavior is indirectly affected by the impact of housing and labor market processes on the residential and employment choices, and also on the land use and transportation system. If the activity-travel behavior of individuals and households is to be captured properly over a longer timeframe, the interactions with, and the evolution over time of, all these markets should be explicitly considered, along with the sociodemographic processes and the long-term housing and employment choices.

6.3.4 Traffic Simulation

The precise form of the interaction between an activity-based model and a traffic assignment model (as discussed in the previous section) depends on the nature of the assignment model used. In many places where activity-based models have been implemented in practice, it is not uncommon to convert the activity-travel patterns into trip tables by travel mode for four to five broad time periods of the day, and then load the time period-specific trip tables using a traditional static traffic assignment (STA) methodology. This static assignment methodology uses analytic link volume-delay functions, combined with an embedded shortest path algorithm, to determine link flows and link travel times (see Section 4.11). In such a static assignment approach, there is, in general, no simulation of individual vehicles and no consideration of temporal dynamics of traffic flow.

On the other hand, an important appeal of the activity-based approach is that it predicts activity-travel patterns at a fine resolution on the time scale. Thus, using an activity-based model with a static assignment process undoes, to some extent, the advantages of predicting activity-travel patterns at a fine time resolution. This limitation, and the increase in computing capacity, has allowed the field to move toward a dynamic traffic assignment (DTA) methodology. The DTA methodology offers a number of advantages relative to the STA methodology, including the ability to address traffic congestion, build-up, spillback, and oversaturated conditions through the explicit consideration of time-dependent flows and the representation of the traffic network at a high spatial resolution. As a result, DTA is able to capture and evaluate the effects of controls (such as ramp meters and traffic lights), roadway geometry, and intelligent transportation system (ITS) technology implementations.

Some literature on analytical method-based DTA models exists. However, the implementation of most DTA models relies on a microsimulation platform that combines (and iterates between) a traffic simulation model (to simulate the movement of traffic) with time-dependent routing algorithms and path assignment (to determine flows on the network). In particular, the traffic simulation model takes a network (nodes, links, and controls) as well as the spatial path assignment as input, and outputs the spatial-temporal trajectories of vehicles as well as travel times. The time-dependent shortest path routing algorithms and path assignment models take the spatiotemporal vehicle trajectories and travel times as input, and output the spatial path assignment of vehicles. The two models are iterated until convergence between network travel times and vehicle path assignments. In this process, the traffic simulation model used may be based on macroscopic traffic simulation (vehicle streams considered as the simulation entity and moved using link volume-delay functions), mesoscopic traffic simulation (groups of vehicles considered as "cells" and treated as the simulation entity), or microscopic traffic simulation (each individual vehicle considered as the simulation entity, incorporating intervehicle interactions). Macroscopic and mesoscopic traffic simulation models are less data hungry and less computationally intensive than microscopic models, but also are limited in their ability to model driver behavior in response to advanced traffic information/management systems.

Most earlier DTA efforts have focused on the modeling of private car traffic, though a few recent research efforts (see, for example, Rieser and Nagel, 2009) have integrated mode choice and departure time choice within a microsimulation-based DTA model, thus moving further upstream in integrating activity-based models with dynamic traffic assignment. Recently, there have been other efforts under way that explore the complete integration of activity generation, scheduling, traffic simulation, route assignment, and network loading within a multiagent microsimulation platform. For example, Project C10 of the second Strategic Highway Research Program (SHRP 2), "Partnership to Develop an Integrated, Advanced Travel Demand Model," is developing integrated models that include activity-based demand model and traffic simulation model components, taking advantage of the disaggregate application approach in both components (Cambridge Systematics, Inc. and National Academy of Sciences, 2009; Resource Systems Group and the National Academy of Sciences, 2010).

Activity-based modeling also can be integrated with models of transit passenger simulation. Person tours generated by the activity-based model that are fully or partially made via transit can have their transit paths simulated individually. This individual simulation requires the specification of all transit vehicle runs and stops and the assigning of passenger trips to these runs and stops, along with their walk and auto access and egress components. One of the SHRP2 C10 tasks is incorporating this capability.

The greatest impediments to regionwide traffic simulation are the expensive computational resources and time needed (though distributed and parallel implementation designs are possible), and the costs and complexity of data acquisition/management and model calibration (though GIS tools and GPS-based vehicle survey techniques are making this easier).

Note that the use of DTA does not require an activity-based model; in fact, DTA has been used in connection with conventional (i.e., four-step) models for some time. In such cases, the aggregate results of the conventional models (i.e., trip tables) are converted to disaggregate lists of trips to be simulated. Thus, disaggregate activity-based demand models have often been used with aggregate assignment techniques, and aggregate demand models have been used with disaggregate assignment techniques. The connection between disaggregate demand and assignment models is the subject of much contemporary research and development.

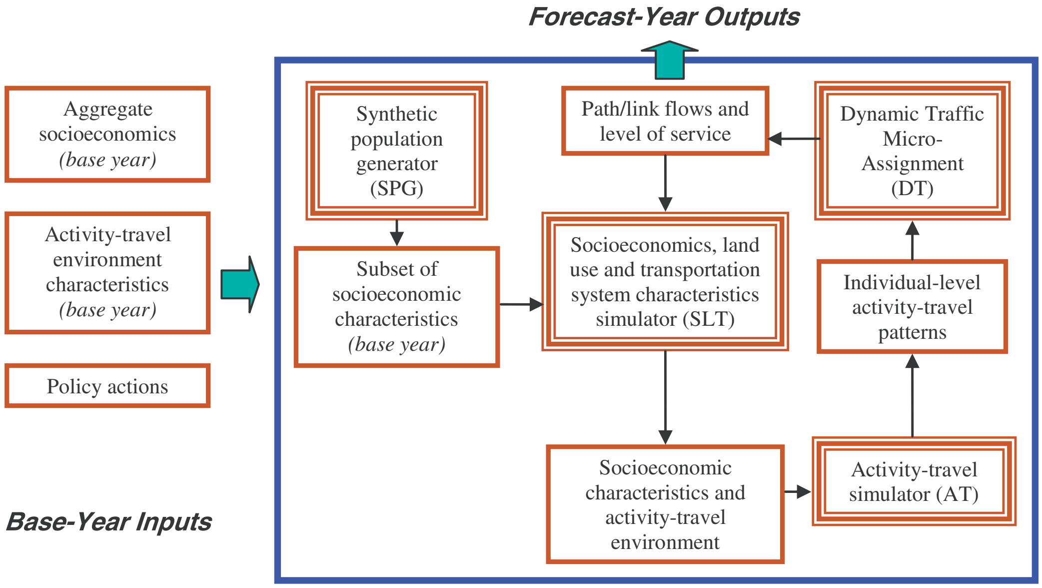
6.3.5 Example of an Integrated Urban Modeling System

In view of the preceding discussion, ideally, activity-based travel demand models should be integrated with other models that can forecast, over a multiyear timeframe, the socio-demographic processes, the housing and employment market processes, and traffic flows and transportation system conditions. The integrated model system should be able to capture the previously discussed demand-supply interactions in the housing, employment, and transportation markets. A conceptual framework of such a system is provided in Figure 6.5.

The integrated system places the focus on households and individuals, and businesses and developers that are the primary decision makers in an urban system. The system takes as inputs the aggregate socioeconomics and the land use and transportation system characteristics for the base year, as well as policy actions being considered for future years. The aggregate-level base-year socioeconomic data are first fed into an SPG module to produce a disaggregate-level synthetic data set describing a subset of the socioeconomic characteristics of all the households and individuals residing in the study area. Additional base-year socioeconomic attributes—related to mobility, schooling, and employment at the individual level and residential/vehicle ownership choices at the household level—that are difficult to synthesize (or cannot be synthesized) directly from the aggregate socioeconomic data for the base year are simulated by the socioeconomics, land use, and transportation (SLT) system simulator.

The base-year socioeconomic data, along with the land use and transportation system attributes, are then run through the daily activity-travel pattern (AT) simulator to obtain individual-level activity-travel patterns. The activity-travel patterns are subsequently passed through a dynamic traffic micro-assignment (DT) scheme to determine path flows, link flows, and transportation system level of service by time of day [see Lin et al. (2008) for a discussion of recent efforts on integrating an activity-travel simulator and a dynamic traffic microsimulator]. The resulting transportation system LOS characteristics are fed back to the SLT simulator to generate a revised set of activity-travel environment attributes, which is passed through the AT simulator along with the socioeconomic data to generate revised individual activity-travel patterns. This "within-year" iteration is continued until base-year equilibrium is achieved. This completes the simulation for the base year.

The next phase, which takes the population one step forward in time (i.e., 1 year), starts with the SLT simulator updating the population, urban form, and the land use markets



Source: Modified from Eluru et al. (2008).

Figure 6.5. An integrated model system.

(note that SPG is used only to generate the disaggregate-level synthetic population for the base year and is not used beyond the base year). An initial set of transportation system attributes is generated by SLT for this next time step based on (1) the population, urban form, and land use markets for the next time step; (2) the transportation system attributes from the previous year in the simulation; and (3) the future-year policy scenarios provided as input to the integrated system. The SLT outputs are then input into the AT system, which interfaces with the DT scheme in a series of equilibrium iterations for the next time step (just as for the base year) to obtain the "one-time step" outputs. The loop continues for several time steps forward until the socioeconomics, land use, and transportation system path/link flows and transportation system LOS are obtained for the forecast year specified by the analyst. During this iterative process, the effects of the prescribed policy actions can be evaluated based on the simulated network flows and speeds for any intermediate year between the base year and the forecast year.

6.4 Summary

Activity-based model systems are different from the conventional trip-based model systems in five major aspects. First, activity-based systems recognize that travel is derived from the need to pursue activities at different points in space and time, and thus focus on modeling activity participation. Second, activity-based model systems use a tour-based structure to represent and model travel patterns. Tours are defined as chains of trips beginning and ending at a same location, say, home or work. Such representation captures the interdependency (and consistency) of the modeled choice attributes among the activity episodes of the same tour. Third, activity-based model systems view individuals' activity-travel patterns as a result of their time use decisions within a continuous time domain, subject to their sociodemographic, spatial, temporal, transportation system, and other contextual constraints. Fourth, activity-based systems accommodate for interactions and joint activity participations among individuals in a household. Finally, activity-based systems simulate the activity-travel patterns of each (and every) individual of the study area using a microsimulation implementation that provides activity-travel outputs that look similar to survey data and can allow analysis of a wide range of policies on specific sociodemographic segments.

Activity-based travel models are increasingly being adopted by the larger MPOs in the country and offer a more comprehensive and potentially more accurate assessment of policies to enhance mobility and reduce emissions. While the principle behind the activity-based analysis approach has existed for at least three decades now, it is only in the past 5 to 10 years that the approach has started to see actual implementation. As a result, there has been no formal analysis of transferability of parameters and model structures in space and/or time in the context of activity-based models. This area will inevitably see increasing attention in the near future. Future versions of this report might include information on the potential transferability of activity-based modeling parameters and possibly some specific transferable parameters.

CHAPTER 7

Case Studies

7.1 Introduction

As discussed in Chapter 5, there are two primary uses for the data provided in this report:

- Developing travel model components when no local data suitable for model estimation are available and
- Checking the reasonableness of model components developed using local data.

In the first case, local data should be collected to validate the models or model components developed based on this report. In the second case, the data in this report can be used to supplement and support the validation and reasonableness checking process.

This chapter presents two case studies to illustrate the use of the report for these purposes. In the first case study, the MPO for a large metropolitan area, Gtown, has recently conducted a household activity/travel survey, and has recalibrated its model using the new data. The information from this report is used to verify that the model parameters and results from this recalibration are reasonable. Note that this case study does not represent the entire validation effort for such a model, which must include other checks (for example, sensitivity tests and checks of forecasts). The second case study is for a small urban area, Schultzville, that has never had a travel forecasting model and does not have any area-specific travel data. The MPO for this area has borrowed the model structure from another small area and is using that structure to develop a model for its area.

7.2 Model Reasonableness Check

Gtown is a large metropolitan area with more than 5 million residents and a diverse public transportation system that includes various rail and bus services. A household activity/travel survey was completed 3 years ago; and data from that survey, transit surveys, and traffic counts have been used by MPO staff to recalibrate the trip-based travel forecasting model for the area. The MPO staff wants to make sure that the newly calibrated model is reasonable and has decided to compare model parameters and selected model results with information contained in this report.

In this section, parameters from the recalibrated Gtown model are compared to those provided in Chapter 4 of this report. The information provided in Chapter 4 often does not use the same variables or uses them at different levels of aggregation. Therefore, throughout this section, either parameters from Chapter 4 or the Gtown data are aggregated to make them comparable. One prime example of this difference relates to trip purpose. The Gtown model has five trip purposes: home-based work (HBW), home-based shop (HBS), home-based other (HBO), nonhome-based work (NHBW), and nonhome-based other (NHBO). Parameters and data in Chapter 4 are provided for three purposes: HBW, home-based nonwork (HBNW), and nonhome based (NHB) (alternatively, for four purposes, including home-based school, but this purpose is not used in the Gtown model). Therefore, for Gtown parameters to be compared to those in this report, the Gtown data for the five trip purposes must be collapsed to the classic three trip purposes.

7.2.1 Trip Generation

Trip Production Rates

Trip production rates for Gtown for all trip purposes are applied using a three-dimensional, cross-classification model with household size, number of vehicles, and income level as variables. All person trips are modeled, including nonmotorized trips.

Table C.5 in Appendix C provides HBW trip rates derived from NHTS data, based on three different cross-classifications; two of which are household size by number of vehicles and household size by income level. However, the income definitions in the Gtown model are significantly different than those in the NHTS data summaries. It was therefore decided to compare the rates using the household size by number of vehicles classification, as shown in the middle section of Table C.5. Table 7.1 shows this comparison. Note that the Gtown model uses only four household size categories (the largest is 4 or more persons), while the NHTS data summary in Table C.5 uses five categories (the largest is 5 or more persons).

As shown in Table 7.1, the Gtown trip production rate is 1.7 HBW trips per household, compared to 1.4 trips per household from Chapter 4; a difference of about 20 percent. This difference seems to be concentrated in smaller households, which predominantly are childless households. The Gtown MPO theorized that the difference may be due to a lower than average rate of retired people living in the region. In addition, Gtown has higher than average transit usage, and there may be more direct trips between home and work than in other areas since auto trips are more likely to include stops on the way to or from work (leading to more HBNW and NHB trips in place of HBW trips). The basic question for the MPO is whether the trip rates derived from their local survey are more reliable than those from the NHTS, which has a higher sample size but is a national sample collected mostly outside Gtown. Certainly, the difference indicates that checks of the Gtown survey data are warranted.

Table C.6 provides HBNW trip rates derived from NHTS data, based on three different cross-classifications, two of which are household size by number of vehicles and household size by income level. Separate rates are presented for areas with populations more than 500,000 and less than 500,000. The appropriate rates to use for this comparison are those for the areas of less than 500,000. It was decided to compare the rates using the household size by number of vehicles classification, as shown in the third section of Table C.6. Table 7.2 shows this comparison.

As shown in Table 7.2, the Gtown trip production rate is 4.6 HBNW trips per household, compared to 5.6 trips per household from Table C.6; a difference of nearly 20 percent. For HBNW trips, the differences seem to be across all household size and vehicle availability categories. Again, the differences indicate that further checks of the Gtown survey data are warranted.

Table C.7 provides NHB trip rates derived from NHTS data, based on three different cross-classifications, two of which are household size by number of vehicles and household size by income level. It was decided to compare the rates using the household size by number of vehicles classification, as shown in the middle section of Table C.7. Table 7.3 shows this comparison.

As shown in Table 7.3, the Gtown trip production rate is 2.3 NHB trips per household, compared to 3.0 trips per household from Table C.7; a difference of nearly 25 percent. For NHB trips, the differences seem to be across most household size and vehicle availability categories, although the differences are higher in larger households. Again, the differences indicate that further checks of the Gtown survey data are warranted.

Table 7.1. Comparison of Gtown HBW trip production rates to NHTS data from Table C.5.

NHTS Data (from Table C.5)

	Persons					
Autos	**1**	**2**	**3**	**4**	**5+**	**Average**
0	0.2	0.7	1.1	1.0	0.9	**0.5**
1	0.6	0.8	1.2	1.7	1.5	**0.8**
2	0.7	1.3	2.0	2.0	2.3	**1.6**
3+	0.9	1.4	2.6	2.9	3.3	**2.3**
Average	**0.5**	**1.2**	**2.0**	**2.3**	**2.4**	**1.4**

Gtown Trip Rates

	Persons				
Autos	**1**	**2**	**3**	**4**	**Average**
0	0.9	1.3	1.4	1.5	**1.1**
1	0.9	1.4	1.8	1.8	**1.3**
2	1.0	1.6	2.0	2.1	**1.8**
3+	1.0	1.7	2.4	2.7	**2.2**
Average	**0.9**	**1.5**	**2.1**	**2.2**	**1.7**

Table 7.2. Comparison of Gtown HBNW trip production rates to NHTS data from Table C.6.

NHTS Data (from Table C.6)

	Household Size					
Vehicles	**1**	**2**	**3**	**4**	**5+**	**Average**
0	1.4	3.8	5.6	7.5	10.0	**3.2**
1	1.9	3.9	6.5	9.0	11.8	**3.7**
2	2.4	4.0	6.5	11.0	14.0	**6.8**
3+	2.5	4.0	7.3	11.0	14.5	**8.6**
Average	**1.8**	**4.0**	**6.7**	**10.6**	**13.4**	**5.6**

Gtown Trip Rates

	Persons				
Autos	**1**	**2**	**3**	**4**	**Average**
0	1.6	2.3	2.9	3.4	**1.9**
1	1.6	3.2	4.4	7.4	**2.8**
2	1.7	3.3	5.4	8.3	**5.1**
3+	1.9	3.4	5.5	9.2	**6.2**
Average	**1.6**	**3.2**	**5.1**	**8.4**	**4.6**

Table 7.3. Comparison of Gtown NHB trip production rates to NHTS data from Table C.7.

NHTS Data (from Table C.7)

	Household Size					
Vehicles	**1**	**2**	**3**	**4**	**5+**	**Average**
0	0.7	1.7	2.0	3.7	3.9	**1.3**
1	1.4	2.3	3.5	3.9	3.9	**2.0**
2	1.6	2.6	3.9	5.5	5.6	**3.5**
3+	1.6	2.7	4.5	5.8	7.1	**4.4**
Average	**1.3**	**2.5**	**3.8**	**5.3**	**5.7**	**3.0**

Gtown Trip Rates

	Persons				
Autos	**1**	**2**	**3**	**4**	**Average**
0	1.0	1.3	1.7	2.1	**1.2**
1	1.4	2.0	2.3	3.1	**1.8**
2	1.7	2.1	2.3	3.2	**2.5**
3+	2.0	2.4	2.5	3.6	**2.9**
Average	**1.5**	**2.1**	**2.3**	**3.2**	**2.3**

When total trips per household by all purposes from the Gtown model are compared to the information presented in Tables C.5 through C.7, the overall rate for Gtown is 8.6 trips per household, 14 percent lower than the total of 10.0 trips per household derived from the NHTS in Chapter 4. Based on this analysis, Gtown rates are lower than the national average. NHTS rates are averages based on urban areas with different characteristics, and the rates for individual areas can be different. Furthermore, the higher Gtown rate for HBW trips, which are generally longer, may compensate for the lower overall rate.

Trip Attraction Rates

Table 4.4 summarizes average trip attraction rates from the MPO Documentation Database for the classic three trip purposes. The Gtown trip attraction model differs from the models shown in Table 4.4 in several ways. First, the employment categories used for the Gtown HBNW and NHB attraction models are defined differently than those in Table 4.4. For comparison purposes, the categories in the Gtown model were redefined to approximate those shown in Table 4.4. Second, the Gtown model stratifies trip attraction rates by area type. Weighted averages of Gtown's area type-specific models were used to compare to the models in Table 4.4.

The resulting comparison of trip attraction models is shown in Table 7.4. The models chosen for comparison from Table 4.4 were Model 1 for HBW, Model 3 for HBNW, and Model 2 for NHB. As can be seen in Table 7.4, the Gtown trip attraction rates are lower than the rates shown in Table 4.4, especially those for HBNW trips. The Gtown trip attraction models will generate fewer attractions than the models shown in Table 4.4. Since trip attractions are typically balanced to match productions, the effects of the lower trip attraction rates might be small, but it makes sense to further check the trip attraction model estimation results, as well as the balancing of productions and attractions. If the balancing process requires factoring up attractions to match productions, perhaps the rates could be adjusted upward.

7.2.2 Trip Distribution

The reasonableness of the Gtown trip distribution model can be assessed by comparing the friction factors used in the Gtown gravity model and the resulting average trip lengths with comparable values provided in Section 4.5.

Average Trip Length

Table C.10 provides average trip length by mode (travel times in minutes) for urban areas of different sizes. The Gtown model results should be compared to the figures from Table C.10 corresponding to areas of "1 million or more with subway or rail."

The Gtown trip distribution model produces a composite travel time that reflects highway and transit travel times. Table 7.5 compares the average trip times for all modes by trip purpose from Table C.10 and compares those trip lengths to the times resulting from the Gtown model. The average trip duration for HBW trips from the Gtown model is 48 minutes, compared to an average HBW trip duration from the NHTS of 32 minutes.

While most large metropolitan areas experience high levels of congestion during peak hours, the Gtown highway network is very congested during the peak periods, which can last 4 or more hours. Since most HBW trips are made during the peak periods, it can be expected that the travel time for those trips will be longer in Gtown than in other areas with a population over 3 million. Furthermore, Gtown encompasses a very large geographic area, also contributing to longer work trips. Another consideration is that Gtown has a relatively high transit share, and transit trips are longer than auto trips, as shown in Table C.10.

Table 7.4. Comparison of Gtown trip attraction rates to those shown in Table 4.4.

		Employment			
	Households	Basic	Retail	Service	Total
Home-Based Work					
Gtown Model					0.9
Model 1 from Table 4.4					1.2
Home-Based Nonwork					
Gtown Model	0.4	0.9	3.4		
Model 3 from Table 4.4	0.7	0.7	8.4	3.5	
Nonhome Based					
Gtown Model	0.1		3.3	0.7	
Model 2 from Table 4.4	1.4		6.9	0.9	

Table 7.5. Comparison of Gtown average trip length to NHTS data from Table C.10.

	All Modes (Minutes)			Average All Trips
	HBW	HBNW	NHB	
Gtown	48	17	20	24
NHTS Averages from Table C.10	32	18	20	22
Difference	16	−1	0	2
Percentage Difference	50%	−6%	0%	9%

Nonetheless, the large discrepancy between the Gtown average trip length for HBW trips and that of other large areas does warrant some further review. The 48-minute average travel time resulting from the model was compared to the time reported in the household travel survey and the 2000 CTPP. The average travel time reported for HBW trips in the household survey was also 48 minutes; and in the 2000 CTPP, it was 45 minutes, thus, confirming the modeled time.

The average travel time for HBNW and NHB trips resulting from the Gtown model compared more favorably to those shown in Table C.10. The mean HBNW travel time for Gtown is 17 minutes, compared to 18 minutes from the NHTS data. NHB travel times also compared favorably with both the Gtown and NHTS averages at approximately 20 minutes. The total travel time for all trips is 24 minutes from the Gtown model, which is 2 minutes longer than the time reported in Table C.10.

