Preface to Tolling White Paper 3

Tolling White Paper 3, *Travel Demand Model Sufficiency*, discusses the requirements for transportation models to accurately predict motorist behavior and resulting demand for toll way or congestion pricing projects. It then critiques existing transportation models in Oregon against these requirements.

This is a complex subject in a rapidly evolving field and the paper in spite of its overall quality may leave the reader with a few misperceptions.

First, the paper is essentially a "snapshot in time". The ODOT and MPO models discussed in the paper are constantly being adjusted and upgraded. Metro, in particular, has made model enhancements since the paper's release conducive to improved predictability under tolling.

Second, the paper used "state-of-the art" model components as the basis for examining existing Oregon models without being sufficiently clear that no model in the country possesses all the features discussed. While using an ideal as a basis for comparisons among existing models is a useful approach, it can seemingly magnify the significance of identified limitations. Oregon's models, as the paper states, are considered excellent from a national perspective.

Third, the paper does not make clear that "post-processing" refinement analysis is *always* necessary for tolling projects. There simply is not enough national experience with how motorists react to the effects of tolling in the wide range of ways and locales in which it can be applied to expect regional or state models to generate results with the assurance required for implementing tolling projects. In fact, there are several specialist firms nationally which perform this type of necessary analysis. It also should be noted that the type of post-processing undertaken can be expected to vary according to how far along a project may be in the development process; the most detailed analysis occurring at the time project finance decisions are made. This means that higher degrees of uncertainty are common, and expected, at earlier stages of development.

The white paper was intended to increase understanding within Oregon of the intricacies of attempting to model motorist behavior under tolling or

congestion pricing and this it does. What is does not do is to fully explain the roll of transportation models in the long complicated process of developing a tolling project and the fact that some uncertainty will always remain regardless of efforts to develop more refined models.

Tolling White Paper 3

Travel Demand Model Sufficiency

Prepared for the Oregon Department of Transportation

by

Parsons Brinckerhoff
and
David Evans and Associates Inc.
Stantec Consulting Services, Inc.

February 2009

Executive Summary

Increasing highway congestion and the projected shortfall in gasoline tax revenues and other traditional sources of highway financing have renewed interest in tolls as both a revenue source and a demand management strategy. The Oregon Transportation Commission (OTC) seeks to understand the opportunities that highway tolling offers for improving the state's transportation infrastructure and managing its growing demand for travel. In recent years the OTC has taken steps to create the institutional and policy framework necessary to study how toll projects can support and advance Oregon's economic, environmental, and social welfare objectives.

Recent technological advancements have enabled the tolling or value pricing of highways in a variety of forms, including different combinations of managed and general purpose lanes, vehicle eligibility by type and occupancy, and toll differentiation by congestion levels or time of day, among others. Tolls are being used both for generating revenue and managing congestion. Pricing scenarios represent a challenge for demand forecasting, because traditional travel models are characterized by simplified representations of pricing and limited capabilities for predicting how travelers would change mode, route, departure time, destination, or even trip frequency in response to pricing.

When tolling is a factor of analysis, travel demand models will produce the necessary information regarding the patronage of the toll facility, as well as the impacts of tolling and pricing on corridor and regional travel demand for different groups of travelers. The accuracy of toll traffic and revenue (T&R) forecasts, however, is crucial for understanding how well the proposed project meets its policy objectives, and for the continued success of a tolling program once the State of Oregon has committed to its implementation.

In addition to the planning, public perception, and political aspects common to all major infrastructure investments, for tolling projects there is added scrutiny by private investors, bond rating agencies, and parties concerned about environmental justice. Bond or finance rating agencies and project sponsors in particular put T&R forecasting procedures under a high level of scrutiny that is in many respects quite different from the model evaluation/validation criteria applied in the public sector. In particular, the financial community seeks a good understanding of the uncertainty in the toll T&R forecast.

The Oregon Department of Transportation (ODOT) and the state's Metropolitan Planning Organizations (MPOs) have developed travel demand models to examine important questions related to the impact of transportation investments and of population and economic growth on the existing transportation infrastructure. Because there is little recent history of tolling in the state, other than the Cascade Locks and Hood River Bridges (currently), and several other Columbia River bridges (in the past), the travel demand models developed throughout the state are largely untested in terms of their sufficiency to predict motorist behavior for tolling situations. These models cannot be assessed by establishing how well they match current travel behavior or traffic patterns, since nowhere in the state are travelers required to choose between toll and free roads. Instead, the models need to be compared to national best practices for

modeling and forecasting of toll traffic. In addition, opportunities for incorporating recommendations from recent research on toll traffic forecasting methods should be investigated.

This paper examines current travel demand modeling practices in Oregon with regard to tolling applications. This assessment evaluates the capability of the existing models to produce T&R forecasts for a wide range of tolling applications. It provides a detailed assessment of current modeling practices in Oregon, including a comparison to the national state-of-the-practice. Included are an explanation of technical aspects of travel demand models, an evaluation of the capability of existing models across a range of potential tolling applications, a description of the requirements placed upon the models by private investors, and general recommendations for improving model performance.

Our assessment of the sufficiency of Oregon's travel demand models to evaluate tolling applications is not limited to comparing the state's models to prevailing modeling practice. Nor are our recommendations for model improvement solely intended to upgrade these models to the state-of-the-practice. Advanced modeling practice and even state-of-the-art methods have been included among the recommended model improvements whenever relevant and applicable to overcome some of the known limitations and deficiencies of state-of-the-practice models.

We find that all of Oregon's MPO models meet state-of-the-practice modeling standards, when compared to models for metropolitan regions of similar size. The Portland Metro model goes a step beyond the state-of-the-practice, by including advanced modeling features. The Statewide Integrated Model (SWIM) is in a category all by itself; it is in fact among the most advanced integrated land use/transport models worldwide, and incorporates many of the characteristics recommended for state-of-the-art, yet practical activity based models. None of these models, however, was specifically developed for evaluating tolling applications, and therefore all of them lack to varying degree one or more of modeling features essential for road pricing analyses. Furthermore, given the requirements placed upon travel demand models by the financial community, and recent advances in bringing travel behavior research into practice, Oregon statewide and MPO models could and should be improved to reflect state-of-the-practice tolling methodologies, and even some advanced features, prior to using them to forecast toll traffic and revenue.

A model structure that adequately incorporates all the known, relevant responses to road pricing – which include selection of route, trip departure time, mode, and destination, among others, is a necessary condition, and in our opinion the most important factor that contributes to the sufficiency of a travel demand model. For this reason much of this paper is dedicated to a discussion of essential and desirable model features. Another important contributing factor to model sufficiency is related to how well a model reproduces current travel conditions at a regional, corridor and facility level. Regional travel demand models are typically evaluated in terms of how well they reproduce regional travel patterns. However, this level of model validation may be insufficient for the specific facility, corridor, or subarea under study. Therefore a critical step before initiating a road pricing or traffic and revenue study is ensuring that the model is well-validated at a geographic scale commensurate with the scale of the project.

Equally as important as the improvement of the models themselves is the undertaking of a fundamental shift in how models are used to produce toll traffic and revenue forecasts. A thorough analysis of the risks associated with the forecast needs to become an integral part of the forecasting process. Typical risks

associated with toll projects are related to the model itself, to the model input data, and to specific circumstances associated with particular projects. This paper offers specific recommendations for implementing a toll application risk analysis program.

The development of better models through more behaviorally-based model structures and improved model validation, and a more rigorous risk assessment approach, will help increase the credibility of toll traffic and revenue forecasts, as well as better integrate the transportation modeling culture with the culture of the investment analysis community.

Introduction

Increasing highway congestion and the projected shortfall in gasoline tax revenues and other traditional sources of highway financing have renewed an interest in tolls as both a revenue source and a demand management strategy. The Oregon Transportation Commission (OTC) seeks to understand the opportunities that highway tolling offers for improving the state's transportation infrastructure and managing its growing demand for travel. In recent years the OTC has taken steps to create the institutional and policy framework necessary to study how toll projects can support and advance Oregon's economic, environmental, and social welfare objectives.

Recent technological advancements have enabled the tolling or value pricing of highways in a variety of forms, including different combinations of managed and general purpose lanes, vehicle eligibility by type and occupancy, and toll differentiation by congestion levels or time of day, among others. Tolls are being used both for generating revenue and managing congestion. Such pricing scenarios represent a challenge for demand forecasting, because traditional travel models are characterized by simplified representations of pricing and limited capabilities for predicting how travelers would change mode, route, departure time, destination, or even trip frequency in response to pricing.

This paper examines current travel demand modeling practices in Oregon with regard to tolling applications. Because there is little recent history of tolling in the state, other than the Cascade Locks and Hood River Bridges (currently), and several other Columbia River bridges (in the past), it is difficult to validate the ability of current travel demand models to predict motorist behavior for tolling situations based on actual tolling applications. These models cannot be assessed by establishing how well they match current traffic patterns; instead, the models need to be compared to national best practices for modeling and forecasting of toll traffic. In addition, opportunities for incorporating recommendations from recent research on toll traffic forecasting methods should be investigated whenever relevant and applicable to overcome some of the known limitations and deficiencies of state-of-the-practice models.

This paper is organized as follows:

- Current state of the practice for modeling, including a summary of best-practice modeling principles related to tolling and an overview of how the Oregon-based travel demand models incorporate tolls or road prices in the model structure
- Types of tolling applications applicable to Oregon and related travel demand model needs
- Modeling requirements for investment-grade forecasts
- Incorporation of travel time reliability on travel demand models
- Sources of uncertainty and systematic bias in T&R forecasts
- Evaluation of the capability of Oregon's travel demand models to estimate tolling impacts
- Recommendations for improving Oregon's travel demand models for tolling applications
- Recommendations for a data collection program to support model improvements

Section 1.0: Current State of Oregon's Travel Demand Models

1.1. A Primer on Travel Demand Forecasting

In order to understand how Oregon's models assess tolling, a basic understanding of how travel demand models work is needed.