If the Gtown trip generation rates and travel times are viewed together, they seem more reasonable. Studies have shown that people will only travel a certain amount of time for all purposes during a given day. Thus, the longer-than-usual amount of time spent making work trips can result in fewer and shorter trips for other purposes. Thus, the lower HBNW and NHB trip generation rates in the Gtown model may result from higher HBW trip rates and longer travel times.

Gamma Function and Friction Factors

The Gtown model distributes trips separately for each of four income groups and five purposes. A useful reasonableness check is to compare the Gtown estimated model parameters to those developed in other regions. The estimated friction factors calibrated for Gtown are represented by gamma functions that can be compared to those reported by areas of similar size. Table 4.5 provides trip distribution gamma function parameters for eight MPOs, three of which are large. One way to compare friction factors used in the Gtown model to those resulting from the gamma functions for large MPOs in Table 4.5 is to compare the resulting graphs of friction factors to see if they are comparable.

Figure 7.1 is a graph of the HBW friction factors for Gtown compared to those for the three large MPOs reported in Table 4.5. Friction factors for the three large MPOs and for the four HBW income groups in the Gtown model are shown in Figure 7.1. The Gtown friction factors for the two higher incomes are almost exactly the same as those for MPO 3. The friction factors for the two lower incomes are not as steep but are comparable to those for the three sample MPOs.

Figure 7.2 is a graph of the HBS and HBO friction factors for Gtown compared to the HBNW friction factors for the three large MPOs. All of the Gtown friction factors lie between the values for MPO 1 and MPO 3, and the slopes for almost all purposes and income groups are very similar to that for MPO 1.

Figure 7.3 is a graph of the NHB friction factors for Gtown compared to those for the three large MPOs reported in Table 4.5. The Gtown friction factors for NHBO trips are similar to the NHB values for MPO 2. The Gtown friction factors for NHBW trips are not as steep as those for any of the MPOs. Since neither the NHBO or the NHBW friction factors are as steep as those from any of the large MPOs, it is unlikely that friction factors for a combination of NHBO and NHBW trips would match the values for any of the MPOs. However, since the average travel times for NHB trips from the Gtown model are the same as those from the NHTS, the difference in friction factors may not be significant.

7.2.3 Mode Choice

The Gtown model uses a nested logit mode choice model with coefficients for the classic three trip purposes. Auto submodes include drive alone and shared ride; and transit submodes include local, premium, and rail submodes (as well as separate models for auto and walk access). Variables used in the Gtown model include in-vehicle time, out-of-vehicle time, and a single cost variable. The coefficients of these variables are summarized in Table 7.6.

Tables 4.8, 4.11, and 4.14 present mode choice model parameters, by purpose, that are used by MPOs included in the MPO Documentation Database. For HBW trips, Models B, C, D, F, G, and I from Table 4.8, all of which are for urban areas

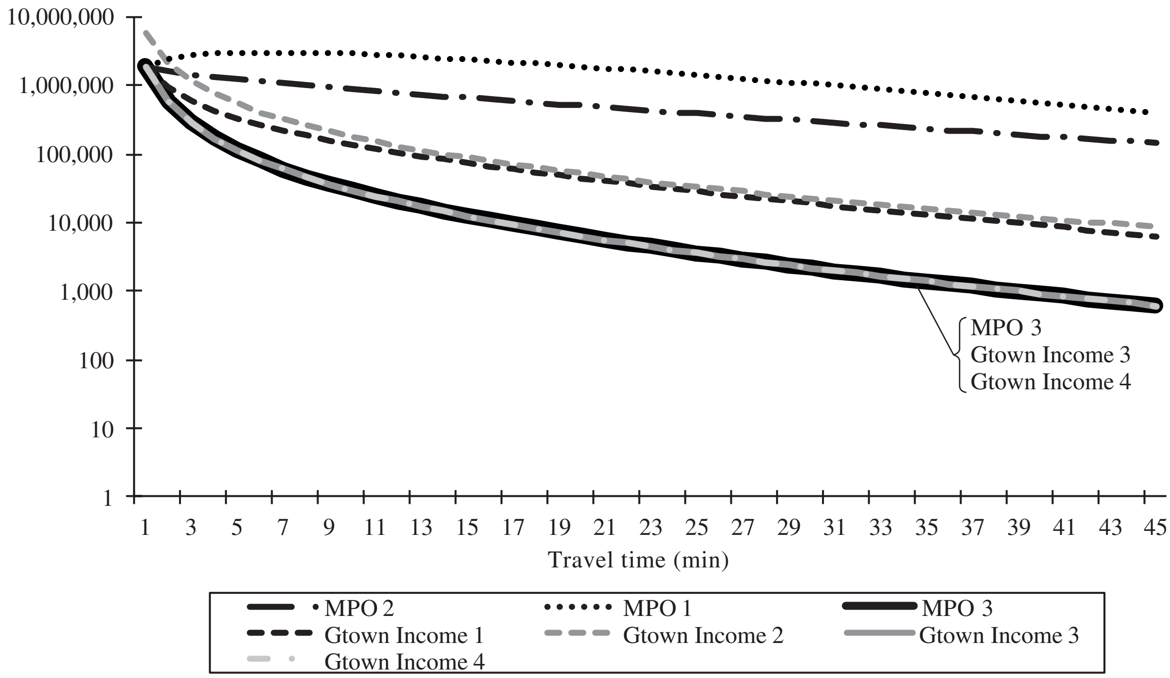


Figure 7.1. Home-based work trip distribution friction factors.

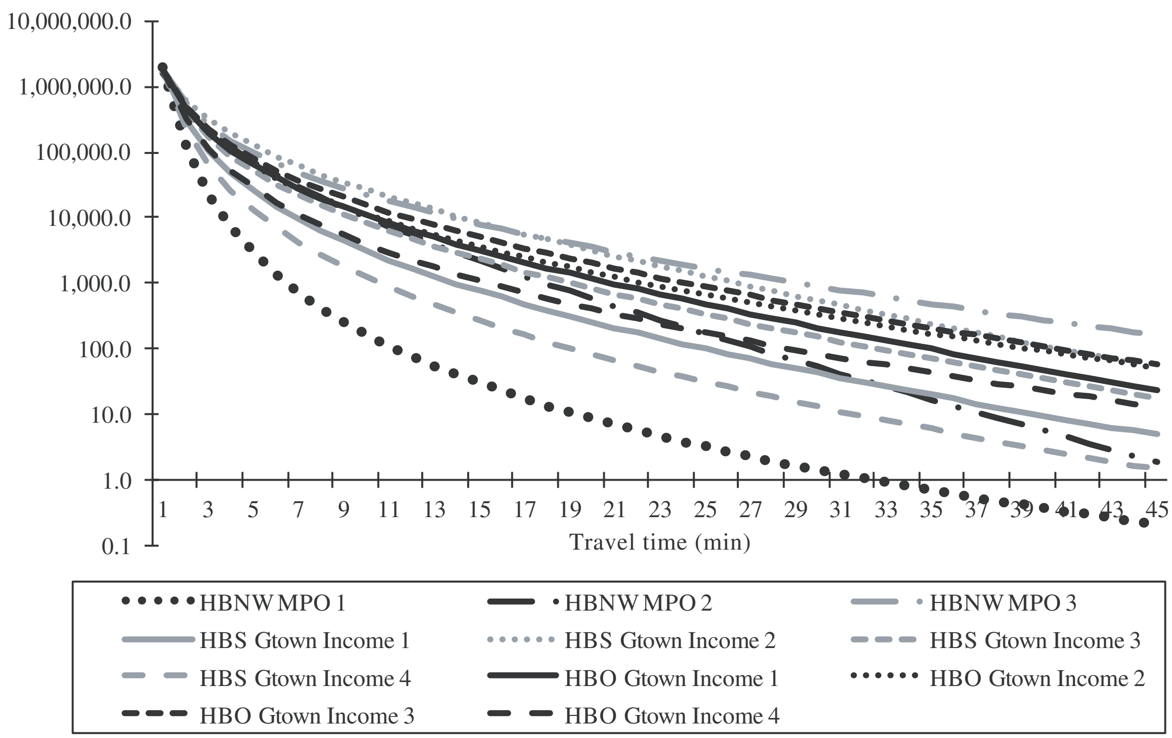


Figure 7.2. Home-based nonwork trip distribution friction factors.

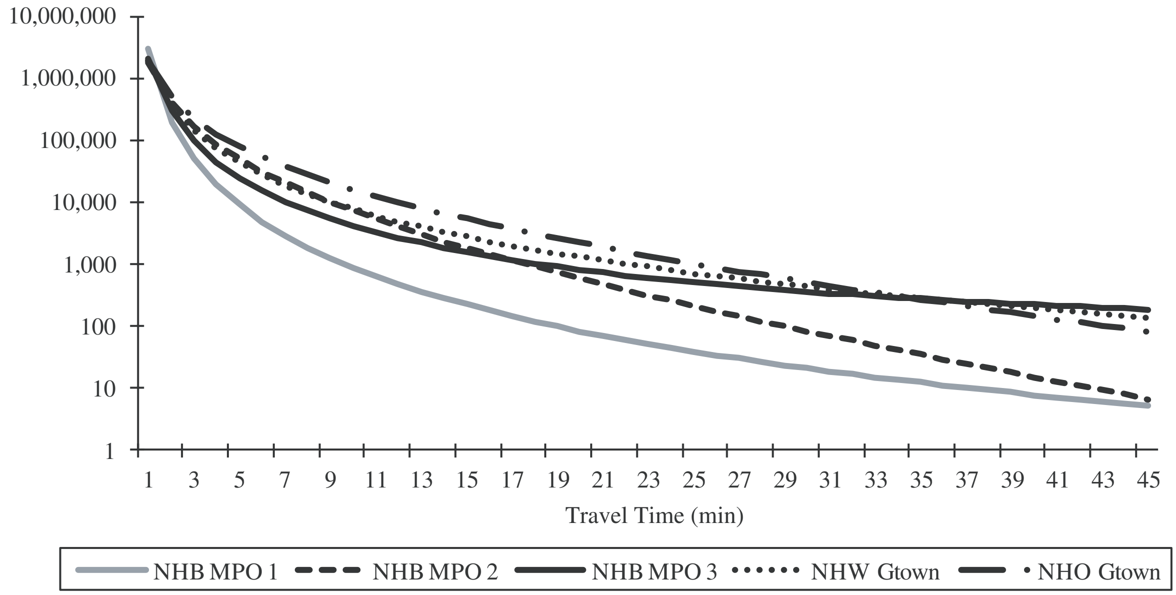


Figure 7.3. Nonhome-based trip distribution friction factors.

with populations of more than 1 million, have comparable variables to those in the Gtown model. Models F, G, and I are nested logit models. The coefficients of the Gtown HBW mode choice model are not too different from those of Models F, G, and I, although the Gtown cost coefficients are lower in absolute value.

Looking at the relationships between coefficients, Table 7.7 shows that the ratio of the out-of-vehicle time and in-vehicle time coefficients in the Gtown model is comparable to those for Models F, G, and I, as shown in Table 4.9. The value of time in the Gtown model, however, is significantly higher than in the models from other areas. This comparison holds for most of the other models shown in Tables 4.8 and 4.9.

For HBNW trips, Models E, G, I, and K from Table 4.11 are for urban areas with populations of more than 1 million and have comparable variables. The in-vehicle time coefficient of the Gtown HBNW mode choice model is higher than those in the models from Table 4.11, while the Gtown cost coefficients are lower in absolute value. Looking at the relationships between coefficients, Table 7.8 shows that the ratio of the out-of-vehicle time and in-vehicle time coefficients in the Gtown model is a bit lower than those of the other models, as shown in Table 4.12. The value of time in the Gtown model, however, is significantly higher than in the models from other areas. This comparison holds for most of the other models shown in Tables 4.11 and 4.12.

For NHB travel, models F, G, and I from Table 4.14 are most comparable to Gtown. The coefficients in the Gtown HBNW mode choice model are fairly comparable. Looking at the relationships between coefficients, Table 7.9 shows that the ratio of the out-of-vehicle time and in-vehicle

Table 7.6. Gtown mode choice model parameters.

	HBW	HBNW	NHB
Parameter			
In-Vehicle Time	−0.0212 minute	−0.022 minute	−0.029 minute
Out-of-Vehicle Time	−0.043 minute	−0.0449 minute	−0.0572 minute
Cost (low income)	−0.0014 cent	−0.0015 cent	−0.0099 cent
Cost (high income)	−0.0005 cent	−0.0006 cent	−0.0099 cent
Derived Relationships			
Out-of-Vehicle Time/ In-Vehicle Time Ratio	2.0	2.0	2.0
Value of In-Vehicle Time	\$9.08/hour (low income) \$25.44/hour (high income)	\$8.80/hour (low income) \$22.00/hour (high income)	\$1.76/hour

HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

Table 7.7. Relationships between coefficients from home-based work mode choice models for Gtown and from Table 4.9.

Model	Out-of-Vehicle Time/ In-Vehicle Time	Value of In-Vehicle Time
Gtown	2.0	$9.08 to $25.44/hour
Model F (Table 4.9)	2.0	$3.94/hour
Model G (Table 4.9)	2.3	$3.05/hour
Model I (Table 4.9)	2.0	$3.00/hour

Table 7.8. Relationships between coefficients from home-based nonwork mode choice models for Gtown and from Table 4.12.

Model	Out-of-Vehicle Time/ In-Vehicle Time	Value of In-Vehicle Time
Gtown	2.0	$8.80 to $22.00/hour
Model E (Table 4.12)	3.0	$3.69/hour
Model G (Table 4.12)	4.6	$0.21/hour
Model I (Table 4.12)	3.1	$0.48/hour
Model K (Table 4.12)	3.0	$1.40/hour

Table 7.9. Relationships between coefficients from nonhome-based mode choice models for Gtown and from Table 4.15.

Model	Out-of-Vehicle Time/ In-Vehicle Time	Value of In-Vehicle Time
Gtown	2.0	$1.75/hour
Model F (Table 4.15)	2.0	$4.04/hour
Model G (Table 4.15)	11.3	$0.46/hour
Model I (Table 4.15)	2.1	$2.00/hour

time coefficients and value of time in the Gtown model are (as shown in Table 4.15) fairly comparable to those in Models F and I, but Model G appears to be an outlier. The other models shown in Tables 4.14 and 4.15 have coefficient values that vary widely, but the coefficients from Gtown fit well within this range.

In summary, the value of time, indicating the willingness to pay for travel timesavings by switching modes, seems high for home-based trips in the Gtown model. The related model coefficients, mainly the cost coefficients for these trip purposes, should be reviewed.

7.2.4 Automobile Occupancy

The Gtown mode choice model forecasts auto driver and auto passenger trips by purpose separately. Table 7.10 provides a comparison of the resulting Gtown auto occupancy rates compared to the values reported from the NHTS in Table 4.16. As Table 7.10 shows, the Gtown home-based auto occupancies are within 5 percent of those from the NHTS. Gtown NHB auto occupancies are noticeably lower than those from the NHTS. The NHB mode choice model should be checked regarding how auto driver and passenger choices are made.

Table 7.10. Comparison of average daily vehicle occupancy by trip purpose.

			Nonhome Based		
	HBW	HBNW	NHBW	NHBO	All Trips
Gtown	1.05	1.64	1.10	1.48	1.39
Table 4.16	1.10	1.72	1.66		1.55

HBW = home-based work; HBNW = home-based nonwork; NHBW = nonhome-based work; NHBO = nonhome-based other.

Table 7.11. Comparison of time of day for auto trips.

Time Period	Gtown	Table C.11	Difference	Percent Difference
6:00 a.m.–9:00 a.m.	14.4%	17.1%	–2.7%	–16%
9:00 a.m.–3:00 p.m.	34.4%	35.6%	–1.2%	–3%
3:00 p.m.–7:00 p.m.	27.4%	32.1%	–4.7%	–15%
7:00 p.m.–6:00 a.m.	23.8%	15.2%	8.6%	57%
Total	**100.0%**	**100.0%**		

The household survey is another source against which auto occupancy rates by purpose can be checked.

7.2.5 Time of Day

Table 7.11 provides a comparison between the modeled times of day for auto trips in the Gtown model with those derived from NHTS data that are shown in Table C.11. As Table 7.11 shows, the percentage of travel occurring in peak periods is lower in Gtown than in the national survey, and the nighttime percentage of travel is substantially higher in Gtown. As mentioned earlier, the Gtown highway system is very congested, and the peaks are much longer than in other comparable cities. It would seem reasonable, therefore, that peak spreading would be more prevalent in Gtown. This finding could be confirmed using other data sources such as traffic counts.

7.2.6 Summary

This section provides a comparison of model parameters and results produced by the model for a hypothetical large MPO and the values in this report. Overall, the Gtown model parameters and results appear to be reasonable when compared to the values in Chapter 4 of the report, although some Gtown model parameters, such as cost coefficients in the mode choice models for home-based trip purposes, should be checked further. The congested nature of Gtown does appear to result in fewer nonwork trips, very long work trips, and extended peak periods.

7.3 Model Development Case Study for a Smaller Area without Data for Model Estimation

This case study is for a small urban area that never had a travel forecasting model and does not have any local data from which to estimate model parameters. The MPO for this hypothetical city, Schultzville, borrowed the model structure from another small area and used that structure to develop its own model. Schultzville is an urban area of about 100,000 people. It has very little in the way of public transportation, so the MPO decided to develop a daily (i.e., no time of day), three-step model with auto trips only, using the classic three trip purposes.

7.3.1 Zone and Highway Network Definition

Highway Network Definition

A highway network for the Schultzville area was developed to obtain acceptable volumes on minor arterials; therefore, collectors and local roads were included in the network. Digital street files available from the U.S. Census Bureau (TIGER/Line files) were used to create the highway network shown in Figure 7.4. Freeways, major arterials, minor arterials, collector links, and some local roads were coded into the network. The following are examples of some of the fields coded for nodes and links in the network:

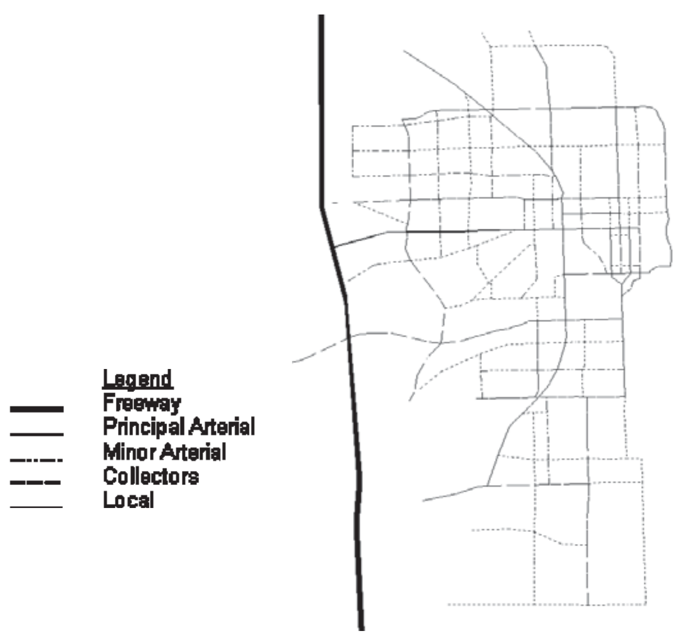


Figure 7.4. Schultzville highway network.

- **XY coordinates**—Geographic coordinates for nodes;
- **Node identifiers** (anode/bnode)—Unique numbers assigned to each end of a link;
- **Distance**—Distance in miles between anode and bnode;
- **Functional (link) classification**—Type of facility (e.g., major arterial, minor arterial, etc.);
- **Traffic count volume**—Average daily volume of traffic on link (where available);
- **Number of lanes;**
- **Facility type;**
- **Area type**—Location and development characteristics of area that link serves (e.g., urban, suburban, rural, etc.); and
- **Link capacity and free-flow speed**—Link capacities are a function of the number of lanes on a link. Area type and facility type were used to define per-lane default capacities and speed. The number of lanes was also checked using field verification or aerial imagery to ensure accuracy.

Transportation Analysis Zone Definition

A map of Schultzville transportation analysis zones is shown in Figure 7.5. Each TAZ has a centroid, which is a point that represents all travel origins and destinations in a zone.

7.3.2 Socioeconomic Data

Socioeconomic data—household and employment data for the modeled area—were organized into the TAZs. Estimates of base-year socioeconomic data by TAZ were developed for use in model development. The population and household data for Schultzville came from the decennial census. Data such as income and vehicle availability were derived from the ACS.

Basic socioeconomic data by TAZ were derived for Schultzville, including households, population, total employment, retail employment, service employment, manufacturing employment, nonmanufacturing employment, and school enrollment. More detailed data, such as number of persons per household, household income, workers per household, and vehicles owned per household, as well as cross-classifications of households by zone, were also derived from the U.S. Census and ACS.

Employment data by TAZ were derived from data provided by the state employment commission. Each employer was identified by a federal identification number, number of employees, and a geocodable address, which were allocated to TAZs. Since these data were keyed to where the payroll is prepared for employees, the MPO made adjustments to allocate employment to the proper TAZ, where necessary. School enrollment data by school were provided by the Schultzville School District and allocated to the appropriate TAZs; this information was supplemented by information the MPO collected directly from the larger private schools in the region.

Figure 7.5. Schultzville TAZs.

7.3.3 Trip Generation

Trip Productions

The MPO was able to develop estimates of households cross-classified by household size and number of vehicles, and by workers by number of vehicles for each zone. The information in Tables C.5 through C.7, which shows trip rates derived from 2009 NHTS data, was used to estimate productions by trip purpose. The HBNW trip rates for areas with less than 500,000 residents in Table C.6 were used. These trip generation rates were applied to the socioeconomic data for each zone to create total productions by purpose by zone.

An example calculation is provided for home-based work trips in Table 7.12. Trip production rates from Table C.5 were multiplied by the households cross-classified by workers and vehicles to obtain a total of 1,092 HBW trip productions occurring in the sample zone. (Note that Table C.5 provides rates for households with three or more vehicles, while data for Schultzville were only available for households with two or more vehicles; therefore, the rates for two vehicle and three vehicle households were averaged for use in Schultzville.)

Trip Attractions

The values for trip attraction rates for motorized trips, shown in Table 4.4, were used as a trip attraction model for Schultzville. Model 1 from this table was used for each trip purpose. An example calculation is provided for home-based

Table 7.12. Example trip production calculation.

Number of Autos	Workers 0	1	2	3+	Total
Home-Based Work Trip Production Rates					
0	0.0	1.1	2.0	4.0	
1	0.0	1.1	2.5	4.3	
2+	0.0	1.3	2.6	4.5	
Example TAZ Data					
0	20	30	10	0	
1	65	155	75	4	
2+	4	90	170	24	
Example Zone Trip Productions					
0	0	33	20	0	
1	0	171	188	17	
2+	0	116	442	106	
Total Productions	0	319	650	123	**1,092**

work trips in Table 7.13. Data for households, employment, and school enrollment for each Schultzville TAZ were multiplied by the trip attraction rates from Table C.7 to achieve a total of 130 HBW, 583 HBNW, and 306 NHB trip attractions occurring in the sample zone.

7.3.4 Trip Distribution

The doubly constrained gravity model, described in Equation 4-5, was used as the trip distribution model for Schultzville. The inputs to the trip distribution model include:

- The trip generation outputs—productions and attractions by trip purpose for each zone;
- Highway travel time, as the measure of travel cost between each pair of zones; and
- Friction factors, as discussed in the following section.

The outputs are trip tables, production zone to attraction zone, for each trip purpose. Because trips of different purposes have different levels of sensitivity to travel time and cost, trip distribution is applied separately for each trip purpose, with different model parameters.

Development of Travel Time Inputs

Zone-to-zone (interzonal) travel costs. This case study used the simplest cost variable, highway travel time, which is an

Table 7.13. Trip attractions calculation for sample TAZ.

Trip Purpose	Households	School Enrollment	Employment Basic	Retail	Service	Total	Trip Attractions
Home-Based Work							
Model 1						1.2	
Sample TAZ Value						108	
Trip Attractions						130	130
Home-Based Nonwork							
Model 1	0.4	1.1	0.6	4.4	2.5		
Sample TAZ Value	320	210	34	10	64		
Trip Attractions	128	231	20	44	160		583
Nonhome Based							
Model 1	0.6		0.7	2.6	1.0		
Sample TAZ Value	320		34	10	64		
Trip Attractions	192		24	26	64		306
Total Trips Attracted to Sample TAZ							**1,019**

Table 7.14. Gamma function parameters for Schultzville.

Parameter	HBW	HBNW	NHB
a	26,000	130,000	260,000
b	−0.265	−1.017	−0.791
c	−0.04	−0.079	−0.195

HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

adequate measure for a small area such as Schultzville. This area does not have a significant level of auto operating cost beyond typical per-mile costs—for example, relatively high parking costs or toll roads—or extensive transit service. The zone-to-zone highway travel time matrix was developed through "skimming" the highway network using travel modeling software.

The highway assignment process does not require that times be coded on the centroid connectors since those links are hypothetical constructs representing the travel time within zones. Initial skim times from the network assignment did not include time representing travel within zones, or terminal time.

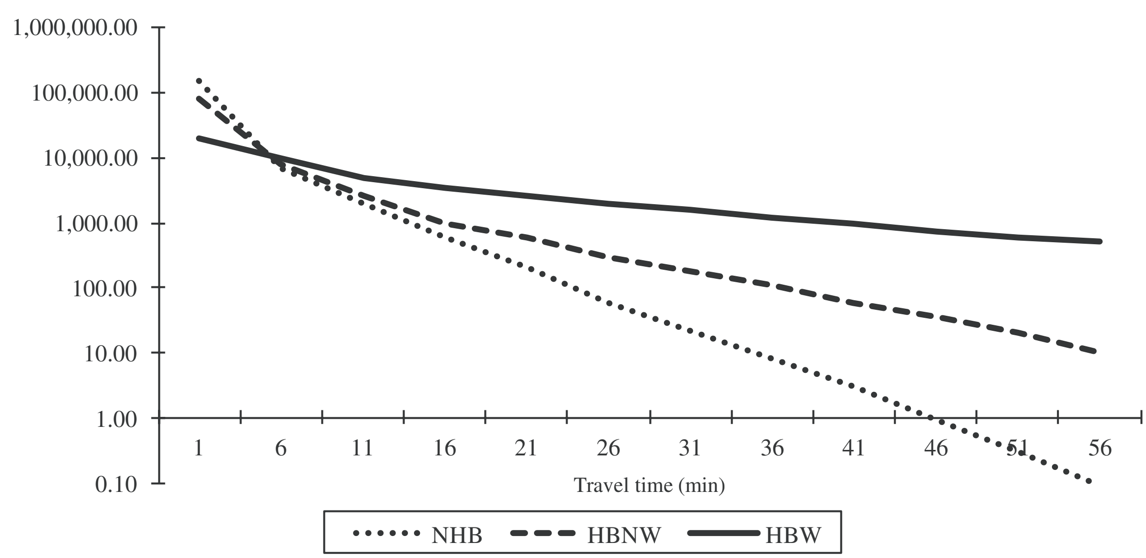
Intrazonal time. Intrazonal times were defined as one-half of the average of the skim times to the three nearest neighboring zones.

Terminal time. Terminal times, which represent the time required to park a vehicle and walk to the final destination, or vice versa, were added to the intrazonal time. Terminal times of 4 minutes were added to the time for any trip where a trip end was in the business district, and 2 minutes were added for trip ends elsewhere.

Friction factors. Friction factors were derived for each purpose (HBW, HBNW, and NHB trips) using a gamma function (described in Equation 4-6) using the *b* and *c* values shown in Table 4.5 for Small MPO 1. The gamma function parameters, including the scaling factor *a*, are shown in Table 7.14. The resulting friction factors are plotted in Figure 7.6.

The resulting average travel times by trip purpose from this first application of the gravity model were evaluated to determine if the distribution was acceptable. Friction factors were calibrated to match average travel times using an iterative process. No local data existed regarding average travel times, so the best option in this situation was to start with parameters from another modeling context. Average trip lengths by trip purpose are presented in Table C.10, and were used as a basis of comparison with trip lengths resulting from the initial trip distribution in Table 7.15.

As can be seen in Table 7.15, the average trip lengths resulting from this initial set of friction factors are lower than the average travel times reported in Table C.10. Since Schultzville is a small geographic area with little congestion, one might expect that the average trip length would be lower than the NHTS average reported for all areas with a population less than 500,000. However, the initial mean travel times were judged too low. The initial friction factors were adjusted iteratively to test variations



HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

Figure 7.6. Schultzville case study initial friction factors.

Table 7.15. Initial evaluation of Schultzville mean travel times.

	HBW	HBNW	NHB
Urban Area Population from Table C.10	Less than 500,000	All population ranges	Other urban area
Value from Table C.10	20 minutes	18 minutes	18 minutes
Schultzville	15 minutes	12 minutes	9 minutes
Difference	5 minutes	6 minutes	9 minutes

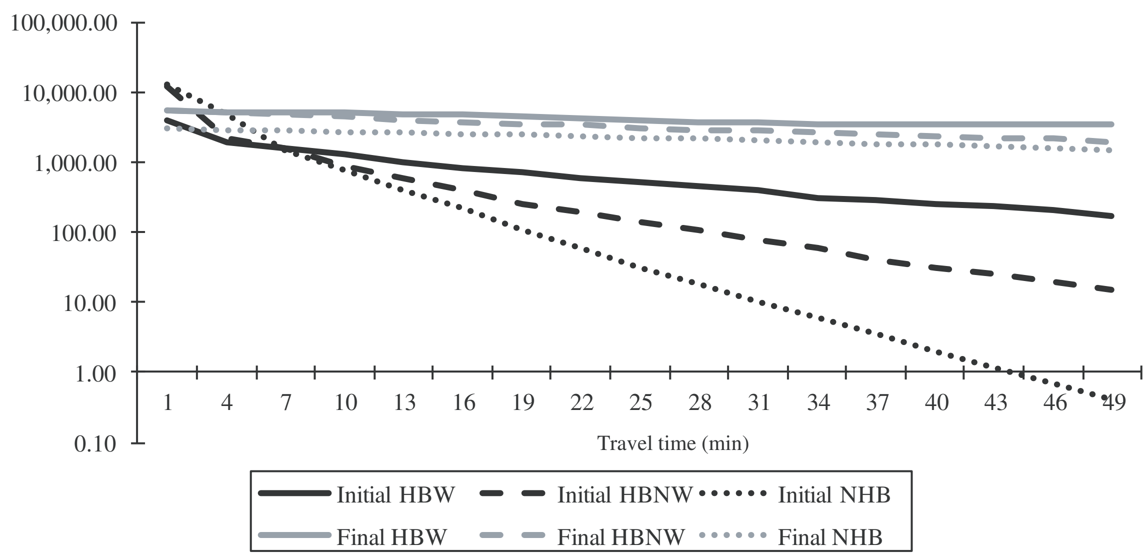
HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

that achieved a higher average trip length for all purposes. The friction factors resulting from this fitting process are shown in Figure 7.7. The comparison of the mean travel times resulting from the use of these revised friction factors with those from Table C.10 is shown in Table 7.16. The final friction factors are not as steep as those that were initially used and result in mean travel times closer to those shown in Table C.10.

7.3.5 External Trips

The best source of data for estimating external trips (EI and EE) is a roadside survey conducted at external stations; however, no such survey was available for Schultzville. The state in which Schultzville is located has a statewide travel model that provided information on EE trips and EI trips for the study area. The statewide model provided the origin and destination station, as well as the volume for EE trips.

For EI trips, a select link assignment from the statewide model provided the number of trips entering and leaving each external station allocated to the statewide model zones. These needed to be suballocated to the Schultzville model zones based on the relative internal attractions and productions in each TAZ compared to the total in the larger statewide model zones.



HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

Figure 7.7. Schultzville case study final friction factors.

Table 7.16. Evaluation of Schultzville mean travel times using adjusted friction factors.

	HBW	HBNW	NHB
Urban Area Population from Table C.10	Less than 500,000	All population ranges	Other urban area
Value from Table C.10	20 minutes	18 minutes	18 minutes
Schultzville	17 minutes	15 minutes	15 minutes
Difference	3 minutes	3 minutes	3 minutes

HBW = home-based work; HBNW = home-based nonwork; NHB = nonhome based.

7.3.6 Vehicle Occupancy

The highway assignment step, discussed in Section 7.3.7, requires tables of vehicle trips, while the output of early model steps was in person trips. Person trips made by auto from the earlier steps were converted to vehicle trips using the factors provided in the first row of Table 4.16, which represent all auto modes for daily travel. These factors—1.10 for HBW, 1.72 for HBNW, and 1.66 for NHB—were applied to the auto passenger trip tables produced by the trip distribution step, as described in Section 7.3.4.

7.3.7 Highway Assignment

Trip tables from origins to destinations (O-D format) are required for the daily highway assignment; however, the HBW and HBNW trip tables resulting from the previous steps provide trip tables from productions to attractions (P-A format). The P-A trip tables were converted to O-D trip tables by splitting the value in each cell in half to create two duplicate matrices, transposing the values in one of the matrices, and adding the two matrices together. The resulting O-D trip tables were then ready to be assigned to the highway network.

A user equilibrium assignment using the BPR formula for capacity restraint was used for assigning vehicle trips to the highway network. Values for the α and β parameters were needed for application of the BPR formula (described in Section 4.11.1). Table 4.26 presents BPR function parameters used by 18 MPOs. The most appropriate values for Schultzville are those shown for areas with a population less than 200,000:

$\alpha = 0.15$ for freeways,
0.45 for arterials; and
$\beta = 8.8$ for freeways,
5.6 for arterials.

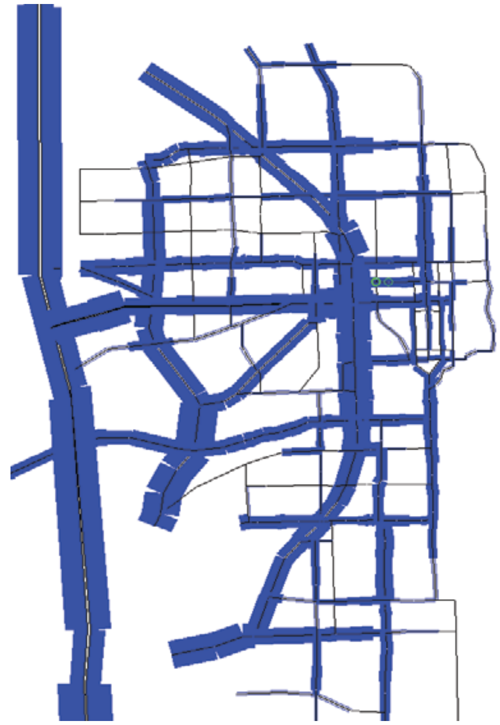


Figure 7.8. Schultzville case study final assigned volumes.

The results of the traffic assignment are shown as a bandwidth plot in Figure 7.8. In this diagram, the width of each link in the network is proportional to the volume on that link.

An assessment was made of the quality of the traffic assignment on links where traffic counts were available by comparing the root mean square error (RMSE) of assigned values to traffic counts by facility type. As can be seen in Table 7.17, the RMSE is within an acceptable range for all facility types, except local roads. Since the goal of the model was to get acceptable values for minor arterials, the results were deemed acceptable.

Table 7.17. RMSE comparison of modeled volumes with traffic counts.

Functional Class	Links	ADT	Error	Percentage Error	Acceptable Error
Freeways	18	228,340	15,021	6.6%	+/–7%
Principal Arterials	90	538,210	37,674	7.0%	+/–10%
Minor Arterials	226	730,030	80,303	11.0%	+/–15%
Collectors	218	304,110	66,904	22.0%	+/–25%
Locals	14	20,000	10,400	52.0%	+/–25%

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APPENDIX A

Federal Planning and Modeling Requirements

This appendix discusses federal agency requirements for transportation planning and travel models in urban areas. The requirements for three agencies are presented—the Environmental Protection Agency, the Federal Highway Administration, and the Federal Transit Administration—and are up to date as of the time of the writing but are subject to change based on updated legislative and rulemaking actions.

A.1 Environmental Protection Agency

The most specific federal agency requirements for travel demand forecasting are found in the Transportation Conformity Rule, promulgated by the Environmental Protection Agency (EPA) under the Clean Air Act (CAA) [42 U.S. Code (USC) 85 § 7401 et seq.].

A.1.1 Background

The EPA is the federal agency charged with implementing the requirements of the CAA, a comprehensive federal law that regulates air pollutant emissions from areawide, stationary, and mobile sources. Under the CAA, EPA established National Ambient Air Quality Standards (NAAQS), which set limits on concentrations of specific air pollutants throughout the United States. Each state is responsible for monitoring the concentrations of air pollutants within its borders and reducing emissions of those pollutants that exceed the NAAQS.

Areas within each state that currently exceed the NAAQS for specific pollutants are designated as **nonattainment areas**. Each nonattainment area is classified according to the amount by which it exceeds the NAAQS for each type of pollutant. The CAA establishes timetables (depending on the nonattainment classification) by which the area must reduce its pollutant concentrations in order to meet the NAAQS. When a nonattainment area reduces its pollutant concentrations below the NAAQS, it is redesignated as a **maintenance area.** Maintenance areas must continue to monitor their air pollutants and maintain NAAQS for a period of 20 years after their redesignation.

Each state must develop a **state implementation plan (SIP)** that explains how it will reduce air pollutant emissions in each nonattainment area to meet and maintain the NAAQS. Every SIP includes an emissions budget, which sets limits on the amount of pollutants each nonattainment area in the state can emit.

Transportation conformity is required under the CAA to ensure that federally funded and approved highway and transit activities in nonattainment and maintenance areas are consistent with (i.e., "conform to") the SIP. According to the CAA, a conforming transportation activity must not:

- Create any new air quality violations;
- Increase the frequency or severity of existing violations; or
- Delay timely attainment of NAAQS.

The Transportation Conformity Rule [40 Code of Federal Regulations (CFR) Parts 51 and 93], which establishes criteria and procedures for determining whether transportation activities conform to the SIP, was first promulgated under the authority of the 1990 CAA amendments in November 1993. Current conformity regulations reflect a comprehensive revision of the 1993 rule and were published on August 15, 1997 (Federal Register, 62, p. 43780).

The Federal Highway Administration (FHWA), Federal Transit Administration (FTA), and metropolitan planning organizations (MPOs) are responsible for making conformity determinations, based on criteria and procedures described in the conformity rule. Transportation activities that require a conformity determination include long-range transportation plans (LRTP), transportation improvement programs (TIP), and federally funded or approved transportation projects.

To demonstrate conformity, forecasts of regional emissions resulting from a LRTP or TIP must not exceed the motor vehicle emissions budgets for each specified pollutant, as defined in the SIP. Regional motor vehicle emissions must be estimated using EPA-approved emission factor models (e.g., MOBILE, MOVES, or EMFAC), per 40 CFR 93.111. These emission factor models, in turn, require estimates of vehicle speeds and travel volumes [in vehicle miles traveled], which are derived from the travel models used by transportation planning agencies to forecast travel demand under alternative transportation scenarios.

The 1997 conformity rule amendments, among other changes, mandated the use of network-based travel models to support conformity determinations in certain nonattainment areas, and included other requirements relating to model structure, input assumptions, included variables, and validation procedures. These requirements are described in the next section.

A.1.2 Travel Model Requirements in the CAA Transportation Conformity Rule

The specific requirements for travel models are described in Section 122 of the Transportation Conformity Rule [40 CFR 93.122 (b)]. However, these requirements apply only to serious, severe, and extreme ozone nonattainment areas or serious carbon monoxide nonattainment areas whose metropolitan planning area contains an urbanized area population over 200,000 (based on the most recent decennial census conducted by the U.S. Census Bureau).

In those areas meeting the above criteria, estimates of regional transportation-related emissions used to support conformity determinations must be made at a minimum using network-based travel models according to procedures and methods that are available and in practice and supported by current and available documentation. Agencies must discuss these modeling procedures and practices through the interagency consultation process, as described elsewhere in the Transportation Conformity Rule [40 CFR 93.105 (c) (1) (i)]. Network-based travel models must, at a minimum, satisfy the following requirements:

- Network-based travel models must be validated against observed counts (peak and off-peak, if possible) for a base year that is not more than 10 years prior to the date of the conformity determination. Model forecasts must be analyzed for reasonableness and compared to historical trends and other factors, and the results must be documented.
- Land use, population, employment, and other network-based travel model assumptions must be documented and based on the best available information.
- Scenarios of land development and use must be consistent with the future transportation system alternatives for which emissions are being estimated. The distribution of employment and residences for different transportation options must be reasonable.
- A capacity-sensitive assignment methodology must be used, and emissions estimates must be based on a methodology which differentiates between peak and off-peak link volumes and speeds and uses speeds based on final assigned volumes.
- Zone-to-zone travel impedances used to distribute trips between origin and destination pairs must be in reasonable agreement with the travel times that are estimated from final assigned traffic volumes. Where use of transit currently is anticipated to be a significant factor in satisfying transportation demand, these times also should be used for modeling mode splits.
- Network-based travel models must be reasonably sensitive to changes in the time(s), cost(s), and other factors affecting travel choices.

Additionally, reasonable methods in accordance with good practice must be used to estimate traffic speeds and delays in a manner that is sensitive to the estimated volume of travel on each roadway segment represented in the network-based travel model.

Highway Performance Monitoring System (HPMS) estimates of vehicle miles traveled (VMT) shall be considered the primary measure of VMT within the nonattainment or maintenance area and for the functional classes of roadways included in HPMS, for urban areas that are sampled on a separate urban area basis. For areas with network-based travel models, a factor (or factors) may be developed to reconcile and calibrate the network-based travel model estimates of VMT in the base year of its validation to the HPMS estimates for the same period. These factors may then be applied to model estimates of future VMT. In this factoring process, consideration will be given to differences between HPMS and network-based travel models, such as differences in the facility coverage of the HPMS and the modeled network description. Locally developed count-based programs and other departures from these procedures are permitted subject to the interagency consultation procedures described elsewhere in the rule.

In all areas not otherwise subject to network-based modeling requirements, regional emissions analyses must continue to use such models and procedures if the use of those procedures has been the previous practice of the MPO. Otherwise, areas may estimate regional emissions using any appropriate methods that account for VMT growth by, for example, extrapolating historical VMT or projecting future VMT by considering growth in population and historical growth trends for VMT per person. These methods also must consider future economic activity, transit alternatives, and transportation system policies.

A.2 Federal Highway Administration

The FHWA has very few explicit regulations related to the use of travel demand forecasting. The joint FHWA/FTA Statewide and Metropolitan Transportation Planning Regulations (23 CFR Parts 450 and 500) include only one specific reference to travel demand forecasts. That single reference, cited below, is included in the section of the metropolitan planning regulations dealing with the development and content of the metropolitan transportation plan:

> *(f) The metropolitan transportation plan shall, at a minimum, include:*
> *(1) The projected transportation demand of persons and goods in the metropolitan planning area over the period of the transportation plan [23 CFR 450.322 (f)(1)]*

Every designated MPO is required, as part of the metropolitan transportation planning process, to prepare a metropolitan LRTP that considers at least a 20-year planning horizon:

> *The MPO shall review and update the transportation plan at least every 4 years in air quality nonattainment and maintenance areas and at least every 5 years in attainment areas to confirm the transportation plan's validity and consistency with current and forecasted transportation and land use conditions and trends, and to extend the forecast period to at least a 20-year planning horizon [23 CFR 450.322 (b)].*

The joint planning regulations provide no other specific requirements or guidance as to how future transportation demand shall be forecast, leaving the determining of such forecasts up to the discretion of each MPO.

A transportation management area (TMA) is defined as an urbanized area with a population over 200,000, as defined by the Census Bureau and designated by the Secretary of Transportation, or any additional area where TMA designation is requested by the Governor and the MPO and designated by the Secretary of Transportation. An MPO with less than 200,000 may be designated a TMA if it contains any part of an adjacent TMA. Those MPOs that do not represent a designated TMA and not in an air quality nonattainment or maintenance area may request approval from FHWA and FTA to develop a simplified transportation plan, subject to the complexity of the transportation problems in the metropolitan planning area. No further elaboration is included in the regulations on what elements of the transportation plan may be simplified, but this element of the regulations has generally been interpreted to allow smaller MPOs with no significant plans for major transportation improvements (i.e., no capital investments in new highway or transit capacity) to continue to receive federal funding for system maintenance, etc.

MPOs that are in air quality nonattainment or maintenance areas for ozone or carbon monoxide must make a conformity determination for any updated or amended transportation plan in accordance with EPA's transportation conformity regulations [23 CFR 450.322 (l)]. EPA's Transportation Conformity Regulations [40 CFR 93.122 (b) and (c)], described elsewhere in this section, do include specific requirements for travel forecasting models.

Although the FHWA has few specific regulatory requirements pertaining to travel forecasting models, the agency has a long history of supporting research and providing technical assistance to state departments of transportation (DOTs) and MPOs in travel demand estimation and forecasting. Currently, most research and technical assistance on travel demand forecasting funded by FHWA is coordinated through the Travel Model Improvement Program (TMIP), administered out of the Office of Planning. A recently established companion program focusing on freight models is administered out of the FHWA's Office of Freight Management and Operations.

FHWA and FTA oversight of the metropolitan transportation planning process is handled through a formal certification review, conducted jointly by FHWA and FTA field planners in each TMA at least every 4 years. MPOs representing urbanized areas that are not designated as TMAs are allowed to self-certify that they are meeting all federal transportation planning requirements.

Historically, the TMA certification process focused on process requirements (e.g., existence of a metropolitan transportation plan and public participation plan; composition of the MPO policy board(s); coordination agreements with key stakeholders) and rarely addressed technical issues such as the travel models used in forecasting future passenger and freight demand. In an effort to encourage its field planners to increase awareness of the importance of travel models at MPOs, the FHWA developed a "certification checklist for travel forecasting methods" (Federal Highway Administration, 2009), to be used in certification reviews. The checklist does not include questions on the specific modeling components used at the MPO but rather focuses on three, generally nontechnical, categories of questions: (1) issues or proposed projects for which forecasts will be used as indicators of model scrutiny by external organizations; (2) key indicators of the MPO's technical capabilities; and (3) availability of documentation on current conditions, planning/modeling assumptions, and forecasting methods. The certification checklist is intended to act as a rough first filter to help identify those MPOs that may require additional technical assistance in forecasting, or whose forecasting approach may not be suitable for intended applications.