A travel demand model predicts the number of trips between trip origins and destinations, such as between a place of residence and work. Trips are estimated by time of day for an average weekday, and then are distributed around the geographical area being analyzed (trip distribution), assigned to a travel mode (mode choice), and then to a route taken (trip assignment).

By definition, the scope of a travel demand model is regional; that is, it forecasts trips for the entire population of a metropolitan (or larger) region using all relevant facilities and transit services.

As graphically summarized in Figure 1, there are two major approaches for structuring a demand model:

- Traditional *trip-based* models constitute the majority of travel models used by most Metropolitan Planning Organizations (MPOs) and states in the United States. All regional models in Oregon are trip-based models. This type of model is often referred to as a four-step model because its original formulation included four submodels: trip generation, trip distribution, trip mode choice and trip assignment.

- Activity-based or *tour-based* models have been used since the early 2000s and currently constitute the majority of newly developed models in large metropolitan areas. The Oregon statewide model is an activity-based model. An activity-based model was developed for the Portland metropolitan region in the 1990s but was not widely used; a new generation activity-based model for the Portland region is currently under development. These types of models are often referred as tour-based models, because the unit of analysis is a sequence of trips (a tour) that starts and ends at home.

Both trip-based and tour-based models are essentially sequences or chains of submodels, applied in the order shown in Figure 1 (first trip generation, then trip distribution, etc.). To ensure consistency between the inputs to any given submodel and the results of submodels down the chain, the model uses "feedback loops". For example, after highway assignment, travel time on every road segment is calculated as a function of the estimated road volume, and then the entire sequence of models is repeated, using the newly estimated travel times. When the travel times between consecutive highway assignments are approximately the same, it is said that the model has achieved "convergence". Convergence is very important when modeling tolling applications, because the effect that charging a toll has on road volumes, and consequently on travel times, is known only after the highway assignment step.

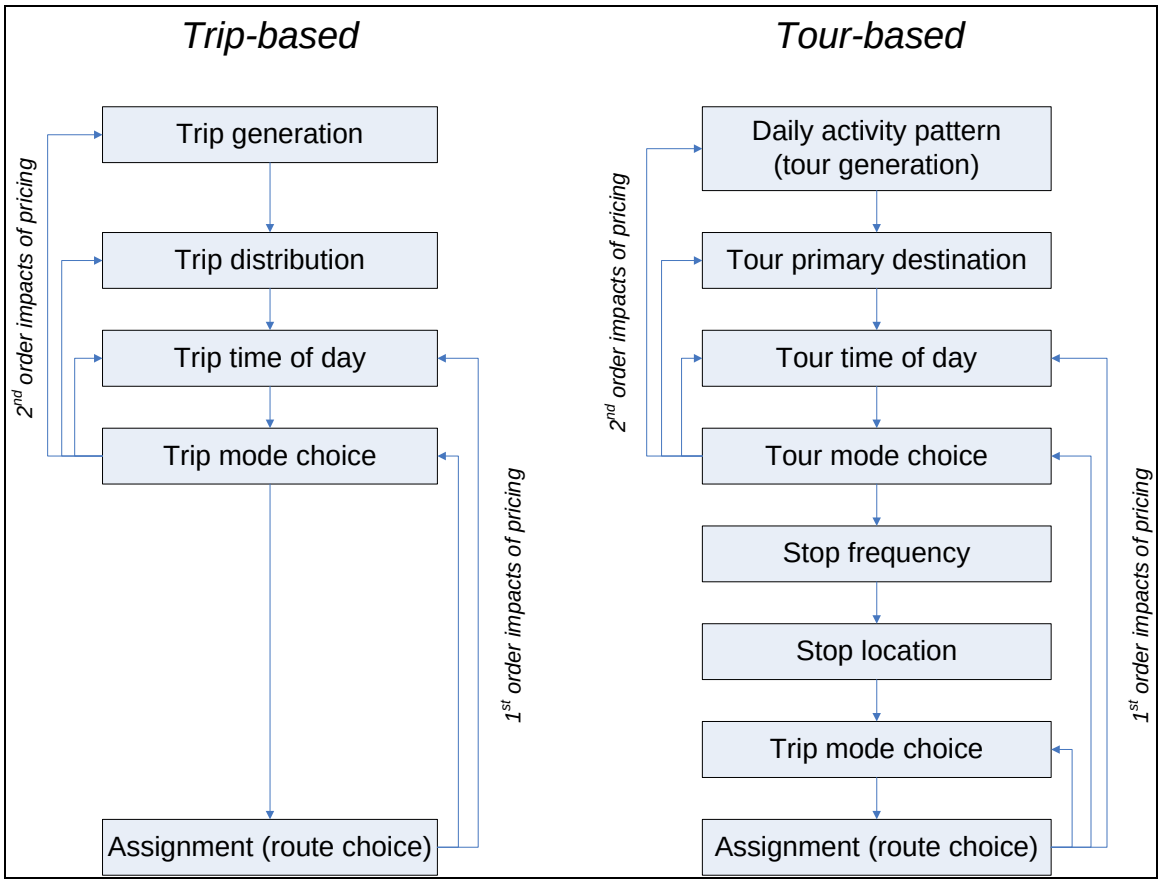


Figure 1: Typical Demand Mode Structures

When tolling is a factor of analysis, travel demand models will produce the necessary information regarding the patronage of the toll facility, as well as the impacts of tolling and pricing on corridor and regional travel and for different groups of travelers. How *well* the model predicts patronage and revenues depends on the structure of the model, how well it is calibrated and validated, and how it is applied to quantify the uncertainty inherent in any forecast of future economic activity:

- A *model structure* that adequately incorporates all the relevant responses to road pricing is a necessary condition, and in our opinion the most important factor that contributes to the sufficiency of a travel demand model. Three structural characteristics are most important, and are discussed below in detail in Sections 1.2 to 1.4: representation of relevant travel choice decisions, representation of travel costs, and representation of travelers' willingness to pay.

- Another important contributing factor to model sufficiency is related to *model calibration and validation*; that is, how well the model reproduces current travel conditions at a regional, corridor and facility level. Regional travel demand models are evaluated in terms of how closely they reproduce regional travel patterns, such as traffic volumes on major facilities, transit ridership, and origin-destination person movements. However, this level of model validation may be insufficient for the specific facility, corridor, or subarea under study. Therefore a critical step before initiating a

road pricing or traffic and revenue study is ensuring that the model is well-validated at a geographic scale commensurate with the scale of the project.

- A traffic forecast is necessarily made under conditions of uncertainty. Therefore the *quantification of uncertainty* and its impact on toll road traffic and revenue should be an integral part of the forecasting process, and provides important information to investors and decision-makers about the likelihood of achieving the anticipated revenue and other goals related to the realized traffic volume. Uncertainty and risk analysis are treated in more detail in Sections 3.0 and 5.0.

1.2. Travel Decisions Influenced by Tolling and Congestion Pricing

How travel demand models estimate tolling effects can be classified into *first-order* and *second-order* responses. A *first-order* response estimates how a traveler would immediately or most directly react to being tolled. This response includes the following travel choices: route choice (whether to use the toll road or an alternative free route), mode choice (for example, if pricing is applied, some users may choose to use a reasonable transit alternative instead of paying the toll), and time-of-day choice (for example, a traveler may choose to travel at a different time of day when tolls may be reduced).

Tolling models incorporate a "feedback loop" in which the results of the initial travel assignments, resultant travel times, and costs are fed back through the model until the input and output travel times and costs do not fluctuate much (called "convergence").

The *second-order* responses are the additional pricing impacts that can affect almost any travel choice. For example, as a response to tolling, travelers can change the destination of their trip, decide not to implement the trip and substitute it with some other activity, or link the trip to another tour or outing as a stop on the way to their final destination. These impacts are characterized by little or no immediate change in behavior to pricing, though the accumulated effects over a long time period can still be very significant and even affect the population's residential choices and the region's land use development. They are also more difficult to directly measure and require more extensive feedback iterations to achieve the model's convergence.

Table 1 below summarizes the wide range of possible responses to congestion and pricing that can be incorporated into a travel demand model.

Most of the models used to evaluate road pricing up to this time, both in research and in practice, have focused on trip-level short-term responses and therefore capture the most direct effects of pricing on travel demand. To date, there are only a few examples of full integration across all the short-term choices listed in Table 1; two examples are the models developed for Columbus, Ohio, and Montreal, Quebec.