A.3 Federal Transit Administration

The FTA conducts periodic workshops on travel forecasting for transit New Starts applications. The goal of these workshops is to share with project sponsors and their model consultants how FTA evaluates travel forecasts. Furthermore, the workshops serve as a forum for FTA to establish acceptable modeling procedures, inputs, and outputs essential for producing reliable forecasts that are sensitive to socioeconomic and level-of-service changes.

The material presented in this section is a synthesis of the information that the FTA provided during the September 2007 travel forecasting workshop in St. Louis, Missouri (Federal Transit Administration, 2007).

A.3.1 FTA Requirements

The FTA provides guidance on the following key aspects of travel forecasting for New Starts:

- Properties of travel models;
- Rider surveys; and
- Calibration and validation.

The subsections that follow discuss the FTA's requirements for each of these items.

Properties of Travel Models

The FTA's requirements for the properties of travel models are fairly broad. The FTA supports a localized approach to travel modeling and forecasting. The rationale for such a requirement is that there are no standard or "correct" methods that are universally applicable to all regions. Models will need to reflect the fact that each metropolitan area has unique conditions and must be responsive to local decision making.

Because models are used to forecast transit ridership, it is essential that they explain the current transit conditions and capture the tradeoffs between travel times and costs. These favorable properties are heavily dependent on the model calibration and validation procedures (discussed in the subsection after next). In addition to capturing current conditions, the models will need to fulfill their ultimate objective of yielding reasonable forecasts. Specifically, FTA requires reasonable "deltas" (changes in ridership between a base year and forecast year) for ridership that are consistent with the underlying socioeconomic growth as well as level-of-service improvements. Unreasonably high or low ridership forecasts are clear indications that the model parameters may need further examination.

The evaluation of a proposed New Starts transit project relies on the cost-effectiveness ratio of the project. The cost-effectiveness ratio relates the cost of the project to the expected benefits, usually expressed as time savings, from the project. Obviously, the estimated cost of the project is independent of the travel modeling procedures; however, the expected user benefits are inextricably linked to the modeling procedures and inputs. A major component of the FTA's guidance on model properties, therefore, relates to the user benefits implied by the model. The FTA requires that models adequately support the case for a new transit project by capturing appropriate user benefits for various market segments. Further, the models should be amenable to an analysis of the primary causes of the benefits.

The FTA recognizes that a range of modeling approaches can be used to obtain the desired model properties. These approaches could include either the traditional trip-based models or the more advanced tour and activity-based models, as long as due attention is paid to the model properties and the implied user benefits.

In summary, the FTA recognizes good models based on coherent forecasts. Careful calibration and validation coupled with rigorous quality assurance checks will help achieve the ultimate objective of developing models to gain insights into performance and benefits of the alternatives.

Rider Surveys

Rider surveys are an important source of current transit information and are crucial to calibrating models that reflect the current conditions accurately. Where possible, the FTA recommends surveys before and after project opening to get a time-varying picture of ridership patterns and also to evaluate the model predictions. In cases where only the older survey data are available, the usefulness of the data in explaining current patterns depends to a large extent on the rate of growth in the metropolitan area as well as on any major transit system changes in the area. To the extent that these changes are minimal, the FTA deems the older data acceptable for current day predictions.

The success of rider surveys in capturing the current transit travel patterns depends on the design of the surveys in terms of the sampling plan, the questionnaire, and the data items included in the questionnaire.

The FTA recommends that the sampling plan be designed with the transit markets in mind. The transit markets are determined not only by the socioeconomic attributes but also by the geographic attributes such as the area type of the origin and/or destination of the trip. Because these markets have

Traveler characteristics		
Items	Y	Comments
Driver's license	Y	Required
Age	?	
Disabilities	?	
Household drivers	Y	Required
Household workers	?	
Household adults	?	
Household persons	?	Marginally useful
Household vehicles	Y	Required
Household income	?	Necessary if used in mode choice model

Source: Session 4: Data Collection, Slide 46 (Federal Transit Administration, 2007).

Figure A.1. FTA comments on frequently included traveler characteristics.

different response rates and different travel patterns, the FTA urges sample allocation and survey methods that account for these differences and improve overall response rates.

The FTA's guidance on questionnaire design relates to the visual and interpretational aspects of the survey. Specifically, the FTA recommends that the surveys be simple in terms of layout, readability, and wording. Attention to these three aspects can help avoid round-trip reporting and can provide better data on trip origins and destinations.

Successful surveys are succinct. Recognizing this, the FTA has identified several key data items that must be included in the surveys and several others that either require the use of discretion or are simply unnecessary. Figures A.1, A.2, and A.3 show the FTA's comments on the usefulness of various commonly included traveler, trip, and other characteristics, respectively, in rider surveys.

In addition to the rider surveys, the FTA recommends the use of other ridership data, where available, to inform the modeling process. These data could include on-off counts and park-and-ride utilization counts.

Calibration and Validation

As indicated previously, the FTA emphasizes that forecasts should be based on models that are tested rigorously against current transit ridership patterns. The FTA requires that the model forecasts serve as a useful basis for quantifying and understanding user benefits from the proposed New Starts projects. The implications of a careful calibration and validation methodology are threefold: first, it necessitates better current data; second, it calls for a better focus on transit markets; and third, it requires better tests and standards.

Trip characteristics		
Items	?	Comments
O and D purposes	Y	Required
O and D locations	Y	Required
O and D access modes	Y	Required
Park-ride location	Y	Required
All routes in O-D path	Y	Required
Xfer from, Xfer to	?	Redundant; useful for path checking?
Number of Xfers	?	Redundant; useful for path checking?
O-on and D-off locations	?	Desirable, but adds complexity, length
Fare paid / method	?	Desirable, but adds length

Source: Session 4: Data Collection, Slide 45 (Federal Transit Administration, 2007).

Figure A.2. FTA comments on frequently included trip characteristics.

Other data items

Items	Y	Comments
Options if no transit	?	Best for "captivity"
Vehicle available for trip	N	Ambiguous
Path attribute weights	?	May inform pathbuilder calibration
Previous behavior	y	Useful in Before-After studies
Customer satisfaction	?	Length/responsiveness/funding
Open-ended comment	?	Responsiveness
Contact information	?	Call-backs for QC checks; responsiveness

Source: Session 4: Data Collection, Slide 47 (Federal Transit Administration, 2007).

Figure A.3. FTA comments on frequently included other characteristics.

The FTA recommends that project sponsors take advantage of the funding and guidance opportunities available from the FTA to collect good quality "before" and "after" survey data. The issue of better focus on transit markets can be achieved through an evaluation of model performance by each trip purpose, socioeconomic group, production-attraction area types, and transit access modes. The FTA deems the matching of overall target totals as an insufficient measure of model calibration. The standards for model calibration must rely as much on behavioral significance as they do on statistical significance. The FTA defines validation as a valid description of travel behavior as well as plausible forecasts of "deltas" for the future year. The FTA recommends careful documentation of key transit markets, current transit modes, and calibration forecasts to help evaluate the overall effectiveness of the model for New Starts analysis.

The FTA provides guidelines on the allocation of resources to the three important tasks of model development, calibration, and validation. Because of the critical importance of model validation, the FTA recommends that estimation be conducted only where necessary and that the testing (calibration and validation) task be fully funded. In model estimation, statistical procedures are used to develop values for model parameters that will provide a best fit with observed travel data. The FTA's guidance here indicates that it may be acceptable in many cases to transfer previously estimated parameters from another area's model and then calibrate and validate them to local data in the new area.

The FTA has provided guidance on specific properties of travel models to ensure proper calibration and validation. The FTA has found that many travel models have one or more of the following problems:

- Unusual coefficients in mode choice models;
- Bizarre alternative-specific constants;
- Path/mode choice inconsistencies;
- Inaccurate bus running times; and
- Unstable highway-assignment results.

Since naïve calibration leads to bad alternative-specific constants and has the cascading effect of producing errors in trips and benefits, the FTA suggests that modelers ask themselves if patterns across market segments are explainable.

The FTA also suggests that there be conformity between parameters used in transit path selection and mode choice utility expressions for transit choices. That is, the path-building process must weigh the various travel time and cost components in a manner that is consistent with the relative values of the mode choice coefficients. The consequences of inconsistencies include the following:

- Better paths may look worse in mode choice; and
- Build alternatives may lose some trips and benefits.

The FTA requires that level-of-service estimates for transit (and highway) must:

- Replicate current conditions reasonably well;
- Predict defensible deltas by comparing conditions today versus the future; and
- Predict defensible deltas when comparing conditions across alternatives.

The FTA recommends a careful analysis of highway and transit travel times between carefully selected origins and destinations to understand the quality of the model networks. Spurious values of travel time can distort the magnitude as well as the pattern of predicted trip making and can adversely affect the quality of project user benefits.

A.3.2 Summary of FTA Guidelines

The FTA's requirements are geared toward reasonably accounting for current patterns and predicting reasonable future ridership for the proposed New Starts projects. The FTA does not provide rigid targets for parameters in travel models. Rather, the FTA recommends methods that can be used to ensure that models reflect current travel behavior and predict reasonable future patterns.

The FTA's expectations from travel models and the New Starts process can be summarized as follows:

- Coherent narrative of the model parameters, inputs, and outputs;
- Regular and early communication regarding model parameters and forecasts to ensure that the agency/sponsor is proceeding in the proper direction;
- Reasonable model forecasts in light of the expected land use growth, service characteristics, and other project-related attributes; and
- Proper documentation and uncertainty analysis, which is directly related to the requirement of the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU) of 2005 that asks the FTA to provide the U.S. Congress with an assessment of contractor performance. The FTA will rate contractors based on the following measures:
  – Comparison of predicted and actual ridership;
  – Quality of documentation;
  – Uncertainty analysis, including magnitude of impact; and
  – Before and after studies for various stages, including alternatives analysis, preliminary engineering, pre-project construction, and 2 years after opening.

References

Federal Highway Administration (2009). "Certification Checklist for Travel Forecasting Methods." http://www.fhwa.dot.gov/planning/certcheck.htm (As of September 15, 2011.)

Federal Transit Administration (2007). Travel Forecasting for New Starts Workshop, St. Louis, Missouri. http://www.fta.dot.gov/documents/Sessions_01-04.pdf (As of February 8, 2012.)

APPENDIX B

Review of Literature on Transferability Studies

In preparing this report, a literature review of transferability of model parameters was undertaken. This appendix presents the results of this review, which are mixed regarding the validity of transferring model parameters in many cases. The purpose of this appendix is not to warn practitioners against transferring parameters but to provide background information on research findings regarding transferability and information that may be helpful in areas where some data may be available for model estimation but not enough to estimate a complete set of model components. It is recognized, however, that many areas do not have enough data for model estimation and must use transferred parameters such as those presented in Chapter 4.

The literature review found that while transferability was valid in some studies, its validity could not be demonstrated in others. In general, transferability was demonstrated for trip generation and mode choice in some cases but not others, while the literature on transferability of other parameters, including trip distribution, time of day, and freight/truck modeling, was insufficient to draw any conclusions. More research into model transferability, the conditions under which transferability is most likely to be valid, and ways in which the validity of transferred parameters could be improved is needed. This appendix includes several references that describe methods for scaling that could be used if limited model estimation data (possibly from a small household activity/travel survey or NHTS samples in the model region) are available.

B.1 Trip Generation

B.1.1 Spatial Transferability

Several studies in the literature have examined spatial transferability in the context of trip generation, as discussed in the following paragraph.

Caldwell and Demetsky (1980) evaluated spatial transferability of linear regression models of household-level trip generation and zonal-level trip generation, using data from three cities in Virginia: Roanoke, Harrisonburg, and Winchester. In the household-level model, they considered two explanatory variables (auto ownership and household size) and used total trip productions per household as the dependent variable. In the zonal-level model, they used a single explanatory variable (zonal-level number of cars), with total zonal trip productions classified by home-based work, home-based nonwork, and nonhome-based productions as the dependent variable. Overall, the results of the study suggest that trip generation models can be transferred between cities, at least as long as care is taken in selecting "similar" cities. "Similar" cities are implicitly defined in the study as those with similar household size, household auto ownership levels, and per capita income.

Gunn et al. (1985) examined the transfer scaling approach for spatial transferability using two adjacent urban regions of the Netherlands: one located around Rotterdam and The Hague and the other located around Utrecht. The transferability analysis was based on data collected at each of the two urban regions, though the data were collected at the two locations at different points in time, as well as at different times of year. To accommodate the intrinsic differences in background variables across the two spatial contexts due to different times of data collection and different periods within the year of data collection, the authors used a nationwide travel survey as a control data set and then examined the spatial transferability of a daily shopping trip generation model as well as a personal business trip generation model (which are parts of a linked disaggregate-level nested logit system of mode-destination and trip generation specific to each trip purpose). The overall empirical results indicate that a simple uniform scaling of the coefficients between the joint model components of the base area and the transfer area is quite adequate relative to separate locally estimated models for the two areas, both from a statistical log-likelihood ratio fit perspective as well as from a prediction perspective on a suite of predefined market segments. This is quite interesting, given that the specifications adopted in these joint models are not particularly comprehensive in trip determinant variables. Specifically, the independent variables included level-of-service variables, demographic variables (cars per licensed driver, gender, and a central business district destination dummy variable), and an intrazonal trip dummy variable.

Koppelman and Rose (1983) indicated that aggregate models are not likely to be spatially and temporally transferable, even in cases where the underlying disaggregate-level behavioral process is similar. This is because of differences in the distribution of variables within aggregate population groups in the estimation and application contexts. In their empirical analysis, the authors, among other things, examined the intraregional transferability of household-level linear regression trip generation models between two sectors of each of three urban areas, Baltimore, Minneapolis-St. Paul, and Washington, D.C. The dependent variables in the analysis included number of stops and number of tours. The results indicate large differences in parameter estimates of the trip generation model between sectors in each urban region. However, the authors found reasonable predictive ability of the transferred models based on typical goodness-of-fit and prediction measure comparisons between the transferred models and locally estimated models. At the same time, their statistical tests reject transferability, despite the closeness of goodness-of-fit and prediction errors.

Wilmot (1995) also examined the transferability of household-based linear regression trip generation models. He used total trips per household as the dependent variable and considered household size and number of workers as the independent variables. He examined transferability within cities, between areas in a city, and between several cities in South Africa. His results suggest that model specification does influence the level of transferability, as does the difference in average income between the estimation and application contexts. Wilmot also emphasized the need to have quality data in the application context to evaluate transferability. In his study, he found a substantial improvement in transferability when the constant in the linear regression model is updated based on application context data.

Agyemang-Duah and Hall (1997) built upon the earlier research in two ways. First, they used an ordered-response model that respects the discrete and ordinal nature of number of trips and includes built-in upper limits for trip rates as the values of the explanatory variables increase. Second, they included variables related to cost of travel and accessibility in evaluating spatial transferability. The research focused on weekday home-based shopping trips made by households with one or more vehicles in the metropolitan Toronto area, based on a 1986 travel survey. The independent variables included household size, number of children less than 16 years old, number of vehicles in the household, number of full-time employed individuals working outside the home, number of part-time employed individuals working outside the home, number of individuals employed at home, number of unemployed individuals, and accessibility to shopping opportunities. Spatial transferability was examined by evaluating models estimated on a core area (estimation area) to predict trip generation in a periphery area (application context). Similarly, spatial transferability also was examined between the eastern and western parts of the metropolitan area, and among three pairs of municipalities. The transferability was assessed for a simple transfer scheme as well as a transfer updating scheme where factors (or scales) are applied to the latent index contribution of socioeconomic variables and the accessibility variable (the model coefficients used here are as obtained in the estimation context). Transferability was evaluated using a transferred pseudo R^2 measure (or the fraction of the constants-only log-likelihood ratio value in the prediction context explained by the model coefficients obtained from the estimation context), comparison of predicted versus observed aggregate shares, weighted root mean square error (the average relative error in the aggregate predicted shares weighted by the predicted shares), and two other related measures. The results indicate that the simple transfer mechanism works quite well for model transfer, though the transfer updating procedure substantially improves the predictive ability of the transferred model.

Kawamoto (2003) examined the spatial transferability of a linear regression model of total home-based trip productions at the person level between two urban areas in Brazil: Sao Paulo and Bauru. They used a standardized form of the regression model, where the dependent and independent variables are represented in standardized form and are unit free. This procedure requires the values of the mean and standard deviation of each model variable in the application area, and represents a transfer updating scheme where the scaling is done on a variable-by-variable basis. Transferability was evaluated based on a Wald test statistic of parameter equality in the regression models in the estimation and application contexts after accommodations for variance differences in the two contexts. The variables considered in the analysis included relationship with householder, educational attainment, number of cars in household, student status, employment status, and if the individual is a child younger than 11 years. The results indicate that the standardized regression models are indeed transferable between the two cities, though the unstandardized versions are not. This is interesting, especially given that the Sao Paulo data was collected in 1987, while the Bauru data was collected in 1998.

Cotrus et al. (2005) examined the spatial transferability of linear regression and Tobit models of person-level trip generation models, using data from Tel Aviv and Haifa in Israel. The data were drawn from the 1984 and 1996/1997 Israeli National Travel Habits Survey. The models included age, car availability, possession of a driver's license, employment status, education level, and whether the individual defines herself/himself as the head of the household. The results indicate that the Tobit models fit the data better, but that equality of coefficients in the two areas is rejected for both the regression and Tobit models on the basis of statistical tests. In particular, the coefficients on the license holding and age variables are statistically different, while those of other coefficients are not. However, the transferred models appear to do quite well in terms of aggregate predictions.

Greaves and Stopher (2000) employed the data transferability approach to transfer trip production models. Specifically, they used the 1995 Nationwide Personal Transportation Survey (NPTS) data and clustered households into relatively homogenous groups for each of six trip purposes: home-work, home-school, home-shop, home-other, other-work, and other-other. A classification and regression tree method, combined with the standard analysis of variance procedure, was adopted to determine the clusters. The number of clusters varied from six groups for the home-work, home-school, and work-other purposes to 16 groups for the remaining purposes. The clustering variables included household size, number of workers, number of vehicles, and number of children and adults by age group. Within each cluster for each trip purpose, a cumulative frequency distribution was developed for number of trips produced. They then applied the cluster scheme to predict the trip productions for a survey sample of households in the Baton Rouge MPO region. For this process, they applied the clustering scheme to the add-on sample as developed earlier from the main NPTS sample, and then drew a random realization from the cumulative trip production frequency distribution for each purpose and each Baton Rouge region sample household based on the cluster to which the sample household is assigned. Next, they compared the trip production predictions from their method and from a borrowed model that is based only on household size as the independent variable, using the survey-collected trip productions as "ground reality." They found that their approach does better than the borrowed model, a result that is not surprising given that the borrowed model is based only on a single household size variable, while the authors' approach effectively uses several independent variables. They also compared the model estimates obtained from estimating trip production models using their synthesized trip production data and the actual survey trip production data, and concluded that the trip production models for "home-work and home-school are well estimated, home-shop and work-other are acceptably estimated, and home-other and other-other are marginally well estimated."

Stopher et al. (2003) undertook a similar analysis as Greaves and Stopher, except that they examined the effectiveness of their approach in application areas (Dallas and Salt Lake City) where household travel surveys may not be based on the same survey collection methodology as NPTS (the Baton Rouge household travel survey used earlier was patterned after the 1995 NPTS). Specifically, the household travel surveys were collected over the fall or spring of a year, rather than the year-round data collection of NPTS, and were based on an activity survey rather than the trip-based survey of NPTS. The study also examined if the travel characteristics are a function of city characteristics in addition to demographic attributes that formed the clustering basis in the earlier work. Their results show that the simulation does not work well for the Dallas and Salt Lake City areas, though this result may simply be an artifact of the way the survey questions were worded and interpreted by respondents. They also conclude that city characteristics do matter in trip production estimates, and they recommend using contextual variables such as city population size and transit service quality. In addition, they suggest the use of a Bayesian updating of the travel characteristics for the clusters using small samples from the application context.

Reuscher et al. (2002) also pursued a data transferability analysis of vehicle trips per household, vehicle miles of travel (VMT), person trips per household, and person miles of travel (PMT) rates. They used a combination of cluster/regression analysis, judgment, and well-established relationships between VMT and area type and demographics. In particular, they first classified the census tracts in the United States into nine groups defined by area type (urban, suburban, and rural) and income (very low, very high, and other). Next, they developed household size-specific, number of vehicles-specific, and census tract (CT) cluster-specific vehicle trip, VMT, person trips, and PMT rate estimates (and standard error of estimates) using the 1995 NPTS data. Based on this initial classification, they subsequently undertook a clustering analysis procedure to determine the final clusters based on a combination of household size, number of vehicles, and the initial CT clusters. Once this clustering was established, the travel characteristics for any CT tract in the United States could be determined based on the cluster to which it belongs. The authors assessed their approach using data from Baton

Rouge and three NPTS add-on samples from New York, Massachusetts, and Oklahoma, and found their approach to be better than other approaches that cluster CT tracts based on metropolitan statistical area (MSA) size, census region, and census division.

Mohammadian and Zhang (2007) used methods similar to the earlier data transferability studies but considered a more comprehensive set of variables to cluster households on, including demographics, pedestrian-friendly environment characteristics (such as intersection density, road density, and block size), transit usage, and congestion factors (the Urban Mobility Index measure, total number of road users divided by road density, and the percentage of workers driving to work divided by road density). A combination of principal component analysis and cluster analysis was undertaken to define a total of 11 relatively homogenous groups of household types using the 2001 NHTS. This clustering scheme was then transferred to the NHTS add-on samples from New York, Wisconsin, Texas, Kentucky, and Hawaii. The transferred travel characteristics from the original NHTS survey were then compared to the actual travel characteristics directly collected in add-on samples, as a way of assessing the performance of transferability. They found reasonable transferability on such travel characteristics as person/vehicle trips and tours by purpose.

Zhang and Mohammadian (2008a) applied the data transferability approach by generating a synthetic population for the application context using well-established population generation methods. Their application context corresponded to the New York region. They classified the generated population using the approach in Mohammadian and Zhang (2007) and compared the mean values of trips per person and trip distance per person from the simulated data with the mean values from corresponding clusters from the actual observed survey data (from the New York NHTS add-on sample). The results show good fit of the simulated and observed travel characteristics.

Zhang and Mohammadian (2008b) further improved upon Zhang and Mohammadian (2008a) by fitting a gamma distribution for the trip rate per person and trip distance per person for each cluster using the main NHTS survey, and next updated the parameters of this distribution using a small sample randomly selected from the NHTS add on for New York (as suggested by Stopher et al., 2003). The authors used a Bayesian approach to updating and compared the parameters of the updated gamma distribution within each cluster with the equivalent best fit gamma distribution parameters from the corresponding cluster of households from the entire New York add-on sample. The authors note that the parameters of the updated gamma distribution are closer to those from the New York add-on sample compared to the unupdated gamma distribution parameters.

B.1.2 Temporal Transferability

There have been relatively few studies of temporal transferability in the context of trip generation. Ashford and Holloway (1971) employed data from the Pittsburgh area collected in 1958 and 1967 to examine the temporal stability of parameters from a zonal-level linear regression model as well as a household-level linear regression model (more specifically, a cross-classification model).[1] The authors found substantial differences in the estimated coefficients between the regression models for the 2 years and concluded that trip generation projections over long-term planning horizons are likely to be unreliable other than for gross level-of-magnitude estimates.

Kannel and Heathington (1972) performed a similar analysis of stability of parameters for a household-level linear regression model using data from Indianapolis in 1964 and 1971. The independent variables considered in this analysis were household size and auto ownership. The study found substantial and statistically significant differences in estimated coefficients of the linear regression models estimated in 1964 and 1971, reinforcing the finding from Ashford and Holloway (1971).

Doubleday (1976) evaluated the temporal transferability of a linear regression model of the cross-classification type using employment status and profession, presence and age of children, and household car ownership as determinant variables of individual-level trip generation by trip purpose. The data were drawn from the Reading area in England from 1962 and 1971. The results indicate, among other things, that the trip generation models provide good predictive results for employed males, but not so for retired individuals, homemakers, and employed females. The inclusion of the presence and age distribution of children appeared to provide more stable results over time.

Badoe and Steuart (1997) studied the temporal transferability of linear regression home-based trip generation models at the household level with a simple transfer method and using data from the Greater Toronto area from 1964 and 1986. Specifically, they examined model parameter stability and the predictive ability of models estimated from the 1964 data to explain household-level trip generation in 1986. The independent variables used were household size, number of vehicles owned by household, number of licensed drivers in the household, and number of employed individuals.

[1]Cross-classification is but a form of linear regression where the effects of independent variables (such as car ownership, household size, etc.) are allowed to have a general non-linear effect. An equivalent linear regression formulation would have appropriately defined dummy variables to represent the effect of each combination value of the independent variables.

The empirical results indicate generally large differences in the sensitivity to explanatory variables of total home-based trips, home-based work trips, home-based shopping trips, home-based social and recreational trips, and home-based personal business trips. Badoe and Steuart then evaluated predictive ability using a transfer R^2 measure (i.e., the R^2 measure as computed using the 1964 linear regression models on the 1986 trip generation data without any adjustments of the 1964 regression results), a transferability index (the ratio of the transfer R^2 measure and the R^2 measure from the 1986 linear regressions), the transfer root mean square error (RMSE) of the predictions using the 1964 models for the 1986 data, and a measure of relative RMSE (the ratio of the transfer RMSE and the RMSE from the 1986 linear regression models). These results indicate, as expected, that the transferred measures are not as good as the prediction measures based on the 1986 linear regression models though the differences are rather marginal. The differences in the transfer and 1986 model predictive abilities narrow further when the linear regression predictions are aggregated to obtain zonal-level trip ends. This is, of course, because of compensating errors and the loss of variation in the aggregation of trips to the zonal level. But the results do show statistically significant biases (overpredictions) in using the 1964 model to predict zonal-level trip ends in 1986. Overall, the authors find good temporal transferability of the 1964 models for total home-based trips and home-based work trips, but quite poor forecast performance for the home-based nonwork trip categories. However, they also note that the poor forecast performance for the nonwork categories can be partly attributed to the generally low ability to explain nonwork trips using the explanatory variables they used as well as ignoring trip chaining behavior.

Cotrus et al. (2005), in their study as discussed under spatial transferability, also examined temporal transferability of trip generation models in Haifa and Tel Aviv over time. Their results indicate statistically significant differences in coefficients in each urban area over time, rejecting temporal stability in the behavioral relationship characterizing trip generation. However, the authors acknowledge that their result may be an artifact of not considering several other explanatory variables in the models, including income, land use variables, spatial structure attributes, the economic conditions, and the transportation system characteristics. In addition, the results may also be affected by the different survey designs, periods of data collection, and variable definitions used in the 1984 and 1996/1997 Israeli Travel Habits Surveys.

B.1.3 Summary

The results of studies of the spatial and temporal transferability of trip generation models have been rather mixed. Unfortunately, it is difficult to synthesize the results from the various efforts to provide any conclusive guidelines for transferability because of the different variable specifications used, the different dependent variables adopted (some of which are at the person level and some at the household level), the different trip purposes considered, the different geographic and temporal periods of the studies, the different model forms employed, and the different independent variable specifications in the models. Besides, most of the trip generation studies have not controlled for land use, accessibility, and transportation system characteristics when studying spatial and temporal transferability. A study by Lin and Long (2007) highlights this issue and suggests that including these additional variables can enhance spatial transferability. However, the study by Lin and Long focuses only on household auto work trips and not on other kinds of trips that are likely to exhibit more variation in trip generation relationships across space and time.

In general, however, it appears safe to say that trip generation transferability will be improved with better variable specifications, a disaggregate-level analysis at the household or person level rather than at an aggregate zonal level, a model structure that reflects the ordinal and discrete nature of trips, and a transfer approach that involves transfer scaling of coefficients. In the context of transfer scaling, it should be pointed out that most trip generation analyses of transferability have focused on a simple transfer approach, rather than on a transfer approach that combines some limited information from the application context to update the estimation context relationships for use in the application area.

Another important issue to note in the earlier trip generation studies is that they have all been trip based and do not consider trip chaining and the more general interdependence among trips of individuals. Thus, separate models for home-based trips and nonhome-based trips are developed, without any consideration of the dependence between these categories of trips. Consequently, differences in trip chaining tendencies from one area to another, or from one time period to another, could immediately result in findings of poor trip generation transferability, even if models of the number of stops (out-of-home activity participations) have good transferability. This issue needs careful attention in the future and suggests the need for transferability analysis in the context of tour-based and activity-based frameworks for travel demand modeling.

B.2 Trip Distribution/ Destination Choice

B.2.1 Temporal Transferability

The literature on transferability of trip distribution/destination choice is relatively limited and has been focused on temporal transferability, not spatial transferability. Volet and Hutchinson (1986) evaluated the ability of growth factor-based and gravity-based trip distribution models for commuting trips estimated in the Toronto region in 1971 to predict the spatial distribution of commuting trips in 1981. They developed models for three different spatial resolutions of the traffic zone system in the Toronto region: a 38-zone system, a 77-zone system, and a 124-zone system. The overall conclusion of this study is that the growth factor model outperforms the gravity model in predicting the 1981 spatial patterns, though both the growth factor and gravity models have difficulty in replicating commute trend shifts due to changes in the urban spatial structure of employment centers and residential locations. Duffus et al. (1987) conducted a similar temporal transferability analysis with gravity-type trip distribution models using data from Winnipeg in the years 1962, 1971, 1976, and 1981. The authors used a rather coarse spatial resolution, partitioning the Winnipeg planning area into 36 "super" zones. The results indicate that transferability in terms of zone-to-zone forecast errors deteriorates with the length of time of the temporal transferability period and with the inclusion of K-factors in the estimation phase. Elmi et al. (1999) examined the temporal transferability of entropy-type aggregate trip distribution models for commute trips based on data collected in the Toronto region in 1964, 1986, and 1996. The number of zones was 815 in 1964, and 1,404 in 1986 and 1996 (it is not clear how the authors reconciled this difference in zone systems in their empirical analysis). The authors also examined the influence of an improved model specification on transferability through the stratification of the trip data into two spatial markets (the Toronto Central area and the rest of the Greater Toronto area), and segmentation based on gender, auto ownership level, driver's license status, and worker occupation. Their results show that the coefficient on the impedance parameter (represented as the auto travel time between zones) is not temporally stable, though the transferred model forecasts are comparable to those obtained from locally (in time) estimated models. In addition, the extent of transferability deteriorates with an increase in time span between the estimation and application years, as also found by Duffus et al. Further, the authors observe that improved model specifications through the trip data stratifications enhance transferability significantly as measured by the disaggregate transfer log-likelihood value fits. However, this result did not carry over to transferability as measured by the zone-level root mean square forecast errors. Overall, the authors conclude that, from a pragmatic perspective, a simple model devoid of any stratification is adequate in forecast performance.

The above studies have used an aggregate trip distribution model, with auto travel time as the only measure of travel impedance. In contrast, Karasmaa and Pursula (1997) examined temporal transferability in the context of a disaggregate nested logit trip destination-mode choice model, which effectively considers travel time and cost characteristics by multiple modes (walk, car, and public transport) in destination choice decisions. However, like the earlier trip distribution models, Karasmaa and Pursula also confined their attention to home-based work trips in the paper. The research is based on data from the Helsinki metropolitan area, collected in 1981 (estimation context) and 1988 (transfer context). The authors examined the effects of model specification by using travel time and travel-cost variables only, and then adding the number of cars per household as an additional socioeconomic variable. Four transfer approaches were evaluated: transfer scaling, Bayesian updating, combined transfer, and joint context estimation. The influence of the size of the application context data on transferability was also examined by using five different samples. The authors found no substantial differences in disaggregate transfer predictive fit across different sample sizes and different updating methods. All sample sizes and transfer methods did well in disaggregate predictive fit compared to the locally estimated joint choice model (i.e., the model directly estimated using 1988 data). However, the implied money value of time was quite different based on estimation sample size and transfer updating procedure (the research restricted the implied money value of time to the same across modes and across the mode and destination choice dimensions). Also, the transferred model's predictions of changes in behavior due to an across-the-board 30 percent increase in public transport travel time varied substantially based on sample size and transfer updating method. The authors made some tentative conclusions about the effectiveness of the alternative transfer methods based on the model's predictions of behavioral changes, including the superiority of the transfer scaling approach for simple models and large transfer biases (i.e., large differences in the locally estimated parameter values in the estimation and application contexts), and the better performance of the combined transfer approach when the sample size in the application context is large and the transfer bias is small.

Gunn et al. (1985) also examined destination choice model transferability, as part of their joint system of mode, destination, and trip generation system.

B.2.2 Summary

There has been little previous research on studying transferability of trip distribution and destination choice models. Further, the earlier studies in this area have been confined to temporal transferability of work trips. Within this restricted context, the results from earlier studies suggest that trip distribution/destination choice models transfer reasonably well over time in terms of predictive fit and forecast errors, though the behavioral parameters do show temporal instability. However, there seems to be no clear indication of which type of updating method would be best suited for what type of transfer context. Of course, the trip-based nature of earlier studies completely ignores issues of destination linkages of stops and identifies the need for transferability analysis in the context of tour-based and activity-based frameworks for travel demand modeling.

B.3 Mode Choice

B.3.1 Spatial Transferability

Watson and Westin (1975) studied the spatial transferability of binary logit intercity mode choice models among different subareas in the Edinburgh-Glasgow area of Scotland. Specifically, they identified six travel "corridors" in the Edinburgh-Glasgow area based on whether the origin and destination ends were in the central city, the suburbs, or peripheral to the urban area. The modes considered were the automobile and train. They included level-of-service variables and a mode-specific constant, but no socioeconomic characteristics of the travelers. The models estimated in the six travel corridors were then compared for similarity in model coefficients, and each model also was transferred to the other five corridors to evaluate modal split predictions. Their findings indicate that there is a high level of model transferability between the three models estimated in the corridors with a trip-end in the central city. However, this is not the case for the models estimated in the remaining three corridors that did not have a trip-end in the central city.

Atherton and Ben-Akiva (1976) examined the spatial transferability of a home-to-work trip mode choice model estimated on data collected in Washington, D.C., in 1968 to New Bedford, Massachusetts, and Los Angeles. Data from 1963 in New Bedford and 1967 in Los Angeles were available to test the extent of transferability of the multinomial logit model estimated from Washington, D.C. The alternatives considered in the mode choice model included driving alone, sharing a ride, and public transit. The authors conclude, based on statistical tests of parameter equality and predictive ability in the transfer contexts, that the Washington, D.C. model is transferable to the other two application areas. They further examined the benefit of updating approaches that (1) update the constants only based on aggregate shares of the alternative modes in the application area, (2) update the constants as well as estimate a single factor that scales the other coefficients, and (3) use a Bayesian update method based on the inverse of the variance-covariance matrices of the coefficient estimates from the estimation context and the application context as weighting factors. The results indicate that the Bayesian update approach works best, especially when the disaggregate sample available from the application context is small in size and the original estimation context choice model is well specified. However, there is little difference in the extent of transferability between the model with no updating and that with even the Bayesian update.

Talvitie and Kirshner (1978), in their study of urban commute mode choice model transferability between Washington, Minneapolis-St. Paul, and San Francisco, used the same variable specification as that in Atherton and Ben-Akiva. The modal alternatives are drive alone, shared ride, and bus with walk access (the individuals choosing the Bay Area Rapid Transit System in the San Francisco Bay area were removed from the analysis). The authors examined transferability both within each region and between regions. The within-region transferability was examined by partitioning the sample from each region in three ways: (1) urban travel versus suburban travel (not done for the San Francisco sample), (2) central business district (CBD) travel versus non-CBD travel, and (3) a random split of the sample into two subsamples. Overall, the results of statistical tests of parameter equality between the samples within each region were mixed and inconclusive although there was more evidence of nonequality of parameters than equality of parameters. The between-region transferability in terms of model parameter equality also was statistically rejected with a high level of confidence. These results are clearly different from the results of Atherton and Ben-Akiva. The authors suggest that several factors may have played a role in their findings, including variations in network coding routines and differential trimming of outlying data points across the data sets.

Galbraith and Hensher (1982) emphasized the need to consider both level-of-service variables as well as a reasonably extensive set of socioeconomic and contextual characteristics in mode choice models before evaluating transferability. They also identified the need to use consistent data (i.e., same measurement procedures, sampling procedures, variable definitions, questionnaire wording, etc.) in the estimation and application contexts to engage in any meaningful debates about the extent of model transferability. Their empirical analysis of the spatial transferability of mode choice models involved examining the intra-urban transferability of commute binary mode choice coefficients from two suburban areas in Sydney. The alternatives included car and rail. In addition to the usual level-of-service variables, the final specification used in the paper included variables representing gross annual individual income, number of licensed drivers in the household, and number of cars in the household. Their statistical tests reject parameter equality of the logit models in the two suburban regions though they find that a specification that normalized travel cost by income transferred relatively better than a specification that used a non-normalized travel-cost variable. However, in an evaluation of predictive ability at the mode share level, the simple transferred models without any updating performed quite adequately relative to the locally estimated model. They find a Bayesian transfer update approach to perform somewhat better than the approach without any updating and the approach that updates the constants/scale.

Koppelman and Wilmot (1982) focused on the intraregional transferability of a commute mode choice model for breadwinners who work in the central business district of Washington, D.C. They caution against the sole use of model parameter equality as an indicator of whether a model is transferable or not, indicating that model parameter equality is a symmetric property between two contexts, while transferability is a directional property. In their empirical analysis, they used disaggregate measures of transferability (transfer log-likelihood ratio, transfer log-likelihood index, and the transfer rho-squared) as well as aggregate measures of transferability (root mean square error and relative root mean square error). The data sample was partitioned into three groups based on three predetermined geographic sectors in the Washington, D.C. area, and model transferability was studied between the resulting three pairs of sectors. The alternatives included drive alone, shared ride, and transit, and the variables included in the specification are level-of-service variables, income, vehicles per driver, a government worker dummy variable, and the number of workers in the household. The results reject parameter equality across the models for the three pairs of sectors. Further, the disaggregate measures of transferability reject the hypothesis of intraurban transferability, even if the modal constants are adjusted to match the application area modal shares. However, the transferred models provide close to 80 percent of the information provided by local models, indicating that the extent of transferability is not bad at all from a nonstatistical perspective. Further, the transferred models perform quite well compared on the basis of aggregate modal share predictions. This seeming inconsistency between statistical tests and transfer errors is not uncommon, and the authors recommend that "although statistical tests can be used to alert the planner or analyst to differences between models, they must be considered with reference to the magnitude of errors that are acceptable in each application context."

Koppelman and Rose (1983) studied the intraregional transferability of a multinomial work mode choice model by partitioning the Baltimore region into a North sector and a South sector. The modal alternatives were drive alone, shared ride, and transit, while the independent variables included level-of-service variables as well as socioeconomic variables such as income and cars per driver. The results reject transferability based on parameter equality, disaggregate measures of transferability, and aggregate measures of transferability, though there is substantial improvement in the aggregate measures of prediction when the estimated model constants are adjusted based on the aggregate modal shares in the applicant region. The authors conducted a similar analysis of intraregional transferability of mode choice models from the Washington, D.C. area and Minneapolis-St. Paul, and found that the transfer performance is much better in these other urban areas relative to Baltimore. However, even in these other areas, intraregional transferability is rejected based on statistical tests.

Koppelman et al. (1985) examined the effectiveness of model updating using limited data from the application context on intraregional and interregional work travel mode choice transferability. Specifically, they studied the effect of updating alternative specific constants and the scale of the model. The data used for the intraregional transferability analysis were from Washington, D.C., with the same use of three sectors as defined in Koppelman and Wilmot (1982). The data used for interregional transferability were from Washington, D.C., Minneapolis-St. Paul, and Baltimore. The independent variables used included three level-of-service variables, a car per driver variable specific to the drive-alone and shared-ride alternatives, and modal constants. The same transferability measures as developed in Koppelman and Wilmot (1982) were used in evaluating transfer effectiveness. The results indicate that transferability is improved substantially when the constants are updated, and even more so when the constant and scale are updated. However, the returns from updating the constant and scale are not as high as with updating the constant only. This holds for both interregional and intraregional transferability.

Gunn et al. (1985) conducted a similar evaluation of the effect of model updating as Koppelman et al. (1985), using a joint system of mode, destination, and trip generation system (see discussion of this paper under Section B.1.1). Their results corroborate the findings of Koppelman et al. (1985) that updating constants and the scale leads to improved model transferability.

McComb (1986) assessed spatial transferability using data from a single "high-quality" data source (the transportation supplement of the Canadian Labor Force Data) for 10 cities in Canada. He used the same uniform model specification and consistent data collection and preparation across the cities and examined socioeconomic moderating effects of sensitivities to level-of-service variables. The work trip mode choice model developed for the City of Winnipeg was used as the estimation context, while the other cities were considered as the application contexts. Four modal alternatives were considered: drive alone, shared ride (driver and passenger), transit, and walk/other. The independent variables included level-of-service-variables, sex of individual, family income, age, work trip distance, and peak versus off-peak work start time. The author found that coefficient equality cannot be rejected between cities of similar socioeconomic make-up, size, and transportation system quality (such as Edmonton and Winnipeg, and Calgary and Winnipeg, at the time). However, coefficient equality was rejected for cities that are very different in character (such as Toronto and Winnipeg and Ottawa and Winnipeg).

Koppelman and Wilmot (1986) reported an analytic and empirical investigation of omission of variables on the spatial transferability of mode choice models using the same data set and procedures in Koppelman and Wilmot (1982). Three different specifications were considered to evaluate omitted variable effects on transferability, with each subsequent specification, including the variables in the earlier specification and new variables as follows: (1) three level-of-service variables and modal constants, (2) addition of cars per driver variables specific to drive alone and shared ride, and (3) addition of a government worker dummy variable and a number of workers in the household variable, both specific to the shared-ride mode. The results indicate substantial improvement in transferability with improved specifications, and with modal constant updating based on the aggregate share in the application context. The authors also indicate that models with only level-of-service variables and constants are unlikely to achieve adequate levels of transferability for practical use.

Koppelman and Pas (1986) also examined spatial transferability of a mode choice model using the Washington, D.C. data, but added a multidimensional element to the analysis. The main focus was on whether a nested logit model of auto ownership and mode choice is more or less transferable than a simpler joint multinomial logit model of auto ownership and mode choice. The nested logit model was estimated using a two-step sequential estimation approach, which can lead to a loss of efficiency. In the empirical analysis, the nested logit model's logsum parameter is not statistically significantly different from 1 at the 0.05 level of significance. The results show that the transferred models without updating are able to capture more than 85 percent of the information obtained from locally estimated models for both the multinomial and nested logit models, indicating that both these models are transferable across three sectors in the Washington, D.C. area. The multinomial logit model has a small advantage in the extent of transferability though this improvement over the nested logit model is marginal. However, this result is likely to be specific to the empirical context in the study, because the nested logit specification essentially collapsed to the multinomial logit specification for all the three sectors in the Washington, D.C. area. Further analysis is needed to examine the effect of model structure on transferability.

Abdelwahab (1991) examined spatial transferability of intercity mode choice models between two regions in Canada encompassing travel between 23 major metropolitan areas. He used the 1984 Canadian Travel Survey (CTS) in the analysis and geographically divided the 23 metropolitan areas into two regions: an eastern region, including Thunder Bay and cities east of Thunder Bay, and a western region, including Winnipeg and cities west of Winnipeg. The intercity travel in each of these regions was categorized based on trip length (short trips less than 600 miles and long trips) and purpose (recreational and business). The author used two transfer updating methods, one being the constant-only update scheme and the second being the Bayesian update method that updates all model coefficients. The independent variables used in the analysis are not provided in the paper. The results indicate that the transferred models explain about 50 to 93 percent of the information (i.e., the difference between the log-likelihood value at convergence and the log-likelihood value at market shares) provided by the locally estimated models. Overall, the findings indicate poor transferability, as measured by disaggregate predictive fit and aggregate error, for both updating methods considered.

Karasmaa (2001) explored the spatial transferability of work trip mode choice models in the Helsinki and Turku regions of Finland. The Helsinki region was used as the estimation context, and the Turku as the transfer context. Four transfer approaches were evaluated: transfer scaling with re-estimation of alternative-specific constants and the scale, Bayesian updating, combined transfer, and joint context estimation. The influence of the size of the estimation context data on transferability also was examined by using four different sample sizes for estimation of the Helsinki mode choice model using a 1995 mobility survey. The results show that the joint context estimation is generally the best method of transfer, especially when the estimated coefficients of the locally estimated models are quite different between the estimation and application contexts. The combined transfer estimation approach is best when there is a large estimation sample and the transfer bias is small between the estimation and application contexts.

All the above transferability studies were focused on a developed country setting. In contrast, Santoso and Tsunokawa (2005) examined spatial transferability in a developing country. Travel survey data from Ho Chi Minh City in Vietnam is used as the case study. A work trip mode choice model with three modes (walking, bicycling, and motorcycles) was estimated for the urban area of the city, and its transferability to the suburban area was assessed. The independent variables included level-of-service variables, sex of the individual, and the ratio of number of vehicles to the number of workers. They considered four updating procedures: updating of only the constants, updating of the constants and scale, Bayesian updating, and the combined transfer approach. The transferability results indicate that the Bayesian updating approach does not provide any tangible improvement over the simple transfer model (with no updating at all), while the other three methods do provide improvements. This result holds up for even small sizes of disaggregate data from the transfer context and is in contrast to the finding of Atherton and Ben-Akiva (1976). Among the remaining three approaches, the approaches involving updating of the constants and scale and the combined transfer approach are particularly effective. Interestingly, while Koppelman et al. (1985) find that the gain from updating the constants and scale is not as high as with updating the constants only, the current study finds substantial gains from updating both the constants and scale, with relatively small gains (compared to the simple transfer approach) when only the constants are updated.