Table 1: Possible Responses to Congestion and Pricing

Choice Dimension	Time Scale for Modeling	Expected Impact
First Order Responses		
Route choice	Short-term – trip episode	Likelihood of choosing the toll road is expected to vary by type of traveler (single vs. multiple occupant vehicle; family carpool, transit user, etc.)
Pre-route choice (toll vs. non-toll)	Short-term – trip episode	Likelihood of choosing the toll road is expected to vary by type of traveler (single vs. multiple occupant vehicle; family carpool, transit user, etc.)
Car occupancy	Short-term – tour/trip episode	Increased likelihood of forming carpools, or increased likelihood of existing carpools to choose the toll road
Mode choice	Short-term – tour/trip episode	Shift to transit, especially to rail and among low/medium income groups
Time-of-day / schedule choice	Short-term – tour/trip episode	Increased likelihood of traveling during non-peak hours (peak spreading).
Second Order Responses		
Destination / stop location	Short-term – tour/trip episode	Improved accessibility effect combined with negative pricing effect on trip distribution for non-work trips
Joint travel arrangements	Short-term – within day	Planned carpool or carpool formed as a result of tolling
Tour frequency, sequence, and formation of trip chains	Short-term – within day	Lower tour frequency and higher chaining propensity
Daily pattern type	Short-term – weekly (day to day)	More compressed workdays and work from home
Usual locations and schedule for non-mandatory activities	Medium-term – 1 month	Compressed / chain patterns; weekly planned shopping in major outlets
Household / person mobility attributes (transponder, transit path, parking arrangements at work)	Medium-term – 1 to 6 months	Higher percentage of transponder users and parking arrangements for high incomes, higher percentage of transit path holders for low incomes
Household car ownership choice	Long-term – 1 year	Stratified response by income group (higher car ownership for high incomes, lower car ownership for low incomes)
School / university location and schedule	Long-term – 1 to 5 years	Choice by transit accessibility; flexible schedules
Job /usual workplace location and schedule	Long-term – 1 to 5 years	Local jobs for low incomes; compressed / flexible schedules
Residential location	Long-term – 5 years +	Income stratification (high income suburbs around toll roads, low income clusters around transit)
Land use development	Long-term – 5 years +	Urban sprawl if no transit; otherwise shift to transit

Other important travel choices and mobility attributes have been less explored. These include responses that go beyond a single trip-related decision, such as joint travel arrangements; the role of subsidized parking, transit passes, electronic toll collection transponders, and other personal/household mobility attributes; and long-term impacts such as those related to work and residential location decisions. All of these dimensions represent fundamental changes in travel behavior patterns that cannot be captured and understood at the single-trip level. Depending on the project scale and time horizon, the second-order responses might become as significant as the first-order responses in a travel demand model. These choice dimensions can be more fully described as follows:

- Trip/tour *destination choice* relates to switching a trip destination to avoid a toll. Mandatory trips, such as those for work or school, are generally less likely to change destination in the short to medium term than trips for shopping or recreational activities.
- Short-term choices that relate to *trip frequency and activity participation on a daily basis* that cannot be fully captured at the elemental trip level. For example, these choices include decisions to stay at home on a given day, decisions to link activities or errands in order to reduce return trips home (trip chaining), and explicit joint travel arrangements. It is important to address these dimensions along with the conventional trip dimensions, particularly when the pricing forms under study are not trip-based.
- Medium-term choices that relate to choice of *usual location and schedule* for activities (like shopping or entertainment) that are not mandatory.
- Medium-term and long-term choices that relate to *person/household mobility attributes* such as car ownership, transponder use, transit passes, subsidized parking, etc.
- *Long-term location choices* of residential place, workplace, and school as well as land use development impacts.

Several of these dimensions represent relatively new choice models that have not yet been widely accepted and explored, and that can be applied only in an activity-based, or tour-based, model framework. It is nonetheless possible to extend traditional trip generation models to investigate some of these congestion and pricing impacts.

1.3 Measuring Travel Costs in a Demand Model

Before examining the impact of tolling or pricing on travel decisions, it is necessary to model a representation of the total cost of going from one place to another. This includes travel time, distance, tolls, parking, fuel, and vehicle maintenance and depreciation costs, as well as fares and waiting times when transit is used, combined in a *generalized cost function*. When included in the core demand model, the generalized cost function helps to determine the impact of tolls on all choice decisions. The specific nature of the generalized cost function varies with each choice decision.

For route choice, the generalized cost associated with using any given road segment includes the cost of travel time, in addition to the tolls, fuel costs, and other monetary costs. Travel time is expressed as a dollar cost using a concept termed the *value of time (VOT)*; a VOT of $15, for example, means that a traveler would be willing to pay $15 to reduce her travel time by one hour. Generalized costs may vary for different

vehicle types, such as private auto (single occupant, two-person carpool, three-person carpool, etc.), light truck, heavy truck, etc. for the following reasons:

- Different vehicle types and occupancy classes may have very different *values of time (VOTs)*. For example, commercial trucks tend to exhibit higher VOTs than personal vehicles.
- *Toll rates might be differentiated* by vehicle types and/or occupancy classes, for example, such as when a high occupancy toll (HOT) lane allows three-person carpools to travel for free, allows two-person carpools to pay half of the toll, and single occupant vehicles pay a full toll.
- General *prohibitions and eligibility* rules can be applied for certain vehicle types on certain facilities (for example, trucks prohibited on expressways or truck-only toll (TOT) lanes) or auto occupancy classes (for example, HOT lanes).

A priced, or tolled, facility may represent a more attractive option because of the enhanced reliability and other considerations that are not directly measured by average time and cost. The approach that has been applied in many models is to estimate an additional *bias constant* associated with priced facilities. This bias constant can be most effectively incorporated in a model element that is frequently referred to as pre-route choice, commonly placed between mode choice and route choice.

To study traveler responses to pricing, which may include changes in mode, destination, time of day, and/or trip frequency, all of these choice decisions must be sensitive to generalized costs. There are two key steps to accomplish this: first, to include the toll costs along with all other modal attributes in the mode choice submodel; and second to calculate the accessibility from each origin to each possible destination by all available travel modes.

Accessibility is often expressed in minutes, yet besides travel time it also includes toll costs, transit fares, and modal preferences for all modes. For example, if a toll is charged to cross a bridge, all destinations beyond the bridge are considered less accessible than before, when one could cross the bridge for free. However, if as a result of the toll, there are no longer delays at the bridge then accessibility will have actually improved for those persons willing to pay the toll. Accessibility is derived from the mode choice submodel because this is where information about all potential travel modes for a given trip resides. Examples of the Montreal and San Francisco mode choice models are shown in Figure 2 and Figure 3.

Once these multimodal accessibilities are known, they are used to represent generalized costs in destination, time-of-day, and trip frequency decisions. Another option, frequently used in practice, is to employ the highway generalized cost itself in the destination choice or time-of-day choice. This simplified option, however, is recommended only if transit usage is very low. A detailed explanation of how to incorporate generalized costs in destination and time-of-day choice models is presented in Technical Appendix 1.

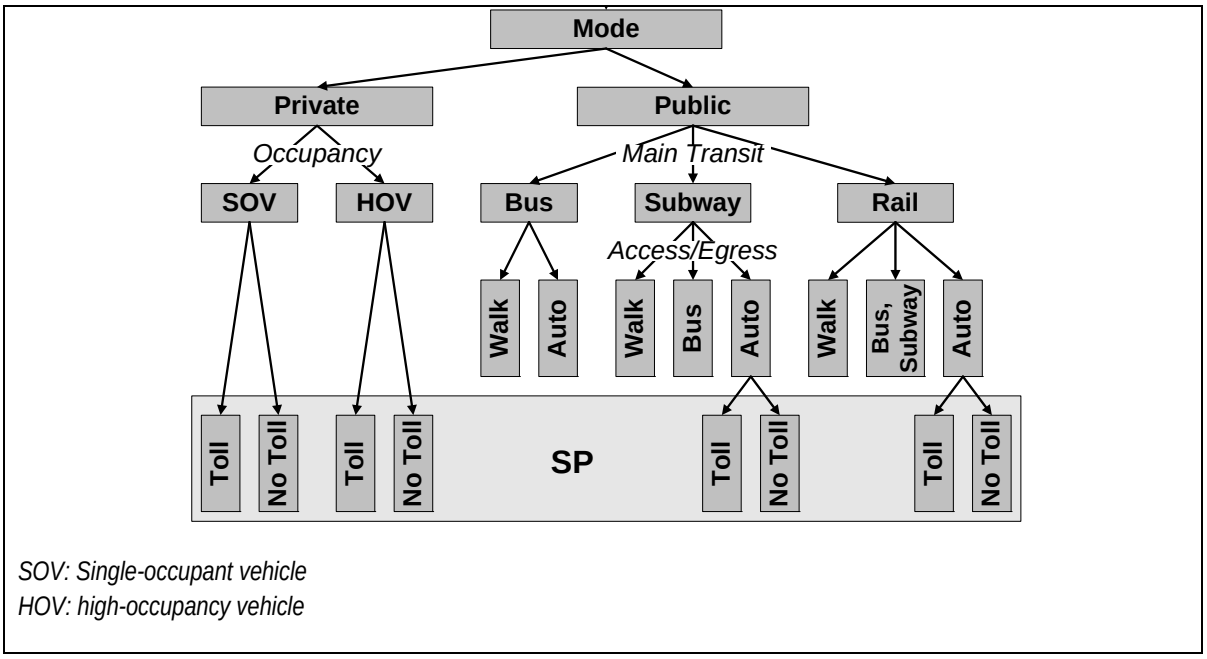


Figure 2:
Montreal Mode Choice Model
Nested Structure Incorporating Free vs. Toll (Pre-Route) Choice