B.3.2 Temporal Transferability

McCarthy (1982) examined the temporal transferability of work trip mode choice models in the San Francisco Bay area using before and after data sets associated with the Bay Area Rapid Transit (BART) study. The research was confined to only those individuals who did not change residences and employment locations in the pre-BART and post-BART samples. Data collected from November 1973 to April 1974 were used to develop a pre-BART sample (with only car and bus as the modes) as well as an immediate post-BART sample (BART was a viable mode). In addition, another short-run post-BART sample was collected in the fall of 1975 after the entire BART system became operational. The explanatory variables used in the analysis are the usual generic level-of-service variables as well as alternative-specific variables for family income, number of vehicles per driver, and a San Francisco employment dummy variable. The results show that the pre-BART binary choice model coefficients are stable in the post-BART data context. Next, a model with the pre-BART coefficients for generic variables, the car-specific coefficients from the pre-BART estimation, and freely estimated alternative-specific coefficients for the BART mode was developed from the immediate post-BART sample, and the transferability of this updated model to the sample from the fall of 1975 was examined. The results indicate that the coefficients are all stable, and a statistical test of coefficient equality can be marginally rejected at the 0.05 level of significance, but not at the 0.01 level of significance. Predictive success indices confirm the good temporal transferability of the updated mode choice model to the post-BART period.

Badoe and Miller (1995a) examined the temporal transferability of a morning peak work trip logit mode choice model in Toronto over the long-transfer period from 1964 to 1986. They also assessed if transferability was related with variable specification. The alternative modes in the analysis were auto driver, transit, and walk. The independent variables included level-of-service-variables as well as spatial, personal, and household characteristics of the commuter. In addition to a single pooled model, the authors also formulated 10 models to represent 10 mutually exclusive and homogeneous (in sensitivity to level-of-service variables) segments. Overall, statistical tests reject the hypothesis of equality of coefficients between the 1964 and 1986 estimations for all the pooled and market-segmented specifications. However, from a pragmatic perspective, the transferred models provide useful information in the application context. Specifically, the pooled models that were transferred provide at least as much as 76 percent of the log-likelihood improvement (over the constants-only log-likelihood) provided by locally estimated 1986 models. Updating the constants and scale increases this percentage to 84 percent. Improved model specifications, in general, provide better transferability, though the segmented model with 10 market segments did not perform well (suggesting overfitting in the estimation context).

Badoe and Miller (1995b) used the same data and approach as in Badoe and Miller (1995a) but focused on comparing the performance of alternative transfer updating schemes for different sample sizes of disaggregate data availability in the application (transfer) context and different model specifications. The joint context estimation and the combined transfer estimation procedure provide the best transferability results. If the estimation data sample is available, the authors recommend the joint context estimation over the combined transfer approach. The simple transfer scaling approach also provides a reasonable method for model transfer. However, the authors state that "the Bayesian approach cannot be recommended as an updating procedure." Finally, model specification improvements led to a substantial improvement in transferability.

Karasmaa and Pursula (1997) also examined the temporal transferability of mode choice models, but within the context of a joint mode-destination choice model. They found the transfer scaling approach to be best for simple models and large transfer biases (i.e., large differences in the locally estimated parameter values in the estimation and application contexts), the combined transfer approach to be best when the sample size in the application context is large and the transfer bias is small, and the joint context estimation and Bayesian update approaches to be best with small sample sizes in the application context.

B.3.3 Summary

There is substantial literature on work trip mode choice model transferability although much of it is focused on spatial transferability rather than temporal transferability. There does not appear to be any published literature on transferability for non-work mode choice.

The literature on work mode choice transferability in space and time is mixed. However, some general conclusions are as follows:

- Coefficient equality between the estimation and application contexts should not be used as the sole yardstick for

assessing transferability; rather disaggregate and aggregate prediction measures that provide an assessment of the amount of information provided by the transferred model also should be considered.
- Transferability improves with improved variable specification.
- Model updating leads to a substantial improvement in transferability relative to a simple model transfer, even if the updating is simply a constants-only updating to reflect the aggregate mode shares in the application context.
- There is no consensus regarding which update method is best, and it would behoove the analyst to consider all of the updating procedures that are possible in order to assess which performs best in any given context.

It is interesting to note that most of the mode choice transferability studies have been undertaken in the 1970s and 1980s, with significantly fewer studies undertaken recently. Also, while there has been substantial focus on tour-based mode choice and activity-based modeling in general in the past two decades, there does not appear to be any analysis of transferability in the context of tour-based mode choice modeling.

B.4 Conclusions

Overall, the literature provides mixed results regarding the effectiveness and validity of transferability though there also is a clear indication that transferability improves with a better variable specification and with a disaggregate-level model (at the individual or household level) in the estimation context (thus capturing more behavioral determinants that effectively get controlled for in the application context). The results also emphasize that, whenever possible, some level of model updating should be undertaken using local data collected in the application context. While the collection of a small disaggregate-level data set in the application context would allow model updating using any of the methods identified earlier in this document (and the analyst can compare alternative updating methods), the synthesis suggests that even simple updating procedures such as a constants-only updating scheme using aggregate travel data in the application context typically provide superior results than the simple (no-update) transfer approach.

However, it is recognized that even aggregate travel data may not be available in some application contexts, and there may not be resources available to collect such data prior to model transfer. In such instances, the results suggest that the simple transfer scheme should be accompanied by a careful selection of the "estimation" city, so that the "estimation" city is similar to the application city in terms of such factors as the distributions of household size, household auto ownership levels, employed individuals, household income, and population density. Further, it would be best to estimate travel models at a disaggregate level in the estimation context, and then apply the disaggregate-level model parameters using explanatory variable data from the application context to forecast travel.

If this is not possible, an alternative approach suggested by Hu et al. (2007) may be considered, which is based on using census tracts as the unit for transfer. Specifically, Hu et al. classify all census tracts in the country into one of 11 clusters based on a combination of household income, household buying power, geo-economic nature of tract (rural/suburban/urban/mega-urban/extreme-poverty), employment rates, life-cycle status, and number of household vehicles. For each cluster, a model is developed using households from the NHTS that are identified as belonging to that cluster. In application, each census tract of the application city is first classified into one of the 11 clusters. Then, for each census tract in the application city, the corresponding model estimated using the NHTS data is applied, with the exogenous variables for the tract extracted from census data. Travel statistics at the tract level (number of person trips by purpose per household, number of vehicle trips per household, PMT per household and VMT per household) are then converted to a traffic zone level using blocks as a linking mechanism. It should be noted, however, that this method does not provide spatial information on trips (origins and destinations of trips) and so may be of limited use for travel modeling. Further, these authors also emphasize the importance of local data collection in the application context.

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APPENDIX C

Transferable Parameters

Table C.1. Percentages of households by number of vehicles for U.S. metro areas.

Metro Area	Percent 0 Vehicle	Percent 1 Vehicle	Percent 2 Vehicle	Percent 3+ Vehicle
Provo-Orem, UT	2.7%	21.3%	44.2%	31.9%
Holland-Grand Haven, MI	2.9%	26.1%	45.8%	25.2%
St. George, UT	2.9%	29.4%	43.3%	24.4%
Coeur d'Alene, ID	3.0%	26.0%	40.4%	30.6%
Cheyenne, WY	3.4%	31.9%	34.1%	30.6%
Bend, OR	3.5%	25.5%	44.7%	26.3%
Lake Havasu City-Kingman, AZ	3.5%	34.7%	40.6%	21.2%
Fort Collins-Loveland, CO	3.6%	29.5%	42.0%	25.0%
Fort Walton Beach-Crestview-Destin, FL	3.6%	30.5%	43.3%	22.7%
Logan, UT-ID	3.6%	23.7%	41.5%	31.2%
Ogden-Clearfield, UT	3.9%	22.9%	43.7%	29.5%
Oxnard-Thousand Oaks-Ventura, CA	3.9%	26.7%	39.4%	30.0%
Boise City-Nampa, ID	4.0%	27.6%	42.6%	25.8%
Pocatello, ID	4.0%	27.1%	40.0%	28.9%
Rapid City, SD	4.0%	27.1%	39.6%	29.2%
Columbus, IN	4.2%	29.5%	38.7%	27.5%
Elizabethtown, KY	4.2%	30.9%	41.6%	23.4%
Mount Vernon-Anacortes, WA	4.2%	26.7%	39.1%	29.9%
Punta Gorda, FL	4.2%	42.1%	40.0%	13.7%
Fayetteville-Springdale-Rogers, AR-MO	4.3%	32.0%	43.4%	20.3%
Greeley, CO	4.3%	24.9%	40.6%	30.2%
Naples-Marco Island, FL	4.3%	42.6%	40.9%	12.2%
Palm Coast, FL	4.3%	35.2%	45.7%	14.8%
Prescott, AZ	4.3%	35.3%	38.4%	21.9%
San Luis Obispo-Paso Robles, CA	4.3%	30.1%	39.3%	26.3%
Abilene, TX	4.4%	36.3%	42.2%	17.1%
Casper, WY	4.4%	31.9%	36.7%	27.0%
Grand Junction, CO	4.4%	27.6%	40.0%	28.0%
Gulfport-Biloxi, MS	4.4%	34.0%	39.2%	22.3%
Huntsville, AL	4.4%	31.2%	39.0%	25.4%
Idaho Falls, ID	4.4%	23.9%	41.9%	29.9%
Monroe, MI	4.4%	27.9%	42.6%	25.0%
Santa Fe, NM	4.4%	31.4%	38.4%	25.7%
Appleton, WI	4.5%	28.3%	44.7%	22.5%
Jefferson City, MO	4.5%	30.0%	39.5%	26.0%
Palm Bay-Melbourne-Titusville, FL	4.5%	38.7%	40.8%	16.0%
Pascagoula, MS	4.5%	28.3%	41.7%	25.5%
Port St. Lucie, FL	4.5%	40.2%	39.6%	15.7%
Wausau, WI	4.6%	25.8%	43.9%	25.7%
Amarillo, TX	4.7%	34.3%	40.0%	21.0%
Bismarck, ND	4.7%	28.7%	36.0%	30.6%
Boulder, CO	4.7%	34.3%	40.7%	20.3%
Cleveland, TN	4.7%	29.2%	40.5%	25.6%
Killeen-Temple-Fort Hood, TX	4.7%	32.4%	43.9%	19.0%
Barnstable Town, MA	4.8%	35.3%	42.0%	17.9%
Colorado Springs, CO	4.8%	29.6%	42.5%	23.1%
Green Bay, WI	4.8%	30.2%	43.0%	21.9%
Lawrence, KS	4.8%	34.4%	38.5%	22.3%
Lewiston, ID-WA	4.8%	30.0%	36.7%	28.5%
Michigan City-La Porte, IN	4.8%	35.1%	39.4%	20.7%

Table C.1. (Continued).

Metro Area	Percent 0 Vehicle	Percent 1 Vehicle	Percent 2 Vehicle	Percent 3+ Vehicle
Morristown, TN	4.8%	28.4%	40.3%	26.5%
Ocala, FL	4.8%	43.1%	37.4%	14.7%
Raleigh-Cary, NC	4.8%	31.8%	42.7%	20.8%
Riverside-San Bernardino-Ontario, CA	4.8%	28.8%	39.0%	27.5%
Vallejo-Fairfield, CA	4.8%	29.0%	37.8%	28.5%
Dalton, GA	4.9%	37.7%	35.7%	21.6%
Janesville, WI	4.9%	32.0%	42.0%	21.1%
Orlando-Kissimmee, FL	4.9%	37.6%	41.1%	16.4%
Sherman-Denison, TX	5.0%	32.6%	41.1%	21.3%
Winchester, VA-WV	5.0%	27.7%	38.1%	29.2%
Cape Coral-Fort Myers, FL	5.1%	43.5%	38.7%	12.8%
Dallas-Fort Worth-Arlington, TX	5.1%	34.6%	42.0%	18.3%
Farmington, NM	5.1%	31.1%	38.4%	25.4%
Midland, TX	5.1%	31.5%	42.9%	20.5%
Decatur, AL	5.2%	27.7%	39.5%	27.6%
Des Moines-West Des Moines, IA	5.2%	30.6%	42.2%	22.1%
Hattiesburg, MS	5.2%	34.0%	38.6%	22.2%
Jacksonville, NC	5.2%	31.5%	41.0%	22.3%
Nashville-Davidson-Murfreesboro-Franklin, TN	5.2%	32.0%	39.5%	23.2%
Olympia, WA	5.2%	29.3%	38.5%	27.1%
Panama City-Lynn Haven, FL	5.2%	34.8%	41.8%	18.2%
St. Cloud, MN	5.2%	26.6%	42.4%	25.8%
Salt Lake City, UT	5.2%	28.6%	40.9%	25.4%
San Jose-Sunnyvale-Santa Clara, CA	5.2%	29.0%	40.9%	24.9%
Santa Rosa-Petaluma, CA	5.2%	30.0%	39.8%	25.0%
Wenatchee, WA	5.2%	27.3%	42.0%	25.5%
Anchorage, AK	5.3%	31.4%	41.0%	22.3%
Auburn-Opelika, AL	5.3%	35.3%	36.6%	22.8%
Austin-Round Rock, TX	5.3%	35.8%	42.2%	16.7%
Bloomington-Normal, IL	5.3%	33.6%	42.9%	18.2%
Indianapolis-Carmel, IN	5.3%	33.5%	41.3%	20.0%
Lincoln, NE	5.3%	33.3%	39.0%	22.4%
Oklahoma City, OK	5.3%	34.3%	40.8%	19.5%
Rochester, MN	5.3%	29.0%	43.0%	22.7%
Billings, MT	5.4%	28.2%	39.6%	26.7%
Bradenton-Sarasota-Venice, FL	5.4%	45.4%	37.3%	11.9%
Eau Claire, WI	5.4%	29.5%	40.9%	24.1%
Kennewick-Pasco-Richland, WA	5.4%	26.8%	36.8%	30.9%
Manchester-Nashua, NH	5.4%	28.9%	43.9%	21.8%
Myrtle Beach-North Myrtle Beach-Conway, SC	5.4%	36.9%	42.0%	15.7%
Bremerton-Silverdale, WA	5.5%	29.1%	38.7%	26.7%
Burlington-South Burlington, VT	5.5%	33.6%	42.0%	19.0%
Deltona-Daytona Beach-Ormond Beach, FL	5.5%	42.0%	37.5%	15.0%
Fort Wayne, IN	5.5%	32.6%	41.2%	20.7%
Gainesville, GA	5.5%	27.9%	41.1%	25.5%
Grand Forks, ND-MN	5.5%	31.7%	42.6%	20.1%
Hickory-Lenoir-Morganton, NC	5.5%	29.2%	36.8%	28.5%
Knoxville, TN	5.5%	33.6%	39.3%	21.6%
Longview, TX	5.5%	33.8%	40.0%	20.7%
Missoula, MT	5.5%	31.8%	40.4%	22.2%

(continued on next page)

Table C.1. (Continued).

Metro Area	Percent 0 Vehicle	Percent 1 Vehicle	Percent 2 Vehicle	Percent 3+ Vehicle
Odessa, TX	5.5%	32.4%	39.4%	22.7%
Sioux Falls, SD	5.5%	28.5%	41.9%	24.1%
Topeka, KS	5.5%	31.1%	38.1%	25.3%
Florence-Muscle Shoals, AL	5.6%	29.5%	37.3%	27.6%
Lubbock, TX	5.6%	36.5%	40.3%	17.7%
Wichita, KS	5.6%	31.5%	39.1%	23.8%
Yakima, WA	5.6%	26.5%	37.0%	30.8%
Ames, IA	5.7%	30.4%	43.6%	20.4%
Charlotte-Gastonia-Concord, NC-SC	5.7%	33.4%	40.8%	20.2%
Columbia, MO	5.7%	33.1%	41.2%	19.9%
Flagstaff, AZ	5.7%	31.8%	39.6%	22.9%
Lakeland-Winter Haven, FL	5.7%	40.4%	38.7%	15.2%
Madera, CA	5.7%	28.6%	38.4%	27.2%
San Angelo, TX	5.7%	37.3%	38.9%	18.1%
Tyler, TX	5.7%	33.4%	40.6%	20.3%
Yuba City, CA	5.7%	27.4%	40.5%	26.5%
Burlington, NC	5.8%	32.1%	38.0%	24.1%
Cedar Rapids, IA	5.8%	30.8%	40.2%	23.2%
Clarksville, TN-KY	5.8%	29.3%	42.5%	22.5%
Grand Rapids-Wyoming, MI	5.8%	32.1%	41.8%	20.3%
Kansas City, MO-KS	5.8%	32.3%	40.7%	21.2%
Las Cruces, NM	5.8%	31.7%	37.4%	25.1%
Medford, OR	5.8%	32.7%	39.4%	22.2%
Wichita Falls, TX	5.8%	33.7%	41.6%	19.0%
Albuquerque, NM	5.9%	34.3%	38.8%	21.0%
Asheville, NC	5.9%	32.1%	38.9%	23.1%
Little Rock-North Little Rock-Conway, AR	5.9%	34.4%	41.4%	18.4%
Oshkosh-Neenah, WI	5.9%	32.5%	42.2%	19.4%
Santa Cruz-Watsonville, CA	5.9%	29.0%	39.0%	26.0%
Springfield, MO	5.9%	33.3%	41.1%	19.6%
Warner Robins, GA	5.9%	32.3%	36.9%	24.9%
Ann Arbor, MI	6.0%	36.0%	40.2%	17.8%
Atlanta-Sandy Springs-Marietta, GA	6.0%	33.0%	40.2%	20.9%
Gadsden, AL	6.0%	30.3%	38.7%	24.9%
Johnson City, TN	6.0%	31.9%	37.0%	25.0%
Napa, CA	6.0%	29.5%	39.0%	25.5%
Pensacola-Ferry Pass-Brent, FL	6.0%	33.6%	41.3%	19.1%
Phoenix-Mesa-Scottsdale, AZ	6.0%	37.5%	39.6%	17.0%
Racine, WI	6.0%	32.9%	41.7%	19.4%
Sebastian-Vero Beach, FL	6.0%	41.6%	40.5%	11.9%
Tulsa, OK	6.0%	33.4%	39.8%	20.8%
York-Hanover, PA	6.0%	27.7%	41.2%	25.2%
Yuma, AZ	6.0%	41.4%	35.4%	17.2%
Anniston-Oxford, AL	6.1%	31.0%	38.7%	24.2%
Dothan, AL	6.1%	35.2%	37.4%	21.3%
Fort Smith, AR-OK	6.1%	33.8%	39.5%	20.6%
Iowa City, IA	6.1%	34.8%	39.6%	19.5%
Lansing-East Lansing, MI	6.1%	35.0%	39.6%	19.3%
Norwich-New London, CT	6.1%	30.9%	40.4%	22.6%
Omaha-Council Bluffs, NE-IA	6.1%	31.3%	40.8%	21.7%

Table C.1. (Continued).

Metro Area	Percent 0 Vehicle	Percent 1 Vehicle	Percent 2 Vehicle	Percent 3+ Vehicle
Portland-South Portland-Biddeford, ME	6.1%	31.9%	42.7%	19.3%
Sacramento-Arden-Arcade-Roseville, CA	6.1%	31.6%	39.9%	22.4%
Sioux City, IA-NE-SD	6.1%	31.0%	40.0%	23.0%
Anderson, SC	6.2%	29.7%	38.6%	25.5%
Brunswick, GA	6.2%	33.1%	39.5%	21.3%
Carson City, NV	6.2%	34.5%	34.3%	25.0%
Columbia, SC	6.2%	32.3%	39.2%	22.2%
Dover, DE	6.2%	31.2%	41.2%	21.4%
Fond du Lac, WI	6.2%	29.6%	41.9%	22.3%
Greenville-Mauldin-Easley, SC	6.2%	32.8%	39.1%	21.9%
Houston-Sugar Land-Baytown, TX	6.2%	34.9%	41.3%	17.6%
Tallahassee, FL	6.2%	36.2%	38.4%	19.1%
Waterloo-Cedar Falls, IA	6.2%	30.0%	39.0%	24.8%
Davenport-Moline-Rock Island, IA-IL	6.3%	33.7%	39.7%	20.4%
Jacksonville, FL	6.3%	35.1%	41.4%	17.2%
Morgantown, WV	6.3%	38.5%	38.5%	16.8%
San Diego-Carlsbad-San Marcos, CA	6.3%	32.0%	39.4%	22.4%
Birmingham-Hoover, AL	6.4%	31.5%	38.0%	24.1%
College Station-Bryan, TX	6.4%	36.4%	38.9%	18.2%
Fairbanks, AK	6.4%	30.4%	38.0%	25.2%
Kingsport-Bristol-Bristol, TN-VA	6.4%	29.2%	39.1%	25.3%
Madison, WI	6.4%	34.0%	41.4%	18.1%
Niles-Benton Harbor, MI	6.4%	36.5%	37.7%	19.4%
Springfield, IL	6.4%	37.9%	37.6%	18.1%
Terre Haute, IN	6.4%	33.1%	38.8%	21.7%
Valdosta, GA	6.4%	33.0%	38.9%	21.7%
Athens-Clarke County, GA	6.5%	32.9%	34.9%	25.7%
Bellingham, WA	6.5%	32.0%	39.0%	22.4%
Blacksburg-Christiansburg-Radford, VA	6.5%	31.2%	36.2%	26.1%
Jackson, MS	6.5%	34.1%	37.5%	21.9%
Joplin, MO	6.5%	31.7%	40.0%	21.7%
Modesto, CA	6.5%	28.8%	39.3%	25.4%
Reno-Sparks, NV	6.5%	32.3%	38.0%	23.2%
Salinas, CA	6.5%	32.0%	36.3%	25.3%
Santa Barbara-Santa Maria-Goleta, CA	6.5%	33.3%	37.0%	23.2%
Sheboygan, WI	6.5%	31.7%	40.2%	21.6%
South Bend-Mishawaka, IN-MI	6.5%	34.7%	39.7%	19.1%
Stockton, CA	6.5%	29.5%	37.4%	26.6%
Tampa-St. Petersburg-Clearwater, FL	6.5%	42.3%	38.3%	13.0%
Virginia Beach-Norfolk-Newport News, VA-NC	6.5%	31.2%	38.7%	23.6%
Bloomington, IN	6.6%	34.4%	37.0%	22.0%
Bowling Green, KY	6.6%	33.5%	38.0%	21.9%
Denver-Aurora, CO	6.6%	33.1%	39.7%	20.6%
Jonesboro, AR	6.6%	33.5%	40.6%	19.2%
Visalia-Porterville, CA	6.6%	31.3%	39.5%	22.6%
Wilmington, NC	6.6%	32.3%	40.7%	20.4%
Charlottesville, VA	6.7%	31.3%	38.3%	23.8%
Hinesville-Fort Stewart, GA	6.7%	34.8%	37.4%	21.0%
Kalamazoo-Portage, MI	6.7%	33.8%	40.1%	19.4%
Peoria, IL	6.7%	32.3%	40.9%	20.0%

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Table C.1. (Continued).