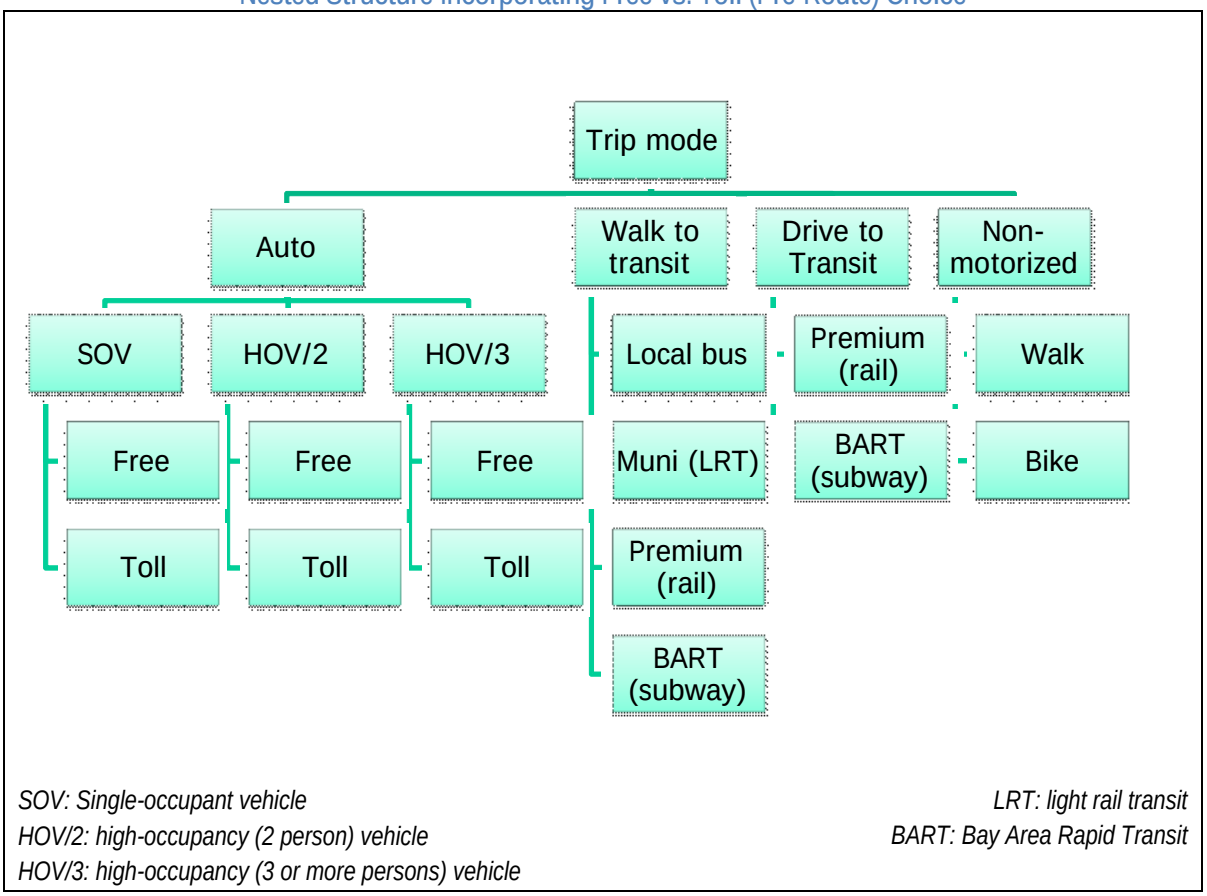


Figure 3:
San Francisco Mode Choice Model
Nested Structure Incorporating Free vs. Toll (Pre-Route) Choice

1.4 Travelers' Willingness to Pay

Willingness to pay refers to the tradeoff that travelers make between time and money, and it is a critical factor for tolling applications. For the price of the toll fee, travelers are "buying" travel time savings or travel time reliability, or some other trip-related improvement. The value of time (VOT) can be thought of as the "price" of travel time savings. The value of reliability (VOR) has a similar interpretation, but it measures willingness to pay for increased travel time reliability for a given trip. Travelers exhibit different VOT and VOR, partly as a function of personal and household characteristics (such as income, gender, worker status, etc.), and partly as a function of the context in which a trip is made (trip purpose, time of day, time pressure, outbound versus inbound trip, etc.), (Spear, 2005; Vovsha, et al, 2005). A person's response to a tolling situation will depend to a large extend on his or her VOT, all else being equal. Therefore, a good travel demand model classifies trips and/or travelers into groups of relatively homogeneous VOT or VOR. This is referred to as *travel market segmentation*.

How to appropriately segment the travel market is a critical modeling issue. The term "aggregation bias" identifies the error that results when travelers with very dissimilar attributes are treated as exhibiting a common "average" attribute value. This error arises from the non-linear nature of travelers' response to road pricing. A typical toll diversion curve, such as that shown in Figure 4, has the steepest (most elastic) part in the middle, while the ends are quite flat. This type of curve gives the likelihood of choosing a toll road as a function of the toll, all else (time savings, distance traveled, etc.) held equal. To illustrate the magnitude of aggregation bias, consider the following example. We assume that the market for this road is composed of two types of users: people who pay the full toll ($4.00), and people who pay a discounted toll ($1.00) because their costs are reimbursed by their employer. If 50% of the market pays the full toll and 50% pays the discounted toll, the average toll paid is $2.5, and the toll road share of the market is 46% (50% * 80% + 50% * 12%). Suppose now that the toll is raised by $1.0, so that now 50% of the people pay $2.0 and 50% pay $5.0. The average toll paid is $3.0, and the toll road share of the market would now be 40% (50% * 70% + 50% * 10%). So a $1.0 toll increase reduced the toll road traffic share by 6 points, from 46% to 40%. When the market is not segmented, market shares would be calculated using the average toll paid. This results, erroneously, in a reduction in toll traffic of 30 points, or the difference between the market share at $2.5 (50%) and the market share at $3.0 (20%). Because market segmentation tends to move distinct groups "away from the middle," all else being equal, it tends to dampen the overall price sensitivity across the modeled population.

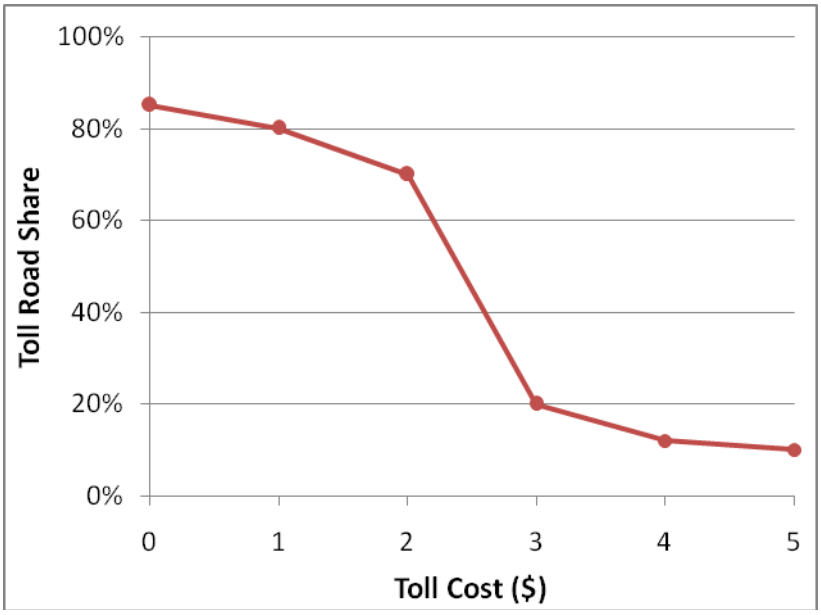


Figure 4 – Sample Toll Diversion Curve

A variety of traveler and trip type dimensions are understood to be important market differentiators. These dimensions can be grouped into attributes of the traveling population (income, age, etc.), attributes of their activities, and attributes of their trips:

Population attributes. These characteristics are independent of any trip-related decision. Thus, their effect on travel choices is achieved either by partitioning the travel market into subgroups (for example high income vs. low income households), or by using them as explanatory variables in the model. The following are the better understood socioeconomic differentiators:

- *Income, age, and gender*. A higher income is normally associated with higher VOT [Brownstone & Small, 2005; Dehghani et al, 2003]. Women and middle-age travelers also tend to exhibit higher VOT than all other travelers (Mastako, 2003; PB Consult, 2003).
- *Worker status*. Employed persons (even when traveling for nonwork purposes) are expected to exhibit a higher VOT compared to nonworkers because of the tighter time constraints.
- *Household size and composition*. Larger households, with children, are more likely to carpool and take advantage of managed lanes (Stockton et al., 2000; Vovsha et al., 2003).
- *Household auto ownership.* Although an attribute of the household, car ownership is oftentimes a modeled decision. Persons without cars, or in households where there are fewer vehicles than workers, are more likely to carpool and use transit.

Activity attributes. These are attributes of the specific activity for which one is traveling, but independent of the trip itself. Activity attributes include the following:

- *Travel purpose*. Work trips, and, in particular, business-related trips, normally are associated with higher VOT (Dehghani et al., 2003; PB Consult, 2003 and 2004). Another, frequently cited high VOT trip purpose is a trip to the airport, to catch an outbound flight (Spear, 2005). The list of special trip purposes with high VOT might also include escorting passengers, visiting a place of worship, going to a

medical appointment, and other fixed-schedule events (theater, sport event, etc). Some recreational or discretionary, flexible schedule trips, such as incidental shopping, tend to exhibit lower VOTs.

- *Day of week: weekday vs. weekend*. There is statistical evidence that VOT for the same travel purpose, income group, and travel party size on weekends is systematically lower than on weekdays (Stefan et al., 2007). This would be an important consideration for a toll road expected to attract large numbers of recreational travelers. Since most travel demand models focus on weekday travel, separate procedures are developed to estimate toll facility traffic and revenue for weekend travelers.
- *Activity/schedule flexibility*. Fixed-schedule activities are normally associated with higher VOT because of the associated "penalty" of being late. This association has manifested itself in many previous research works when VOT for the morning commute proved to be higher compared to the evening commute. For similar reasons, a trip to the theater might exhibit a high VOT, while a shopping trip might be more flexible and exhibit a lower VOT.

Trip attributes. Given that a travel demand model is a sequence or chain of sub-models (as illustrated in Figure 1), attributes of trips that are modeled in one submodel can be used as segmentation variables further down the model chain. For example, if the time-of-day (TOD) model is placed after mode and occupancy choice, then mode and occupancy can be used to segment the TOD model. If the order of models is reversed (TOD choice before mode and occupancy choice), the segmentation restrictions also need to be reversed. Some important trip attributes include:

- *Trip frequency*. More regular trips, and their associated costs, may receive more – or less – formal consideration than those that occur infrequently. For example, a $1.50 toll for an auto trip to work may be perceived as $3.00 per day (assuming the same toll each way on a round trip) and $60 per month, thus receiving special consideration. This perceptional mechanism is likely very different for infrequent and irregular trips, where the toll is perceived as a one-time payment.
- *Time of day*. Prior research confirms that travel during morning and evening peak periods is associated with a higher VOT, as compared to off-peak periods. Also, commuters on their way to work (typically during the morning peak hours) are more sensitive to travel time and, specifically, reliability than on their return home trip (Brownstone et al., 2003).
- *Vehicle occupancy and travel party composition*. While a higher occupancy normally is associated with higher VOT (though not necessarily in proportion to party size), it is less clear how travel party composition (for example, a mother traveling with children, rather than household heads traveling together) affects a party's VOT.
- *Trip length/distance*. For short distances, VOT is comparatively low since the travel time is insignificant and delays are tolerable; for trip distances around 30 miles, VOT reaches the maximum. For longer commutes, however, VOT goes down again, because commuters presumably have self-chosen residential and work places based on the long-distance travel (Steimetz & Brownstone, 2005).
- *Toll payment method*. The toll payment method is an important additional dimension that has not yet been explored in detail. The pricing experiment of the Port Authority of New York & New Jersey has definitively shown that the introduction of E-Z Pass as a toll payment method attracted a significant new wave of users despite a relatively small discount (Holguin-Veras et al., 2005). As with perceived time, the influence of the perceived value of money on road pricing-related choices needs to be examined.

- *Situational context: time pressure versus flexible time.* This trip attribute is recognized as probably the single most important factor determining VOT that has proven difficult to measure and estimate explicitly, as well as to include in applied models (Spear, 2005; Vovsha et al., 2005). There is evidence that even a low-income person would probably be willing to pay a lot for travel time savings if he or she is in a danger of being late for a job interview or is escorting a sick child. This factor is correlated with the degree of flexibility in the activity schedule but does not duplicate it.

Choosing the appropriate level of market segmentation for any given model is a function of several factors, and therefore compromises are inevitable. In addition to a desire to create relatively homogenous travel groups, other primary considerations include the number of person and household attributes that can realistically be forecasted, the size and quality of the home interview survey and other data used to estimate and calibrate the model, the most likely type of forecasting applications, model run time, model complexity, and travel demand software limitations. Tour-based models have the advantage over trip-based models in that additional segmentation can be achieved at a relatively low cost.

Another important issue in segmenting the market relates to *consistency in VOT assumptions* between the *segmentation applied in highway assignment or route choice* and the *segmentation applied in the mode choice model*. Ideally VOT is treated consistently across both choices. The standard practice, however, has been to ignore all mode choice dimensions (mode, trip purpose, household income, etc.) in highway assignments, and to use classes differentiated by auto occupancy alone (single occupant, two occupants, three or more occupants) and vehicle type (private auto and truck types). This practice unnecessarily introduces aggregation biases in route choice. Technical Appendix 1 describes an approach for constructing vehicle classes for assignment that maintains consistency with mode choice VOT segmentation.

1.5. Structure and Tolling-Related Features of Oregon's Travel Demand Models

In the State of Oregon there are travel demand models that operate at the statewide, MPO, and small urban area levels. Most of the current MPO models were originally developed within the past 10 to 15 years, following home interview surveys conducted throughout the metropolitan areas of Portland, Salem, Eugene, and Medford, and in 11 additional counties in Oregon and Southwest Washington. A single, joint model was developed pooling the data for the four MPOs and then individually calibrated and validated for each MPO region. Recently, travel demand models have been calibrated and validated for the two newly designated MPOs, Bend and Corvallis.

The *Portland Metropolitan Area (Metro) Model* is a state-of-the-practice trip-based model that estimates average weekday travel within the Portland-Vancouver metropolitan area. Since its initial development in 1998, it has undergone various updates. This discussion is based on the 2008 ("Ivan") model version. Table 2 shows the major model components and characteristics most critical for modeling tolling applications.

The following characteristics of the Portland Metro model are relevant to its tolling application sufficiency:

- Three of the first-order responses described in Table 1 are explicitly modeled: route choice, mode choice, and generalized costs; all are sensitive to tolls. Time-of-day choice, instead, is insensitive to

level of service attributes (time or costs). Therefore, as currently specified, this model assumes that tolls do not effect shifts in traffic demand across time periods. This is a common simplification among trip-based models, but methods do exist to incorporate time and cost sensitivity in time-of-day choice.

- No pre-route choice model is applied. Instead, the choice of route itinerary or path is determined by the equilibrium highway assignment as a function of travel time and cost only. This is a weakness of the model whenever applied in a context where there is a real choice between toll and free routes because it over-simplifies the time-to-cost tradeoff and ignores other factors that affect toll route choice such as trip distance and reliability.
- As with other mode choice models that lack a specific toll/no toll choice, sensitivity to tolls is largely a function of the magnitude of the time and cost coefficients, and of the tradeoff between travel time and travel cost (essentially, VOT). In the Metro model, VOT varies by trip purpose and household income, as shown in Table 2. VOTs tend to be low, while both time and cost coefficients (not shown in Table 2) are relatively high. Both of these factors tend to increase the cost sensitivity of the model, possibly to the point where it may be more sensitive to cost than is appropriate.
- The destination choice model is sensitive to tolls (a second-order response). This is achieved by using multi-modal accessibilities. Unlike route and mode choice, the destination choice models are not segmented by time period, but they are segmented by trip purpose. Use of multi-modal accessibilities in destination choice is a desirable feature. One needed improvement is a re-evaluation of the accessibility coefficients; as currently implemented the destination choice model may be overly sensitive to changes in level of service (time, cost) factors. An additional improvement would be to introduce time-of-day specific accessibilities.
- The network simulation (highway assignment) is based on four vehicle classes—SOV, HOV, medium trucks, and large trucks—and is typically performed for three time periods (AM peak, midday hour, and PM peak). However, the VOT segmentation considers only two classes: automobiles and trucks. Toll costs are converted to time-equivalent delays prior to highway assignment, so the time delay can be made to vary by each of the four vehicle classes, thus reflecting some of the actual class differences in the toll schedule. As is the case with most trip-based models, the use of additional vehicle classes would reduce aggregation biases and consequently also reduce the model's cost-sensitivity.
- An ancillary model for airport ground access (excluding airport employees) segments these trips into four classes, business/non-business and resident/non-resident, with VOT values showing significant differences only across the trip purpose dimension. Furthermore, contrary to expectation, VOT for non-business trips is larger than for business trips. A more recent air traveler model, not formally adopted at the time of this write-up, exhibits VOTs more consistent with previous expectations.
- Consistency between input and output travel times is achieved by feeding the highway assignment results back into the accessibility functions, and iterating the model from destination choice until the differences between model run iterations is small (typically three to four iterations of the model).
- The development of the truck trip tables takes place outside of the regional travel demand model. The truck model is largely unaffected by transport level of service factors. This is consistent with the state of freight modeling practice. Therefore, the only measurable effect of tolling on truck flows is the choice of route implemented at the assignment stage.

Table 2: Portland Metro Travel Demand Model Tolling-Related Features

Major model feature	Detailed feature / submodel	Model characteristics
Spatial scale		Regional
Demand model structure		Aggregate trip-based four-step
Modeled pricing impacts	Route choice	No pre-route choice. Route itinerary is obtained from the highway assignment. Toll costs are included in the generalized cost function.
	Mode choice and auto occupancy	Toll costs can be incorporated in the utility equations for the three auto modes: drive alone, drive with passenger, and auto passenger. Toll cost incurred when choosing drive with passenger and auto passenger modes is half the toll cost of the drive-alone mode.
	Destination choice	Toll costs affect destination choice through multi-modal accessibility functions.
Willingness to pay / VOT and user segmentation	By vehicle class in the network simulation ($1994)	Auto (SOV or HOV) - $ 9.9 / hr
		Trucks - $ 26.6 / hr
	By trip purpose and income level, in mode choice ($1994)	Home-based work: $3.3/hr - $5.4/hr
		Home-based school: N/A
		Home-based college: $22.8
		Home-based other: $2.7/hr - $5.2/hr
		Non-home-based: $5.2/hr
	By trip purpose ($1994), airport trip mode choice VOT expressed as a function of income. Values shown correspond to a $40,000 income level.	Business travel: $18/hr
		Non-business travel: $27/hr

The *Salem-Keizer Area Transportation Study (SKATS)* model follows a structure similar to that of the Portland Metro model and therefore shares many of the strengths and weaknesses discussed above. The model was estimated and calibrated with the same home interview survey data, complemented by 1990 and 2000 U.S. Census data, as well as land use data maintained in SKATS's geographic information system (GIS) database. The model was validated to 1997 traffic counts and observed ridership on Salem Mass Transit. The SKATS model has not been used on any toll-related project, and therefore it is not set up to handle tolls or road prices. However, the application software is sufficiently flexible to allow for the inclusion of toll costs in mode choice and assignment. From a tolling application perspective, the critical structural differences relative to the Portland Metro model are:

- The destination choice models use travel times, instead of multimodal accessibilities, as the travel accessibility measure. Thus these models are not sensitive to toll costs, and would need to be re-specified and calibrated if one were interested in this second-order effect.
- The mode choice models are segmented by trip purpose and household income, but not by time of day. Instead, all home-based work trips are modeled using peak level of service, while all nonwork trips assume off-peak level of service. Time-of-day segmentation would need to be introduced before these models could be used to study any time-of-day variable pricing scheme.
- Two vehicle classes are used in the user equilibrium assignment—autos and trucks. Generalized cost is a function of travel time only, and therefore no assumptions are made about possible auto or truck VOTs. It would be relatively simple to add toll cost terms to the generalized cost function. This model would benefit from the introduction of more finely segmented vehicle classes, as discussed for the Portland Metro model.