Metro Area	Percent 0 Vehicle	Percent 1 Vehicle	Percent 2 Vehicle	Percent 3+ Vehicle
Waco, TX	6.7%	35.1%	40.9%	17.2%
Canton-Massillon, OH	6.8%	32.3%	39.1%	21.8%
Chattanooga, TN-GA	6.8%	31.3%	38.9%	23.0%
Columbus, OH	6.8%	34.2%	39.7%	19.4%
Greensboro-High Point, NC	6.8%	32.9%	36.6%	23.7%
Hagerstown-Martinsburg, MD-WV	6.8%	28.6%	39.5%	25.1%
Longview, WA	6.8%	28.5%	37.4%	27.2%
Roanoke, VA	6.8%	31.1%	36.6%	25.5%
Rockford, IL	6.8%	32.9%	39.9%	20.3%
Salem, OR	6.8%	31.8%	39.1%	22.3%
Fayetteville, NC	6.9%	33.3%	37.9%	22.0%
Hanford-Corcoran, CA	6.9%	30.7%	39.0%	23.4%
Kingston, NY	6.9%	32.5%	39.1%	21.4%
Owensboro, KY	6.9%	32.1%	38.4%	22.6%
Redding, CA	6.9%	29.2%	39.1%	24.8%
Spokane, WA	6.9%	31.0%	37.8%	24.3%
Akron, OH	7.0%	34.4%	39.3%	19.3%
Bangor, ME	7.0%	32.6%	40.9%	19.5%
Hot Springs, AR	7.0%	38.2%	38.6%	16.2%
La Crosse, WI-MN	7.0%	30.2%	42.3%	20.4%
Lafayette, IN	7.0%	34.0%	40.0%	19.0%
Lawton, OK	7.0%	33.5%	38.8%	20.8%
Lexington-Fayette, KY	7.0%	34.5%	39.9%	18.6%
Minneapolis-St. Paul-Bloomington, MN-WI	7.0%	31.1%	41.7%	20.2%
Richmond, VA	7.0%	29.8%	36.6%	26.6%
Spartanburg, SC	7.0%	32.1%	37.3%	23.5%
Winston-Salem, NC	7.0%	31.7%	37.2%	24.2%
Baton Rouge, LA	7.1%	35.8%	39.8%	17.3%
Bay City, MI	7.1%	31.5%	40.5%	20.9%
Chico, CA	7.1%	31.8%	37.7%	23.3%
Fargo, ND-MN	7.1%	31.4%	40.8%	20.7%
Gainesville, FL	7.1%	41.4%	35.1%	16.5%
Jackson, MI	7.1%	30.9%	41.4%	20.6%
Lake Charles, LA	7.1%	36.6%	39.1%	17.3%
Montgomery, AL	7.1%	34.5%	35.4%	22.9%
St. Joseph, MO-KS	7.1%	32.0%	37.8%	23.1%
Seattle-Tacoma-Bellevue, WA	7.1%	32.7%	37.7%	22.5%
Glens Falls, NY	7.2%	35.4%	39.5%	17.9%
Lebanon, PA	7.2%	31.1%	39.5%	22.2%
Mobile, AL	7.2%	34.2%	37.1%	21.5%
Texarkana, TX-Texarkana, AR	7.2%	34.5%	38.6%	19.8%
Victoria, TX	7.2%	32.6%	42.3%	17.9%
Beaumont-Port Arthur, TX	7.3%	35.0%	40.3%	17.4%
Dubuque, IA	7.3%	29.4%	43.1%	20.1%
Kokomo, IN	7.3%	29.2%	41.5%	22.0%
Springfield, OH	7.3%	33.1%	36.6%	23.1%
Youngstown-Warren-Boardman, OH-PA	7.3%	36.2%	38.1%	18.4%
Anderson, IN	7.4%	34.6%	37.8%	20.2%
Augusta-Richmond County, GA-SC	7.4%	33.7%	37.4%	21.5%
Durham, NC	7.4%	35.7%	36.0%	20.9%

Table C.1. (Continued).

Metro Area	Percent 0 Vehicle	Percent 1 Vehicle	Percent 2 Vehicle	Percent 3+ Vehicle
Evansville, IN-KY	7.4%	31.7%	38.5%	22.3%
Harrisonburg, VA	7.4%	26.4%	35.8%	30.5%
Las Vegas-Paradise, NV	7.4%	38.0%	39.0%	15.7%
St. Louis, MO-IL	7.4%	33.5%	39.2%	19.8%
Allentown-Bethlehem-Easton, PA-NJ	7.5%	30.4%	40.4%	21.7%
Bakersfield, CA	7.5%	30.6%	38.4%	23.5%
Dayton, OH	7.5%	33.6%	38.5%	20.4%
Flint, MI	7.5%	36.9%	37.7%	18.0%
Sandusky, OH	7.5%	31.5%	40.5%	20.5%
Harrisburg-Carlisle, PA	7.6%	32.8%	39.4%	20.2%
Lynchburg, VA	7.6%	29.0%	35.0%	28.4%
Muskegon-Norton Shores, MI	7.6%	34.1%	37.2%	21.1%
Pueblo, CO	7.6%	31.5%	37.2%	23.8%
Worcester, MA	7.6%	33.5%	41.1%	17.8%
Battle Creek, MI	7.7%	35.5%	39.3%	17.5%
Monroe, LA	7.7%	39.4%	37.0%	15.9%
Parkersburg-Marietta-Vienna, WV-OH	7.7%	33.6%	37.6%	21.2%
Poughkeepsie-Newburgh-Middletown, NY	7.7%	29.1%	40.4%	22.8%
Saginaw-Saginaw Township North, MI	7.7%	34.6%	39.1%	18.6%
San Antonio, TX	7.7%	34.9%	38.7%	18.8%
Savannah, GA	7.7%	34.5%	39.9%	18.0%
Charleston-North Charleston-Summerville, SC	7.8%	34.2%	39.3%	18.7%
Great Falls, MT	7.8%	27.7%	35.4%	29.0%
Alexandria, LA	7.9%	35.3%	39.2%	17.6%
Goldsboro, NC	7.9%	31.7%	36.0%	24.4%
Lima, OH	7.9%	30.6%	38.8%	22.7%
Muncie, IN	7.9%	33.1%	37.8%	21.2%
Portland-Vancouver-Beaverton, OR-WA	7.9%	32.5%	38.9%	20.7%
Detroit-Warren-Livonia, MI	8.0%	35.3%	38.4%	18.4%
Elkhart-Goshen, IN	8.0%	30.4%	40.7%	21.0%
Houma-Bayou Cane-Thibodaux, LA	8.0%	32.5%	42.3%	17.2%
Kankakee-Bradley, IL	8.0%	33.4%	39.2%	19.4%
Louisville-Jefferson County, KY-IN	8.0%	33.5%	38.3%	20.3%
Corpus Christi, TX	8.1%	36.7%	39.1%	16.2%
Jackson, TN	8.1%	31.7%	37.5%	22.8%
McAllen-Edinburg-Mission, TX	8.1%	39.7%	35.4%	16.8%
Hartford-West Hartford-East Hartford, CT	8.2%	31.8%	40.1%	19.8%
Lafayette, LA	8.2%	34.2%	41.8%	15.8%
Tucson, AZ	8.2%	39.6%	35.7%	16.5%
Bridgeport-Stamford-Norwalk, CT	8.3%	30.0%	39.5%	22.2%
Rome, GA	8.3%	31.9%	38.2%	21.6%
Toledo, OH	8.3%	35.1%	38.4%	18.1%
Cincinnati-Middletown, OH-KY-IN	8.4%	31.4%	38.5%	21.7%
Corvallis, OR	8.4%	31.8%	37.7%	22.0%
Los Angeles-Long Beach-Santa Ana, CA	8.4%	33.5%	36.7%	21.4%
New Orleans-Metairie-Kenner, LA	8.4%	36.9%	38.7%	15.9%
Duluth, MN-WI	8.5%	32.6%	36.3%	22.5%
Eugene-Springfield, OR	8.5%	32.7%	37.4%	21.4%
Memphis, TN-MS-AR	8.5%	36.7%	36.3%	18.5%
Miami-Fort Lauderdale-Pompano Beach, FL	8.5%	40.4%	37.0%	14.1%

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Table C.1. (Continued).

Metro Area	Percent 0 Vehicle	Percent 1 Vehicle	Percent 2 Vehicle	Percent 3+ Vehicle
Reading, PA	8.5%	29.9%	39.1%	22.4%
Florence, SC	8.6%	33.0%	36.3%	22.0%
Greenville, NC	8.6%	35.1%	35.5%	20.8%
Sumter, SC	8.6%	34.0%	37.1%	20.2%
Fresno, CA	8.7%	33.0%	37.9%	20.4%
Mansfield, OH	8.7%	30.2%	39.6%	21.6%
State College, PA	8.7%	34.4%	38.6%	18.3%
Tuscaloosa, AL	8.7%	31.2%	38.4%	21.7%
El Paso, TX	8.9%	34.0%	38.1%	19.1%
Ocean City, NJ	8.9%	36.7%	38.9%	15.4%
Albany-Schenectady-Troy, NY	9.0%	35.1%	40.0%	16.0%
Champaign-Urbana, IL	9.0%	37.4%	36.7%	16.8%
Decatur, IL	9.0%	35.6%	37.9%	17.5%
Merced, CA	9.0%	29.4%	38.4%	23.2%
Salisbury, MD	9.0%	32.7%	35.2%	23.2%
Altoona, PA	9.1%	33.9%	37.8%	19.1%
Elmira, NY	9.1%	35.5%	39.5%	15.9%
Providence-New Bedford-Fall River, RI-MA	9.2%	35.2%	37.5%	18.2%
Binghamton, NY	9.3%	35.4%	38.1%	17.2%
Macon, GA	9.3%	33.6%	34.4%	22.6%
Shreveport-Bossier City, LA	9.3%	37.9%	37.2%	15.6%
Weirton-Steubenville, WV-OH	9.3%	34.6%	36.9%	19.2%
Rochester, NY	9.4%	33.7%	40.1%	16.8%
Rocky Mount, NC	9.4%	31.5%	33.3%	25.8%
Williamsport, PA	9.4%	32.9%	37.3%	20.5%
Danville, IL	9.5%	34.4%	37.0%	19.0%
Pittsfield, MA	9.5%	39.0%	37.2%	14.3%
Erie, PA	9.6%	37.4%	38.1%	14.9%
Laredo, TX	9.6%	36.5%	35.6%	18.4%
Washington-Arlington-Alexandria, DC-VA-MD-WV	9.6%	33.6%	36.0%	20.9%
Lewiston-Auburn, ME	9.7%	34.6%	36.5%	19.2%
Milwaukee-Waukesha-West Allis, WI	9.7%	35.5%	38.7%	16.2%
Huntington-Ashland, WV-KY-OH	9.8%	33.1%	37.7%	19.5%
Lancaster, PA	9.8%	29.6%	40.9%	19.7%
Cumberland, MD-WV	9.9%	31.1%	36.1%	22.9%
Pine Bluff, AR	9.9%	34.4%	35.1%	20.5%
Scranton-Wilkes-Barre, PA	10.0%	35.7%	36.7%	17.6%
Brownsville-Harlingen, TX	10.1%	40.2%	35.1%	14.6%
Cleveland-Elyria-Mentor, OH	10.3%	36.2%	36.6%	16.9%
Honolulu, HI	10.3%	34.6%	35.0%	20.1%
Syracuse, NY	10.4%	35.9%	38.4%	15.2%
Albany, GA	10.5%	36.0%	32.8%	20.7%
Charleston, WV	10.5%	36.0%	37.3%	16.2%
Columbus, GA-AL	10.5%	35.5%	34.2%	19.9%
New Haven-Milford, CT	10.5%	33.7%	36.7%	19.1%
Utica-Rome, NY	10.5%	35.8%	37.9%	15.8%
Wheeling, WV-OH	10.5%	34.7%	35.7%	19.1%
Springfield, MA	10.6%	37.8%	36.5%	15.2%
Johnstown, PA	10.7%	34.5%	37.0%	17.8%
El Centro, CA	11.0%	33.1%	34.3%	21.6%

Table C.1. (Continued).

Metro Area	Percent 0 Vehicle	Percent 1 Vehicle	Percent 2 Vehicle	Percent 3+ Vehicle
Trenton-Ewing, NJ	11.0%	32.5%	39.2%	17.2%
Vineland-Millville-Bridgeton, NJ	11.1%	34.4%	35.4%	19.1%
Baltimore-Towson, MD	11.2%	32.4%	36.4%	19.9%
Pittsburgh, PA	11.2%	35.6%	37.3%	16.0%
Danville, VA	11.3%	32.1%	29.9%	26.6%
Chicago-Naperville-Joliet, IL-IN-WI	11.5%	35.1%	36.8%	16.6%
San Francisco-Oakland-Fremont, CA	11.8%	34.2%	34.2%	19.8%
Ithaca, NY	12.3%	38.4%	35.2%	14.0%
Buffalo-Niagara Falls, NY	12.6%	38.0%	36.3%	13.2%
Boston-Cambridge-Quincy, MA-NH	12.7%	35.0%	37.0%	15.3%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	13.7%	34.4%	35.9%	16.0%
Atlantic City-Hammonton, NJ	13.9%	34.2%	36.6%	15.4%
Fajardo, PR	19.7%	45.4%	28.3%	6.6%
San Germán-Cabo Rojo, PR	19.7%	40.3%	30.2%	9.8%
Yauco, PR	20.1%	43.5%	28.2%	8.2%
Aguadilla-Isabela-San Sebastián, PR	20.3%	42.4%	27.6%	9.8%
San Juan-Caguas-Guaynabo, PR	20.5%	40.6%	29.0%	9.9%
Guayama, PR	22.1%	43.4%	26.8%	7.8%
Mayagüez, PR	23.5%	41.6%	25.0%	10.0%
Ponce, PR	24.0%	40.4%	26.4%	9.2%
New York-Northern New Jersey-Long Island, NY-NJ-PA	30.3%	32.2%	25.8%	11.7%

Note: Metro areas are ordered by percentage of zero-vehicle households, from lowest to highest.
Source: U.S. Census Bureau American Community Survey data set for 2006–2008 (http://www.census.gov/acs/).

Table C.2. Coefficients for four U.S. logit vehicle availability models.

One-Vehicle Household Utilities

	Model			
	1	2	3	4
Alternative Specific Constant	1.21	1.58	0.64	0.16
0 Workers in Household	0.95			
1 Worker in Household	1.99		0.83	0.79
2 Workers in Household	1.43			1.46
2+ Workers in Household			0.54	
3+ Workers in Household				0.65
Low Income	-1.18			-0.90
Low-Medium Income		1.84	1.16	0.53
High-Medium Income		2.54	0.87	1.93
High Income		0.72	1.78	2.30
1 Person in Household	-0.39			-0.15
2 Persons in Household	0.009			0.50
3 Persons in Household				
4+ Persons in Household				
Percent Regional Employment within 15 Min Transit			-0.03	
Percent Regional Employment within 40 Min Transit				-0.10
Employment within 30 Min Transit	-0.000012			
Accessibility Ratio		0.06		
Population Density per Acre	0.02			

Source: MPO Documentation Database.

Table C.3. Coefficients for four U.S. logit vehicle availability models.

Two-Vehicle Household Utilities

	Model			
	1	**2**	**3**	**4**
Alternative Specific Constant	3.23	-1.90	-0.45	4.21
0 Workers in Household	0.63			
1 Worker in Household	1.72		1.10	-1.02
2 Workers in Household	1.71			0.32
2+ Workers in Household			2.47	
3+ Workers in Household				0.52
Low Income	-2.20			-4.06
Low-Medium Income		2.78	2.18	-1.85
High-Medium Income		4.30	3.04	0.38
High Income		2.97	4.31	1.76
1 Person in Household	-2.77			-2.84
2 Persons in Household	-0.56	3.15		0.42
3 Persons in Household	-0.32	3.02		0.24
4+ Persons in Household	-0.29	3.41		
Percent Regional Employment within 15 Min Transit			-0.08	
Percent Regional Employment within 40 Min Transit				-0.17
Employment within 30 Min Transit	-0.000020			
Accessibility Ratio		0.089		
Population Density per Acre	-0.028			-0.064

Source: MPO Documentation Database.

Table C.4. Coefficients for four U.S. logit vehicle availability models.

Three-or-More-Vehicle Household Utilities

	Model			
	1	2	3	4
Alternative Specific Constant	4.29	-12.38	-2.29	5.18
0 Workers in Household	-1.00			
1 Worker in Household			1.66	-3.78
2 Workers in Household				-2.15
2+ Workers in Household			3.32	
3+ Workers in Household				-1.98
Low Income	-2.73			-4.06
Low-Medium Income		3.04	2.26	-2.45
High-Medium Income		4.88	3.64	
High Income		3.59	5.28	1.76
1 Person in Household	-3.36			-2.84
2 Persons in Household	-1.00	3.09		-0.61
3 Persons in Household		4.14		
4+ Persons in Household		4.35		
Percent Regional Employment within 15 Min Transit			-0.12	
Percent Regional Employment within 40 Min Transit				-0.17
Employment within 30 Min Transit	-0.000020			
Accessibility Ratio		0.12		
Population Density per Acre	-0.052			-0.128

Source: MPO Documentation Database.

Table C.5. Home-based work trip rates.

Number of Workers by Number of Autos

	Workers				
Autos	**0**	**1**	**2**	**3+**	**Average**
0	0.0	1.0	2.4	5.1	**0.5**
1	0.0	1.0	2.6	5.1	**0.8**
2	0.0	1.3	2.6	5.1	**1.6**
3+	0.0	1.3	2.6	5.1	**2.3**
Average	**0.0**	**1.2**	**2.6**	**5.1**	**1.4**

Number of Persons by Number of Autos

	Persons					
Autos	**1**	**2**	**3**	**4**	**5+**	**Average**
0	0.2	0.7	1.0	1.0	1.0	**0.5**
1	0.6	0.8	1.2	1.7	1.5	**0.8**
2	0.7	1.3	2.0	2.0	2.3	**1.6**
3+	0.9	1.4	2.6	2.9	3.3	**2.3**
Average	**0.5**	**1.2**	**2.0**	**2.3**	**2.4**	**1.4**

Number of Persons by Income Level

	Persons					
Household Income	**1**	**2**	**3**	**4**	**5+**	**Average**
i	0.2	0.6	0.8	1.3	1.8	**0.6**
ii	0.3	0.8	1.5	1.6	2.0	**0.8**
iii	0.7	1.0	1.8	2.3	2.6	**1.3**
iv	0.8	1.5	2.4	2.4	2.6	**1.9**
v	0.9	1.6	2.4	2.4	2.6	**2.0**
Average	**0.5**	**1.2**	**2.0**	**2.3**	**2.4**	**1.4**

Note: All averages are weighted.
Source: 2009 NHTS.

Table C.6. Home-based nonwork trip rates.

Number of Persons by Number of Workers, Urban Area Greater Than 500,000 Population

	Household Size					
Workers	**1**	**2**	**3**	**4**	**5+**	**Average**
0	1.8	4.0	5.6	9.2	10.5	**3.5**
1	1.8	4.0	6.6	9.9	12.4	**4.9**
2		4.0	7.0	11.4	14.5	**7.9**
3+			7.0	11.4	14.5	**10.8**
Average	**1.8**	**4.0**	**6.7**	**10.6**	**13.4**	**5.6**

Number of Persons by Number of Workers, Urban Area Less Than 500,000 Population (Including Non-Urban Areas)

	Household Size					
Workers	**1**	**2**	**3**	**4**	**5+**	**Average**
0	1.8	3.6	5.6	8.1	8.8	**3.4**
1	1.8	3.6	6.7	8.7	11.8	**4.6**
2		3.6	6.7	10.1	14.4	**6.8**
3+			6.7	11.2	15.3	**10.8**
Average	**1.8**	**3.6**	**6.7**	**9.5**	**12.9**	**5.1**

Number of Persons by Number of Vehicles, Urban Area Greater Than 500,000 Population

	Household Size					
Vehicles	**1**	**2**	**3**	**4**	**5+**	**Average**
0	1.4	3.8	5.6	7.5	10.0	**3.2**
1	1.9	3.9	6.5	9.0	11.8	**3.7**
2	2.4	4.0	6.5	11.0	14.0	**6.8**
3+	2.5	4.0	7.3	11.0	14.5	**8.6**
Average	**1.8**	**4.0**	**6.7**	**10.6**	**13.4**	**5.6**

Table C.6. (Continued).

Number of Persons by Number of Vehicles, Urban Area Less Than 500,000 Population (Including Non-Urban Areas)

	Household Size					
Vehicles	**1**	**2**	**3**	**4**	**5+**	**Average**
0	1.2	3.3	5.1	8.1	10.3	**2.6**
1	1.9	3.6	6.7	9.5	10.3	**3.5**
2	2.0	3.6	6.7	9.5	12.1	**5.6**
3+	2.0	3.6	6.7	9.5	14.7	**6.9**
Average	**1.8**	**3.6**	**6.7**	**9.5**	**12.9**	**5.1**

Number of Persons by Income Level, Urban Area Greater Than 500,000 Population

	Household Size					
Household Income	**1**	**2**	**3**	**4**	**5+**	**Average**
i	1.7	3.7	5.0	9.1	11.5	**4.1**
ii	1.7	4.1	6.0	9.9	11.5	**4.7**
iii	1.9	4.1	6.9	9.9	13.1	**5.0**
iv	2.0	4.1	6.9	10.4	14.7	**6.2**
v	2.3	4.1	7.1	11.8	15.4	**7.6**
Average	**1.8**	**4.0**	**6.7**	**10.6**	**13.4**	**5.6**

Number of Persons by Income Level, Urban Area Less Than 500,000 Population (Including Non-Urban Areas)

	Household Size					
Household Income	**1**	**2**	**3**	**4**	**5+**	**Average**
i	1.4	3.2	5.1	7.9	7.5	**3.3**
ii	1.9	3.4	6.8	8.9	11.9	**4.1**
iii	1.9	3.7	6.8	8.9	12.4	**4.9**
iv	1.9	3.7	6.8	10.0	14.1	**6.2**
v	2.2	3.7	7.3	10.1	14.8	**7.0**
Average	**1.8**	**3.6**	**6.7**	**9.5**	**12.9**	**5.1**

Note: All averages are weighted.
Source: 2009 NHTS.

Table C.7. Nonhome-based trip rates.

Number of Persons by Number of Workers

	Household Size					
Workers	**1**	**2**	**3**	**4**	**5+**	**Average**
0	0.9	1.8	2.7	3.1	3.1	**1.5**
1	1.6	2.4	3.3	4.7	5.0	**2.7**
2		3.2	4.5	5.9	6.1	**4.5**
3+			4.8	7.0	8.1	**6.7**
Average	**1.3**	**2.5**	**3.8**	**5.3**	**5.7**	**3.0**

Number of Persons by Number of Vehicles

	Household Size					
Vehicles	**1**	**2**	**3**	**4**	**5+**	**Average**
0	0.7	1.7	2.0	3.7	3.9	**1.3**
1	1.4	2.3	3.5	3.9	3.9	**2.0**
2	1.6	2.6	3.9	5.5	5.6	**3.5**
3+	1.6	2.7	4.5	5.8	7.1	**4.4**
Average	**1.3**	**2.5**	**3.8**	**5.3**	**5.7**	**3.0**

Number of Persons by Income Level

	Household Size					
Household Income	**1**	**2**	**3**	**4**	**5+**	**Average**
i	0.7	1.4	2.7	3.4	3.4	**1.6**
ii	1.0	1.8	2.8	3.9	3.9	**1.9**
iii	1.5	2.4	3.5	4.7	5.0	**2.7**
iv	1.8	3.0	4.4	5.5	6.8	**3.8**
v	2.0	3.2	4.6	6.5	8.3	**4.7**
Average	**1.3**	**2.5**	**3.8**	**5.3**	**5.7**	**3.0**

Note: All averages are weighted.
Source: 2009 NHTS.

Table C.8. Home-based school trip rates.