The model of the *Lane Council of Governments* maintains a simple, straightforward four-step model. As is the case for SKATS, tolling applications have not been under study in the Eugene-Springfield area, and therefore the model is not currently set up to handle highway pricing. The most critical model features, from a tolling application perspective, are:

- Gravity models are used for trip distribution and currently use highway travel time to measure destination accessibility. Using a generalized cost function, instead of highway travel time, would introduce toll sensitivity. However use of the gravity model could lead to incorrect distributional responses to tolls. A preferred approach would be to implement destination choice models based on multi-model accessibilities.
- The core demand model is fully segmented into peak and off-peak periods, which allows for testing some variation in tolls by time of day, but only in terms of modal and route shifts.
- The mode choice models are further segmented by trip purpose and income, so they already capture the principal VOT differences.
- Highway route choice is implemented in a single-class user equilibrium assignment (travel-time-only cost functions). Segmentation into vehicle classes, consistent with the VOTs used in the mode choice model, as well as implementation of generalized costs would be necessary prior to using this model for tolling applications.

- Even with the implementation of generalized cost functions in assignment, the lack of a pre-route choice model over-simplifies the time-to-cost tradeoff and ignores other factors that affect toll route choice such as trip distance and reliability.
- Estimated link travel times are fed back to trip distribution; typically two to three iterations are required to achieve equilibrium.

The travel demand models for the *Rogue Valley MPO*, *Bend MPO,* and *Corvallis MPO* all follow a model implementation similar to the Portland Metro model's, albeit somewhat simplified. None of these models has been applied in a road pricing project, and they are therefore not currently set up to handle tolls. These models could be made sensitive to tolls, as has been done in Portland. Their critical model features are:

- Destination choice models use multimodal accessibility functions, similar to those used in the Portland Metro model. The home-based work (HBW) models are segmented by three income levels and therefore reflect three different VOTs. None of the destination choice models is segmented by time of day, so they would not be sensitive to variable tolls.
- The mode choice models use similar VOTs and segmentation as the Metro model; therefore, they could be modified following the Metro model's implementation to handle toll costs.
- The model uses a single-class equilibrium highway assignment. As discussed above, highway assignment would need to be improved (apply segmentation and generalized cost functions) before using this model for tolling applications.
- As discussed for the previous models, the lack of a pre-route choice model is a weakness that needs to be addressed.
- Travel time feeds back to destination choice.

The *Statewide Integrated Model (SWIM)* is an integrated land use and transport model covering the entire state of Oregon, and only one of two such models developed in the United States. It is a second generation model, drawing on previous work done on Oregon1, the first generation statewide model [*Parsons Brinckerhoff, 1999; PBQD, 2001],* and the Eugene-Springfield UrbanSim model *[Waddell et al., 1998]*.

SWIM includes a substantially different, and more advanced, travel demand model than the models currently in use at the MPO level. SWIM combines a spatial economic model with transport models: it models the economic interactions between Oregon and the rest of the world; changes in land use, population, and employment growth; and commercial and person travel. SWIM is disaggregate in nature – each household and person is micro-simulated, allowing for far more market segmentation than is practical with a trip-based model. The transport models are based on tours, instead of trips, so that there is consistency of all the various travel decisions (times of travel, destinations and modes) among all trips within a tour.

The four modules most germane to this discussion are the following:

- The Production Allocations and Interactions (PI) module represents the regional economic relationships among industry, households, and institutions. The PI module locates industry and households in space, generates a set of economic flow matrices for each commodity, and determines

the commodities made and used by each activity, including labor. The PI module is informed by travel accessibilities, including toll costs, in the form of multi-modal accessibilities between origins and destinations.

- The Transport Supply (TS) module performs the trip assignment function. The module also produces travel time and cost for each available mode, for each origin and destination.
- The Person Transport (PT) module generates travel for all household members, in the form of "tours" that start and end at home. Work tours are based on labor flows produced by other modules and influenced by travel times, distances, and costs by all modes of transport from the TS module, and multimodal accessibilities calculated by the PT. The PT module consists of two jointly run subcomponents: short distance transport (SDT), which predicts all regular work commutes regardless of length and noncommute travel patterns less than or equal to 50 miles in length, and long distance transport (LDT), which predicts noncommute travel patterns greater than 50 miles. Toll costs affect PT both directly (in the mode choice model), and indirectly through multimodal accessibility functions.
- The Commercial Transport (CT) module is a micro-simulation model of freight travel demand. Given commodity flow movements, the model attempts to replicate several freight travel choices made by different agents, especially trip linking and the use of intermediate distribution and warehousing centers. Production flows are converted to discrete shipments by commodity and mode of transport. The shipments are further allocated to tour origins, tour destinations, intermediate stops, and vehicles. There is no direct linkage between toll costs and CT; instead, the production and consumption locations of commodities are determined by the PI module, which does so informed by multimodal accessibility functions.

The PT module is a sequence of discrete choice decision models that implement a tour-based approach similar to the one shown in Figure 1. The travel decisions of each person in the state are micro-simulated, with the exception of route choice, which relies on aggregate network assignments similar to those applied by the MPO models. All models in PT except the mode choice models were originally estimated for the state of Ohio and were calibrated and validated using the 1994/96 set of home interview surveys, 2000 Census Transportation Planning Package (CTPP) and Public Use Micro Sample (PUMS) data, American Travel Survey (ATS), and recent observed traffic volumes and transit ridership. The tour and trip mode choice models are based on the first generation models estimated with Oregon data.

The most relevant tolling-related features of SWIM are shown in Table 4. SWIM is the most toll-sufficient model of all the models currently implemented in Oregon, and its disaggregate nature lends itself to various advanced treatments, as is discussed in Section 6. Important tolling-related characteristics of SWIM include:

- SWIM is an activity-based model, and therefore treats individuals on a disaggregated basis (rather than as several homogeneous groups), thus offering the potential for a more accurate representation of the toll travel market.
- The time-of-day choice for work tours could be made sensitive to toll costs within the current structure of the model. Currently, it is sensitive to travel time, in addition to various other person,

trip, and household attributes. Time-of day choice for non-work tours is applied before tour destination choice, so in the current model sequence non-work tour scheduling cannot be sensitive to level-of-service attributes.

- No pre-route choice model is applied. Therefore the weaknesses that arise from relying on the assignment step for the toll vs. free road choice, and discussed before in the context of the MPO models, apply also to SWIM.
- Toll costs influence the choice of tour mode and trip mode. Both the tour mode choice and trip mode choice models are fully segmented by time of day. Their respective VOTs are shown in Table 4. Some of these VOTs, particularly for the low income travelers and non-work purposes appear low and may need to be revised.

Table 4: Oregon Statewide Integrated Model Tolling-Related Features

Major model feature	Detailed feature / submodel	Model characteristics
Spatial scale		Regional
Demand model structure		Disaggregate activity-based, integrated with a spatial model
Modeled pricing impacts	Route choice (TS)	No pre-route choice. Route itinerary is obtained from the highway assignment. Link-based toll costs included in the generalized cost function.
	Mode choice and auto occupancy (PT) *Tour and trip level decisions*	The tour mode choice and trip mode choice utility functions include toll costs for all the auto modes.
	Destination choice (PT) *Primary tour destination decision*	Toll costs affect tour destination choice through multi-modal accessibilities
	Time-of-day choice (PT) *Tour departure time and duration*	Toll costs affect the work tour scheduling models through multimodal accessibilities
	Workplace location (PI/PT)	Toll costs affect the dollar flows of labor between residential and industrial activities via multi-modal accessibilities
	Industry location (PI)	Toll costs affect the dollar flows of labor and commodities between activities via multimodal accessibilities.

Major model feature	Detailed feature / submodel	Model characteristics
Willingness to pay / VOT and user segmentation	By vehicle class in the network simulation ($1994)	Auto: SOV and HOV
		Trucks: Light, Medium, and Heavy
	By tour purpose and income level, in tour mode choice ($2000)	Work and College: $1.5/hr - $11.5/hr
		Non-Work: $1.0/hr - $7.5/hr
	By tour purpose and income level, in trip mode choice ($2000)	Work: $2.0/hr - $3.9/hr
		School: $1.7/hr
		Other: $1.3/hr - $1.4/hr
		Work-based tours: $0.9/hr - $3.0/hr

- Link-based toll costs are included in the generalized cost function used in highway assignment. Vehicle trips are segmented into five classes by VOT. These classes have been constructed largely ignoring VOT segmentation, and therefore could be improved by applying the segmentation scheme described in Technical Appendix 1.
- The nonwork destination choice models are fully segmented by time of day, and use period-specific multimodal accessibility functions; therefore, these models are sensitive to peak versus off-peak toll differences.
- The workplace location model is influenced by toll costs through the allocation of labor flows forecasted by the PI module.
- SWIM includes a state-of-the-art commercial transport model (CT). Trips by truck class are derived from the simulated flow of commodities within the state and to/from out-of-state origins and destinations. These commodity flows are influenced by multi-modal accessibilities. Efforts are on-going to fully validate CT to base year conditions, and to test its sensitivity to tolls.

Section 2.0: Modeling Requirements for Oregon Tolling Applications

An assessment of modeling requirements must necessarily start with a good understanding of the types of tolling applications under study. The tolling applications that are being considered in Oregon are described in a companion paper (Paper 5), and in studies that preceded these White Papers (Cambridge Systematics, 2007). In terms of modeling requirements, the potential tolling applications can be classified as follows:

- Traditional projects: new toll roads and new toll bridges
- Existing freeways or bridge tolling
- Tolled managed lanes: HOT lanes, express lanes, and truck-only lanes
- Cordon or area pricing: at an inner cordon or at the urban growth boundary
- Mileage-based road pricing

There are model requirements that apply to any road pricing study, while others are relevant only for specific applications. Some model requirements are considered essential, while others may be left for advanced stages of the study. Table 5 lists the modeling requirements corresponding to the typology of tolling applications listed above. At a minimum, the mode choice and assignment models must be sensitive to the toll cost through the use of generalized cost functions and adequate VOT segmentation. Inclusion of a pre-route toll versus no toll choice model is also highly desirable. A more advanced treatment would include considering the delays at toll plazas and access ramps (if any), further developing the VOT segmentation, addressing travel time reliability, and equilibrating generalized cost through trip distribution, in addition to mode choice equilibration. There are several examples of U.S. travel demand models that already incorporate at least some of these features, with the exception of travel time reliability.

From a modeling perspective, these applications can be further grouped into two general classes: facility-specific tolling (one or more roads), or cordon/area pricing tolls, which would include mileage-based pricing. The main difference between these two groups is the importance of the trip frequency/trip generation decision. Under cordon/area pricing or ubiquitous mileage-based schemes, it is essential to model the trip suppression effect of the toll. On the other hand, pre-route choice is less important because all possible routes would be tolled, and therefore there would be no free alternative. Table 5 lists the specific requirements for cordon/area pricing schemes, which are understood to be in addition to the requirements listed for all pricing projects, with the exception of pre-route choice. Advanced modeling of the long-term effects of these types of schemes necessarily requires integration with the land use model, so that decisions about residential location and commercial land use can be informed by the region-wide changes in the cost of travel. This is particularly important when the policy under consideration seeks to influence land use patterns. Oregon is well ahead of all other states when it comes to the integration of land use and transport models, both at the MPO and at the statewide level.

Table 5: Model Features Relevant for Oregon Pricing Applications

Type of Pricing Application	Model Features	
	Essential	Advanced
All Road Pricing Studies	Toll facilities coded in the highway network with toll incorporated in the generalized cost functions	Toll plazas and access ramps coded with realistic delay functions
	Segmented VOT by travel purpose and income group in demand model	Perceived highway time by congestion levels/reliability
	Segmented VOT by vehicle class in traffic assignment	Additional vehicle class stratification by VOT
	Pre-route (toll vs. no toll) subchoice	
	Mode choice and assignment equilibration	Inclusion of trip distribution in equilibration through multi-modal accessibilities
Cordon and Area Pricing	Trip generation sensitive to accessibility/generalized cost	Accounting for trends in flexible/ compressed work schedules and telecommuting
		Residential location and commercial land use models integrated with the transport model and sensitive to generalized travel costs
Congestion Pricing – road-, area-, or cordon-based	Peak spreading model	Time-of-day choice model Accounting for trends in flexible/ compressed work schedules and telecommuting
Dynamic (Real-Time) Pricing – road-, area-, or cordon-based		Special network/toll equilibration procedure
HOT/Express Lanes	Car occupancy (SOV, HOV2, HOV3+) subchoice in mode choice	Additional vehicle class stratification by occupancy in assignment
	Mode choice sensitive to household size	Explicit modeling of joint household travel
Truck-Only Lanes	Segmented VOT by truck classes in traffic assignment Pre-route (toll vs. no toll) choice	Agent-based models
Road Pricing in Parallel with Transit Improvements	Mode choice with developed transit nest	Parking location choice model for drive-to-transit trips
	Bus speeds linked to highway congestion	
Road Pricing in Parallel with Parking Policies	Parking cost inclusion in mode choice, and in trip distribution through multi-modal accessibilities	Parking location choice model for auto and drive-to-transit trips with parking constraints

Two other equally important aspects of travel model design are *the nature of the toll schedule*, in particular differences in toll or price across vehicle types and vehicle occupancy, time of day, and static versus dynamic pricing, and *the nature of policies that complement the pricing application*, such as improvements to transit service or parking restrictions. The requirements for the most likely tolling options are also listed in Table 5. These tolling application options cut across the types of projects listed above. For example, a peak spreading and/or time-of-day choice model would be required if the study is considering variable time-of-day pricing, regardless of whether the application is freeway- or cordon-based.

Specific modeling requirements related to the toll schedule and complementary policies are summarized as follows:

- Congestion pricing necessarily implies that tolls would vary by time of day, and possibly by vehicle type; therefore, the model needs to be sensitive to time-of-day travel decisions, whether just within the peak periods (peak spreading model) or across time periods (time-of-day choice model).
- Dynamic pricing requires that the toll be set as a function of congestion levels in a real-time basis. This type of tolling schedule can only be modeled using advanced toll equilibration procedures between the network simulation and the demand model.
- HOT and express lane studies, where the tolls may vary by car occupancy levels, require specific modeling of the occupancy choice, as well as assignment stratification by occupancy levels to restrict unallowed vehicle types from using the managed lanes. Sensitivity to household size is highly desirable, since opportunities to form carpools as well the need to do so are greater in large households and among families with children.
- Transit improvements and restrictive parking policies are often studied as policies complementary to road pricing. To do so requires adequate treatment of the transit options and parking costs throughout the model.

The modeling requirements listed in Table 5 as "essential" for the analysis of truck-only lanes may appear fairly modest, but they reflect the state of the practice. There is a high degree of complexity associated with how the freight transport sector responds to tolls and other road transport level of service attributes, and we are not aware of any operational or even research trip-based model with a proven ability to capture these effects. Among activity-based models, the state-of-the-art is exemplified by CT, the commercial transport model embedded in SWIM. CT can be characterized as an agent-based approach.

The evaluation of what are commonly referred to as "greenfield" projects - new roads and new bridges - does not require any additional model features beyond those listed in Table 5. However, relative to tolling applications implemented on corridors with well-established travel demand, greenfield projects require more detailed, in-depth analysis devoted to the identification of risk factors and the quantification of demand uncertainty. The reasons for this are explained in detail in Technical Appendix 3.

The *geographic scale* of the project also plays a role in the design of the travel demand model. More specifically, while geographic scale does not influence the selection of the relevant modeled travel decisions, it does affect the scale and resolution needed to adequately represent impacted facilities and trip

origins and destinations. Geographic scale also affects the level of effort and resolution employed for calibrating and validating the travel demand model. We can distinguish five levels of geographic scale: statewide, regional, subarea, corridor and facility. It is important to clarify that this classification identifies the geographic distribution of the relevant (tolled) trip origins and destinations, and not the tolled facilities themselves. For example, the impacts of tolling a single facility of regional importance need to be analyzed at the regional level, in addition to the corridor and facility level. It would not be sufficient to limit the study to an evaluation of very localized impacts. In this respect the evaluation of truck-only lanes poses a significant challenge, due to the large share of medium and long-haul trucks with origins and/or destinations outside of the model area of a typical MPO model.

A comparison of the SWIM and MPO models relative to the requirements listed here is the subject of Section 6.0, which evaluates the capability of Oregon's travel demand models.

Section 3.0: Modeling Requirements for Investment-Grade Studies

3.1 Rules of the Financial World

A toll traffic and revenue (T&R) study is considered to be "Investment Grade" if the appropriate level of diligence has been taken so that the results of the study can be used to determine the financial viability of the project. The three major rating agencies—Fitch Ratings, Moody's, and Standard & Poor's—conduct various tests on traffic and revenue forecasts and examine variations in many input parameters as well as the model structure itself to assess revenue forecast reasonableness and financial risk (Standard and Poor's, 2002-2005; Fitch Ratings, 2003-2005). It should be understood that the quality of the forecast may directly affect the project bond rating (i.e., the possibility to obtain the necessary loans and the interest rate associated with them). It should also be understood that a project may ultimately not be rated "investment grade" even if a high quality forecast has been produced.

Investment-grade studies require an advanced and well-calibrated travel model integrated with the network simulation to be able to support the level of analysis required by investors and bond rating agencies. While a general principle that "a good model for an investment-grade study should first of all be a good behavioral model in a common sense" holds true, it is applicable only as a starting point. Investment-grade studies place specific requirements on the travel demand model itself and the way in which the model is applied. These requirements relate to the model structure and calibration, to the way in which the model is applied, and to a number of post-modeling steps that convert the model outputs into the inputs needed for a financial plan.

3.1.1 Model structure and calibration requirements:

- Presence of all three major relevant choice dimensions (route, mode, and time-of-day) that represent first-order responses of the travelers as described in Section 1. Additional relevant features include:
    - More elaborate *time-of-day choice* or *peak-spreading* model distinguishing between the peak hour and time periods immediately before and after the peak;
    - *Trip generation* model sensitive to accessibility improvements; and
    - *Trip distribution* model sensitive to multimodal accessibilities.
- *User segmentation by VOT* across travel purposes, income groups, times of day, vehicle type, and occupancy.
- Extensive, newly collected data and more rigorous *corridor-focused model calibration*. It is essential to recalibrate the model based on the most recently collected data, including traffic counts, special surveys (e.g., users of a particular toll facility), and speed measurements.

3.1.2 Model application requirements:

- *Toll rate optimization* and multiple sensitivity tests with different toll and toll escalation scenarios.
- *Risk analysis and risk mitigation* measures. This includes identification and quantification of risk factors. A good overview of the common risk factors in travel forecasting is provided in the periodical publications of the rating agencies (Standard and Poor's, 2002-2005; Fitch Ratings, 2003-2005), as well as in Washington State's Tolling Study (Cambridge Systematics, 2006). The following general risk factors are under scrutiny by rating agencies:
    - *Start-up Facilities*. Start-up toll facilities are considered the most risky and therefore are very closely scrutinized.
    - *Context*. For example, accurate T&R forecasting in dense urban areas will be less reliable than a river crossing with a clear competitive advantage over limited alternatives.
    - *Established Corridors*. Traffic patterns associated with well-defined, strong radial corridors appear to be more reliable.
    - *Optimism Bias*. Travel demand forecasts prepared by project sponsors and bidders (interested parties) are generally higher than those prepared by investors and bankers; this "optimism bias" is estimated at 20% or more. More aggressive forecasts can be accepted for public-private partnerships that do not need rating.
    - *Aggregation Bias*. VOT miscalculation and improper aggregation across different income groups and travel markets is a common bias. Proper model segmentation is essential.
    - *Economic Outlook*. The economic outlook predicts the likelihood of recessions and economic downturns and their effect on toll road revenues.
    - *Land Use and Population Forecasts*. Reconsideration of population, employment, and income growth forecasts prepared by the MPO or department of transportation for the region/corridor is one of the frequent requests.
    - *Time Savings*. The rating agencies often use lower time savings assumptions or expectations than the modeled ones.
    - *Competition*. Free roads and/or transit services that serve the same markets as the toll road may develop in the future, potentially reducing the anticipated revenue.
    - *Off-Peak and Weekend Traffic*. The rating agencies often use lower off-peak and weekend traffic assumptions (40-50% of weekday) than are normally assumed (70-75% of weekday).
    - *Truck Market*. Assessment of specific risk factors for the trucking market is essential if trucks constitute a significant traffic share:
        - Less reliability should be placed on the forecast if the trucking market is composed of a large number of small, owner-driver general haulers.
        - Markets consisting of several, very large haulage companies transporting high-value or time-sensitive commodities are likely to be less volatile.