Number of Persons by Number of Children

	Household Size					
Children	**1**	**2**	**3**	**4**	**5+**	**Average**
0	0.0	0.0	0.5	1.0	1.1	**0.1**
1	0.0	1.0	1.0	1.7	1.8	**1.1**
2			1.6	1.8	2.6	**1.9**
3+				2.7	2.7	**2.7**
Average	**0.0**	**0.1**	**0.8**	**1.7**	**2.5**	**0.6**

Number of Persons by Number of Vehicles

	Household Size					
Vehicles	**1**	**2**	**3**	**4**	**5+**	**Average**
0	0.0	0.1	0.8	1.5	1.6	**0.3**
1	0.0	0.1	0.8	1.6	2.4	**0.3**
2	0.0	0.1	0.8	1.7	2.6	**0.7**
3+	0.0	0.1	0.8	1.8	2.7	**1.0**
Average	**0.0**	**0.1**	**0.8**	**1.7**	**2.5**	**0.6**

Number of Persons by Income Level

	Household Size					
Household Income	**1**	**2**	**3**	**4**	**5+**	**Average**
i	0.0	0.1	0.7	1.2	1.5	**0.4**
ii	0.0	0.1	0.8	1.6	2.6	**0.5**
iii	0.0	0.1	0.8	1.6	2.6	**0.5**
iv	0.0	0.1	0.8	1.6	2.6	**0.7**
v	0.0	0.1	0.8	1.9	2.8	**1.0**
Average	**0.0**	**0.1**	**0.8**	**1.7**	**2.5**	**0.6**

Note: All averages are weighted.
Source: 2009 NHTS.

Table C.9. Home-based other trip rates (excluding work and school).

Number of Persons by Number of Workers, Urban Area Greater Than 500,000 Population

	Household Size					
Workers	**1**	**2**	**3**	**4**	**5+**	**Average**
0	1.8	3.9	5.1	7.6	8.8	**3.3**
1	1.8	3.9	5.8	8.2	9.7	**4.4**
2		3.9	6.1	9.3	12.1	**6.8**
3+			6.2	9.5	12.1	**9.2**
Average	**1.8**	**3.9**	**5.8**	**8.7**	**10.9**	**4.9**

Number of Persons by Number of Workers, Urban Area Less Than 500,000 Population (Including Non-Urban Areas)

	Household Size					
Workers	**1**	**2**	**3**	**4**	**5+**	**Average**
0	1.8	3.5	5.2	6.7	6.7	**3.2**
1	1.8	3.5	5.9	7.3	9.5	**4.1**
2		3.5	6.1	8.2	11.5	**5.9**
3+			6.1	9.6	12.5	**9.2**
Average	**1.8**	**3.5**	**6.0**	**7.9**	**10.3**	**4.6**

Number of Persons by Number of Vehicles, Urban Area Greater Than 500,000 Population

	Household Size					
Vehicles	**1**	**2**	**3**	**4**	**5+**	**Average**
0	1.4	3.5	5.0	5.9	8.6	**2.9**
1	1.9	3.8	5.6	7.1	9.2	**3.4**
2	2.4	4.0	5.7	9.2	11.1	**6.0**
3+	2.5	4.0	6.4	9.2	12.2	**7.5**
Average	**1.8**	**3.9**	**5.8**	**8.7**	**10.9**	**4.9**

Table C.9. (Continued).

Number of Persons by Number of Vehicles, Urban Area Less Than 500,000 Population (Including Non-Urban Areas)

	Household Size					
Vehicles	**1**	**2**	**3**	**4**	**5+**	**Average**
0	1.2	3.0	4.5	6.8	8.1	**2.4**
1	1.9	3.5	6.2	8.0	8.1	**3.2**
2	2.0	3.6	6.2	8.0	9.9	**5.0**
3+	2.0	3.6	6.2	8.0	11.6	**6.0**
Average	**1.8**	**3.5**	**6.0**	**7.9**	**10.3**	**4.6**

Number of Persons by Income Level, Urban Area Greater Than 500,000 Population

	Household Size					
Household Income	**1**	**2**	**3**	**4**	**5+**	**Average**
i	1.6	3.5	4.0	7.4	9.6	**3.7**
ii	1.7	3.9	5.3	8.0	9.6	**4.1**
iii	1.9	3.9	5.9	8.0	10.4	**4.5**
iv	2.0	4.1	6.2	8,6	12.2	**5.5**
v	2.3	4.1	6.3	9.8	12.4	**6.6**
Average	**1.8**	**3.9**	**5.8**	**8.7**	**10.9**	**4.9**

Number of Persons by Income Level, Urban Area Less Than 500,000 Population (Including Non-Urban Areas)

	Household Size					
Household Income	**1**	**2**	**3**	**4**	**5+**	**Average**
i	1.4	3.0	4.6	6.9	5.7	**3.0**
ii	1.9	3.3	6.0	7.5	9.2	**3.7**
iii	1.9	3.7	6.0	7.5	10.0	**4.4**
iv	1.9	3.7	6.0	8.3	11.3	**5.4**
v	2.2	3.7	6.5	8.3	12.2	**6.1**
Average	**1.8**	**3.5**	**6.0**	**7.9**	**10.3**	**4.6**

Note: All averages are weighted.
Source: 2009 NHTS.

Table C.10. Mean trip length in minutes by mode and trip purpose by urban area population range.

Home-Based Work

	Mean			
Urban Area Population	**Auto**	**Transit**	**Nonmotorized**	**All Modes**
1 million or more with subway or rail	29	55	16	32
1 million or more without subway or rail	25	55	16	26
Between 500,000 and 1 million	22	55	16	22
Less than 500,000	20	55	16	21
Not in urban area	24	55	16	24
All trips	24	55	16	25

Home-Based Nonwork

	Mean			
Urban Area Population	**Auto**	**Transit**	**Nonmotorized**	**All Modes**
All population ranges	18	48	15	18

Nonhome Based

	Mean			
Urban Area Population	**Auto**	**Transit**	**Nonmotorized**	**All Modes**
1 million or more with subway or rail	20	42	14	20
Other urban area	18	42	14	18
Not in urban area	19	42	14	19
All trips	19	42	14	19

Table C.10. (Continued).

Home-Based School

Urban Area Population	Mean: Auto	Transit	Nonmotorized	All Modes
1 million or more with subway or rail	17	45	15	21
Other urban area	15	45	14	18
Not in urban area	17	45	12	23
All trips	16	45	14	20

Home-Based Other (excluding school and work)

Urban Area Population	Mean: Auto	Transit	Nonmotorized	All Modes
All population ranges	18	48	15	18

All Trips

Urban Area Population	Mean: Auto	Transit	Nonmotorized	All Modes
1 million or more with subway or rail	21	48	15	22
Other urban area	18	48	15	18
Not in urban area	20	48	14	20
All trips	19	48	15	19

Source: 2009 NHTS.

Table C.11. Time-of-day distributions by trip purpose and direction.

All Modes

	Home-Based Work		Home-Based Nonwork		Home-Based School		Home-Based Other			
Hour Ending	**From Home**	**To Home**	**From Home**	**To Home**	**From Home**	**To Home**	**From Home**	**To Home**	**Nonhome-Based**	**All Trips**
1:00 AM	0.1%	0.5%	0.0%	0.3%	0.0%	0.0%	0.0%	0.3%	0.2%	0.3%
2:00 AM	0.0%	0.2%	0.0%	0.2%	0.0%	0.0%	0.0%	0.2%	0.1%	0.1%
3:00 AM	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%
4:00 AM	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
5:00 AM	1.4%	0.0%	0.2%	0.0%	0.0%	0.0%	0.2%	0.0%	0.3%	0.4%
6:00 AM	5.2%	0.0%	0.6%	0.1%	0.2%	0.0%	0.7%	0.1%	0.5%	1.3%
7:00 AM	11.5%	0.1%	2.3%	0.3%	6.4%	0.0%	1.8%	0.3%	1.7%	3.6%
8:00 AM	14.3%	0.1%	7.0%	1.0%	28.2%	0.1%	4.2%	1.0%	4.9%	7.9%
9:00 AM	7.7%	0.1%	4.8%	1.3%	12.6%	0.2%	3.9%	1.3%	5.1%	6.1%
10:00 AM	2.8%	0.3%	3.4%	1.4%	1.7%	0.2%	3.6%	1.4%	5.1%	4.6%
11:00 AM	1.3%	0.3%	3.1%	1.9%	0.8%	0.4%	3.4%	1.9%	6.4%	4.9%
Noon	1.1%	1.0%	2.5%	2.4%	0.6%	1.1%	2.8%	2.4%	9.2%	5.8%
1:00 PM	1.6%	1.8%	2.3%	2.9%	0.7%	2.0%	2.5%	2.9%	11.1%	6.8%
2:00 PM	1.7%	1.4%	2.5%	2.7%	0.3%	2.0%	2.8%	2.7%	8.8%	6.0%
3:00 PM	1.7%	2.7%	2.7%	4.7%	0.3%	13.4%	3.0%	4.7%	8.6%	7.3%
4:00 PM	1.1%	6.2%	2.6%	5.9%	0.4%	16.5%	2.9%	5.9%	9.2%	8.6%
5:00 PM	1.0%	9.0%	3.2%	4.6%	0.6%	3.8%	3.5%	4.6%	8.2%	8.2%
6:00 PM	0.5%	10.5%	3.7%	4.9%	0.8%	2.5%	4.0%	4.9%	7.3%	8.5%
7:00 PM	0.3%	4.5%	4.1%	4.0%	0.4%	1.0%	4.6%	4.0%	5.0%	6.7%
8:00 PM	0.1%	1.9%	2.5%	3.8%	0.0%	0.8%	2.8%	3.8%	3.8%	4.9%
9:00 PM	0.1%	1.2%	1.1%	3.7%	0.0%	0.7%	1.2%	3.7%	2.1%	3.5%
10:00 PM	0.2%	1.2%	0.6%	2.5%	0.1%	0.9%	0.6%	2.5%	1.4%	2.3%
11:00 PM	0.3%	1.3%	0.3%	1.3%	0.0%	0.3%	0.3%	1.3%	0.8%	1.3%
Midnight	0.1%	1.4%	0.2%	0.7%	0.0%	0.0%	0.2%	0.7%	0.3%	0.8%
Total	**54.3%**	**45.7%**	**49.5%**	**50.6%**	**54.0%**	**46.0%**	**49.5%**	**50.6%**	**100.0%**	**100.0%**
7-9 AM	22.0%	0.2%	11.8%	2.3%	40.7%	0.3%	8.1%	2.6%	10.0%	14.0%
3-6 PM	2.6%	25.7%	9.5%	15.3%	1.7%	22.8%	10.5%	14.4%	24.7%	25.3%

Table C.11. (Continued).

Auto Modes

Hour Ending	Home-Based Work		Home-Based Nonwork		Home-Based School		Home-Based Other		Nonhome-Based	All Trips
	From Home	To Home	From Home	To Home	From Home	To Home	From Home	To Home		
1:00 AM	0.1%	0.5%	0.0%	0.3%	0.0%	0.0%	0.0%	0.4%	0.2%	0.3%
2:00 AM	0.0%	0.2%	0.0%	0.2%	0.0%	0.0%	0.0%	0.2%	0.1%	0.1%
3:00 AM	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%
4:00 AM	0.1%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
5:00 AM	1.5%	0.0%	0.2%	0.0%	0.0%	0.0%	0.2%	0.0%	0.4%	0.4%
6:00 AM	5.4%	0.0%	0.6%	0.1%	0.2%	0.0%	0.7%	0.1%	0.5%	1.4%
7:00 AM	11.7%	0.0%	1.9%	0.3%	4.0%	0.0%	1.7%	0.3%	1.6%	3.5%
8:00 AM	14.3%	0.1%	6.5%	1.0%	30.6%	0.1%	4.4%	1.1%	4.9%	7.7%
9:00 AM	7.5%	0.1%	4.6%	1.2%	12.8%	0.2%	3.9%	1.3%	5.1%	5.9%
10:00 AM	2.7%	0.3%	3.6%	1.4%	2.2%	0.4%	3.7%	1.5%	5.1%	4.7%
11:00 AM	1.3%	0.3%	3.2%	1.9%	1.2%	0.6%	3.4%	2.1%	6.5%	5.1%
Noon	1.0%	1.0%	2.7%	2.5%	1.0%	1.3%	2.8%	2.6%	9.4%	6.0%
1:00 PM	1.5%	1.8%	2.4%	3.1%	0.9%	2.5%	2.6%	3.1%	10.6%	6.8%
2:00 PM	1.7%	1.4%	2.7%	2.8%	0.5%	2.2%	2.8%	2.9%	8.7%	6.1%
3:00 PM	1.7%	2.7%	2.8%	4.0%	0.5%	8.8%	3.0%	3.5%	8.5%	6.9%
4:00 PM	1.1%	6.3%	2.6%	5.3%	0.7%	12.2%	2.8%	4.7%	9.2%	8.3%
5:00 PM	1.0%	8.9%	3.2%	4.8%	1.0%	4.5%	3.3%	4.9%	8.4%	8.4%
6:00 PM	0.5%	10.6%	3.7%	5.1%	1.3%	3.7%	3.9%	5.2%	7.4%	8.7%
7:00 PM	0.3%	4.4%	4.2%	4.1%	0.7%	1.5%	4.5%	4.3%	5.0%	6.7%
8:00 PM	0.2%	1.9%	2.3%	4.0%	0.1%	1.2%	2.5%	4.2%	3.8%	4.8%
9:00 PM	0.2%	1.2%	1.0%	4.0%	0.0%	1.1%	1.1%	4.3%	2.2%	3.5%
10:00 PM	0.2%	1.3%	0.5%	2.8%	0.2%	1.4%	0.5%	2.9%	1.4%	2.4%
11:00 PM	0.3%	1.3%	0.2%	1.4%	0.0%	0.6%	0.3%	1.5%	0.8%	1.4%
Midnight	0.2%	1.3%	0.2%	0.7%	0.0%	0.0%	0.2%	0.8%	0.3%	0.8%
Total	**54.4%**	**45.6%**	**49.0%**	**51.0%**	**57.7%**	**42.4%**	**48.2%**	**51.8%**	**100.0%**	**100.0%**
7-9 AM	21.8%	0.2%	11.1%	2.2%	43.3%	0.4%	8.3%	2.4%	9.9%	13.6%
3-6 PM	2.6%	25.7%	9.5%	15.3%	3.0%	20.4%	10.0%	14.8%	25.0%	25.4%

(continued on next page)

Table C.11. (Continued).

Transit Modes

Hour Ending	Home-Based Work		Home-Based Nonwork		Home-Based School		Home-Based Other		Nonhome-Based	All Trips
	From Home	To Home	From Home	To Home	From Home	To Home	From Home	To Home		
1:00 AM	0.0%	0.5%	0.0%	0.2%	0.0%	0.0%	0.0%	0.2%	0.1%	0.2%
2:00 AM	0.0%	0.1%	0.0%	0.2%	0.0%	0.0%	0.0%	0.3%	0.1%	0.2%
3:00 AM	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4:00 AM	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
5:00 AM	0.8%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.3%	0.3%
6:00 AM	3.0%	0.0%	1.1%	0.0%	0.8%	0.0%	1.2%	0.0%	1.0%	1.5%
7:00 AM	11.8%	0.0%	2.5%	0.0%	8.4%	0.0%	1.4%	0.0%	4.5%	5.4%
8:00 AM	17.1%	0.0%	7.6%	0.1%	27.1%	0.1%	3.9%	0.1%	6.1%	9.5%
9:00 AM	9.9%	0.2%	6.6%	0.5%	8.0%	0.2%	6.3%	0.6%	7.4%	7.9%
10:00 AM	2.7%	0.1%	6.5%	0.5%	2.0%	0.4%	7.4%	0.6%	5.1%	5.4%
11:00 AM	1.4%	0.0%	6.4%	2.7%	0.5%	0.6%	7.5%	3.1%	6.0%	6.3%
Noon	1.0%	0.5%	3.9%	2.8%	0.3%	1.3%	4.6%	3.0%	6.8%	5.5%
1:00 PM	2.6%	1.6%	1.9%	4.9%	0.7%	2.5%	2.1%	5.6%	9.4%	6.9%
2:00 PM	1.9%	1.6%	2.2%	4.0%	0.9%	2.2%	2.4%	4.0%	6.7%	5.7%
3:00 PM	1.3%	2.0%	1.8%	6.7%	0.1%	8.8%	2.2%	6.0%	7.5%	6.9%
4:00 PM	1.0%	5.5%	2.0%	6.1%	0.0%	12.2%	2.4%	4.2%	7.3%	7.5%
5:00 PM	0.4%	10.8%	1.9%	5.0%	0.8%	4.5%	2.1%	5.0%	8.0%	8.3%
6:00 PM	0.4%	8.8%	1.8%	3.7%	0.6%	3.7%	2.0%	4.1%	9.4%	7.5%
7:00 PM	0.0%	5.0%	1.5%	3.6%	0.0%	1.5%	1.8%	4.1%	6.2%	5.4%
8:00 PM	0.1%	2.0%	1.2%	2.1%	0.0%	1.2%	1.4%	2.2%	4.2%	3.3%
9:00 PM	0.2%	1.2%	0.5%	2.9%	0.0%	1.1%	0.6%	3.0%	1.6%	2.3%
10:00 PM	0.2%	0.4%	0.1%	2.4%	0.0%	1.4%	0.1%	2.0%	1.6%	1.7%
11:00 PM	0.0%	1.2%	0.1%	1.7%	0.0%	0.6%	0.1%	1.9%	0.7%	1.4%
Midnight	0.0%	2.6%	0.0%	0.4%	0.0%	0.0%	0.0%	0.5%	0.3%	0.9%
Total	**55.9%**	**44.1%**	**49.6%**	**50.4%**	**49.9%**	**50.1%**	**49.6%**	**50.4%**	**100.0%**	**100.0%**
7-9 AM	27.0%	0.2%	14.2%	0.5%	35.1%	0.0%	10.2%	0.7%	13.5%	17.4%
3-6 PM	1.8%	25.1%	5.7%	14.8%	1.5%	22.5%	6.5%	13.3%	24.7%	23.3%

Table C.11. (Continued).

Nonmotorized Modes

	Home-Based Work		Home-Based Nonwork		Home-Based School		Home-Based Other			
Hour Ending	**From Home**	**To Home**	**From Home**	**To Home**	**From Home**	**To Home**	**From Home**	**To Home**	**Nonhome-Based**	**All Trips**
1:00 AM	0.0%	0.3%	0.1%	0.2%	0.0%	0.0%	0.1%	0.2%	0.2%	0.2%
2:00 AM	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.2%	0.0%	0.2%
3:00 AM	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%
4:00 AM	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5:00 AM	0.7%	0.0%	0.1%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.2%
6:00 AM	3.0%	0.0%	0.7%	0.4%	0.0%	0.0%	0.8%	0.4%	0.2%	1.0%
7:00 AM	6.4%	0.5%	1.8%	0.9%	1.4%	0.0%	1.8%	1.0%	1.1%	2.4%
8:00 AM	12.2%	0.1%	5.4%	1.8%	26.8%	0.3%	3.3%	1.9%	2.7%	6.3%
9:00 AM	8.7%	0.1%	4.3%	2.1%	14.8%	0.2%	3.3%	2.3%	3.7%	5.8%
10:00 AM	5.2%	0.3%	2.7%	1.7%	1.9%	0.1%	2.7%	1.9%	4.9%	4.5%
11:00 AM	2.0%	0.1%	2.5%	1.8%	0.3%	0.6%	2.7%	1.9%	5.6%	4.5%
Noon	3.0%	1.4%	2.0%	2.1%	0.2%	0.9%	2.1%	2.2%	8.9%	5.3%
1:00 PM	1.7%	3.1%	2.1%	2.4%	0.6%	3.0%	2.3%	2.4%	16.5%	7.6%
2:00 PM	2.6%	1.7%	2.2%	1.9%	0.4%	2.2%	2.4%	1.9%	11.4%	5.9%
3:00 PM	1.6%	3.6%	3.1%	4.8%	0.2%	19.6%	3.3%	3.4%	9.3%	8.1%
4:00 PM	2.1%	6.2%	3.2%	4.8%	0.1%	18.2%	3.6%	3.4%	8.3%	8.1%
5:00 PM	1.4%	8.9%	4.1%	3.7%	0.1%	4.0%	4.5%	3.7%	6.7%	7.7%
6:00 PM	0.3%	10.0%	4.7%	4.7%	0.3%	2.0%	5.1%	4.9%	6.9%	8.7%
7:00 PM	0.4%	5.4%	4.8%	4.4%	0.1%	0.9%	5.2%	4.8%	5.0%	8.0%
8:00 PM	0.1%	1.1%	4.0%	4.1%	0.0%	0.3%	4.3%	4.5%	3.8%	6.7%
9:00 PM	0.0%	1.3%	2.0%	3.0%	0.1%	0.2%	2.2%	3.3%	2.0%	4.1%
10:00 PM	0.4%	0.9%	1.3%	1.9%	0.0%	0.1%	1.5%	2.1%	1.4%	2.7%
11:00 PM	0.1%	0.9%	0.5%	0.9%	0.0%	0.0%	0.5%	1.0%	1.1%	1.3%
Midnight	0.0%	2.2%	0.3%	0.5%	0.0%	0.0%	0.4%	0.5%	0.5%	0.8%
Total	**52.0%**	**48.0%**	**51.7%**	**48.3%**	**47.3%**	**52.7%**	**52.2%**	**47.8%**	**100.0%**	**100.0%**
7-9 AM	20.9%	0.2%	9.7%	3.8%	41.6%	0.6%	6.6%	4.2%	6.3%	12.1%
3-6 PM	3.9%	25.0%	12.1%	13.1%	0.5%	24.2%	13.2%	12.1%	21.8%	24.5%

Source: 2009 NHTS.

Abbreviations and acronyms used without definitions in TRB publications:

AAAE	American Association of Airport Executives
AASHO	American Association of State Highway Officials
AASHTO	American Association of State Highway and Transportation Officials
ACI–NA	Airports Council International–North America
ACRP	Airport Cooperative Research Program
ADA	Americans with Disabilities Act
APTA	American Public Transportation Association
ASCE	American Society of Civil Engineers
ASME	American Society of Mechanical Engineers
ASTM	American Society for Testing and Materials
ATA	American Trucking Associations
CTAA	Community Transportation Association of America
CTBSSP	Commercial Truck and Bus Safety Synthesis Program
DHS	Department of Homeland Security
DOE	Department of Energy
EPA	Environmental Protection Agency
FAA	Federal Aviation Administration
FHWA	Federal Highway Administration
FMCSA	Federal Motor Carrier Safety Administration
FRA	Federal Railroad Administration
FTA	Federal Transit Administration
HMCRP	Hazardous Materials Cooperative Research Program
IEEE	Institute of Electrical and Electronics Engineers
ISTEA	Intermodal Surface Transportation Efficiency Act of 1991
ITE	Institute of Transportation Engineers
NASA	National Aeronautics and Space Administration
NASAO	National Association of State Aviation Officials
NCFRP	National Cooperative Freight Research Program
NCHRP	National Cooperative Highway Research Program
NHTSA	National Highway Traffic Safety Administration
NTSB	National Transportation Safety Board
PHMSA	Pipeline and Hazardous Materials Safety Administration
RITA	Research and Innovative Technology Administration
SAE	Society of Automotive Engineers
SAFETEA-LU	Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (2005)
TCRP	Transit Cooperative Research Program
TEA-21	Transportation Equity Act for the 21st Century (1998)
TRB	Transportation Research Board
TSA	Transportation Security Administration
U.S.DOT	United States Department of Transportation