3.1.3 Model output processing requirements:

- *Annualization* of revenues, including assumptions on weekend and holiday revenues, seasonality, within-week variability, etc.
- *Extrapolation of the early T&R stream.* A very long-term forecast (40 to 50 years and longer) is needed for the financial plan. Capacity constraints and adverse effects of congestion when traffic volume approaches capacity should be taken into account.
- Detailed consideration of a *ramp-up* period. Various ramp-up durations are tested, depending on previous regional experience with tolls, implementation of electronic toll collection (ETC), and other factors. Long ramp-up periods are indicative of high risk projects.
- Detailed consideration of bulk discounts, person/vehicle type discounts, toll evasion (if any), and other *revenue loss factors* such as accidents/incidents, extreme weather, or special events, among others.
- Consideration of how toll rates escalate over time (based on Consumer Price Index, gross domestic product, and a minimum versus maximum change in rate) compared to population *income (and VOT) growth* over a long period of time.
- Processing of the model output in a form suitable for the subsequent analysis. It is important to ensure transparency of the results and identify key areas (origin-destination pairs, core travel markets) for which the calculations can be demonstrated for interested parties (i.e., "open the black box").

3.2 Recommended Steps for Complying with the Financial World Rules

Complying with the specific requirements of private investors and bond rating agencies requires a fundamental shift in how travel demand forecasts are prepared and presented. A review of existing models nationwide (NCHRP, 2008), as well as the tracking history of model applications and associated well-published criticism from the bond rating agencies, demonstrates the need to improve modeling tools and forecasting practice in ways that better address travel behavior decisions, and that account for uncertainty in the forecast explicitly. It should be understood that any model used for investment-grade forecasts must meet the structural requirements listed above. In terms of forecasting practice, the following areas have been identified as those that could most productively be improved:

- *Revenue forecasts have to be presented in a probabilistic form* (not as point estimates, as is typically done) suitable for subsequent investment risk analysis and rating. The current practice is characterized by a sequential implementation of T&R forecast followed by an independent/simplified risk analysis. A better practice would be to conduct a systematic risk analysis that is integrated with the forecasting process.
- Rating agencies and private investors consider *stand-alone start-up projects as the most risky*, uncertain, and subject to over-optimistic modeling assumptions. It must be recognized that static validation of a transportation model for the base year does not guarantee that the model will properly respond to changing travel conditions, including those associated with a new toll road or pricing action, or the construction of a competing free roadway. Therefore, a thoughtful risk factor analysis, examining both model inputs and model parameters, must be employed.

Therefore the forecast needs to be presented as a distribution of outcomes, with associated probabilities that indicate the most and least likely outcomes. For example, instead of predicting annual average daily traffic of 10,000 vehicles per day, given certain assumptions on population growth, VOTs, travel time savings, etc., the forecast required by the financial world is an assessment of how annual average daily traffic will vary with plausible and varying scenarios of population growth, VOT, etc., along with the likelihood that any combination of the input assumptions will be realized. For example, the forecast would say that there is a 50% probability that average annual daily traffic will be between 8,000 and 13,000, a 20% probability that it will be less than 8,000 vehicles, and a 30% probability that it will be more than 13,000 vehicles.

The development of better models and a more rigorous risk assessment approach will help increase the credibility of T&R forecasts, as well as better integrate the transportation modeling culture with the culture of the investment analysis community. Procedures to integrate T&R forecasting with risk analysis for a wide range of parameters and events will be discussed in Section 6, along with the risk factors that have been identified in the literature.

Section 4.0: Incorporating Travel Time Reliability in Travel Demand Models

Measurement of highway time reliability and its impact on travel choices is now considered one of the most important strategic directions for travel model improvement. Several published and ongoing research projects (NCHRP 8-57, NCHRP 8-64, NCHRP Report 618, SHRP2 CO4, SHRP2 LO4) as well as FHWA guidance are devoted to reliability issues. There is a considerable body of research regarding the definition of travel time reliability, its measurement, as well as the computation and treatment of travel time reliability in modeling tools. The suggested reliability measures have been analyzed in the context of effectiveness related to transportation projects and policies, as well as the entire highway system performance. A companion paper (Paper 4) provides detailed definitions of travel time reliability and its economic impacts. This section discusses ways to incorporate reliability into travel demand models. This topic is treated more in-depth in Technical Appendix 2.

4.1. Measuring Highway Time Reliability

In general, there are four methodological approaches for quantifying reliability that are suggested in either research literature or already applied in operational models:

- *(Indirect measure) Perceived highway time* by congestion levels. This concept is based on statistical evidence that in congestion conditions, travelers perceived each minute with a certain weight (NCHRP, 1999; Axhausen et al., 2006; Levinson et al., 2004; McCormick Rankin Corporation & Parsons Brinckerhoff, 2008). Perceived highway time is not a direct measure of reliability, because only the average travel time is considered, though it is segmented by congestion levels. Perceived highway time can, however, serve as a good instrumental proxy for reliability since the perceived weight of each minute spent in congestion is a consequence of associated unreliability.
- *(1st direct measure) Time variability (distribution)* measures. This is considered the most practical direct approach and has received considerable attention in recent years. This approach assumes that several independent measurements of travel time are known, which allow one to create the travel time distribution and calculate some derived measures, like buffer time (Small et al., 2005; Brownstone & Small, 2005; Bogers et al., 2008). One significant technical difficulty is that even if the link-level time variations are known, it is not a trivial task to synthesize the origin/destination level time distribution (reliability "skims") because of the dependence of travel times across upstream/downstream links.
- *(2nd direct measure) Schedule delay cost*. This approach has been adopted in academia for many research works on individual behavior (Small, 1982; NCHRP,1999). According to this concept, the direct impact of travel time unreliability is measured through cost functions (penalties expressed in monetary terms) of being late (or early) compared to the planned schedule of the activity. This approach assumes that the desired schedule is known for each person and activity in the course of the modeled period. This assumption, however, is difficult to meet in practical model settings.
- *(3rd direct measure) Loss of activity participation utility*. This method can be thought of as a generalization of the schedule delay concept. It is assumed that each activity has a certain temporal utility profile and individuals plan their schedules to achieve maximum total utility over the modeled period (for example, day) taking into account expected (average) travel times. Then, any deviation from the expected travel time due to unreliability can be associated with a loss of participation in the

corresponding activity; or gain, if travel time proved to be shorter (Supernak, 1992; Kitamura & Supernak, 1997; Tseng & Verhoef, 2008).

A detailed analysis of all four approaches described above, with application examples, can be found in Technical Appendix 2. A good example of the time variability measure was presented in Small et al. (2005). In that case, the adopted quantitative measure of variability was the upper tail of the distribution of travel times, such as the difference between the 80th and 50th percentile travel times (see Figure 4). The authors argue that this measure is better than a symmetric standard deviation, because in most situations arriving "late" is less preferable than arriving "too early," and many regular travelers will tend to build a "safety margin" into their departure times that will leave them an acceptably small chance of arriving late (i.e., planning for the 80th percentile travel time would mean arriving late for only 20% of the trips). Reliability, as defined above, proved to be valued by travelers as highly as the median travel time.

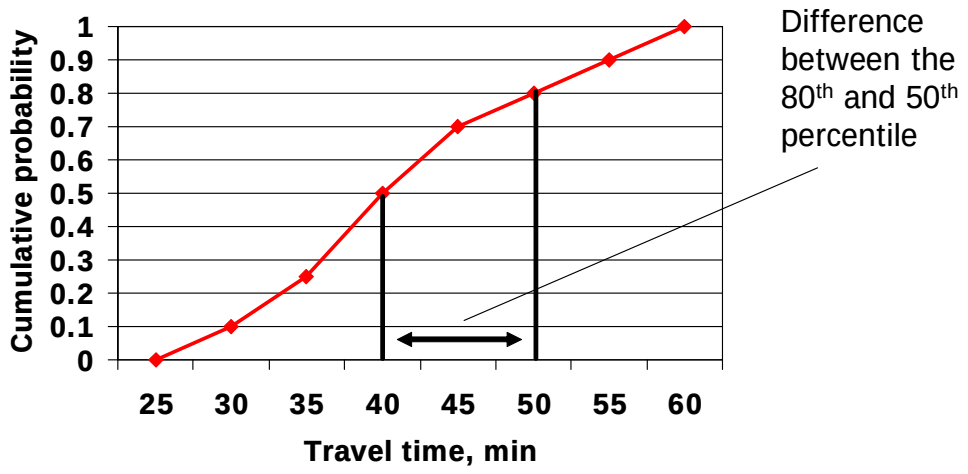


Figure 4: Travel Time Variability Measure

4.2. Including Highway Time Reliability in Operational Models

The research and practice on travel time reliability to date suggests that the best method for incorporating highway travel time reliability in operational models is perceived highway time. The concept in itself is similar to the treatment of time components for transit travel, where time waiting for a bus is perceived as more onerous than time riding in the vehicle, for example. The analogy for highway travel is that time spent in congested conditions is perceived as more onerous than time spent in free-flow traffic.

To use perceived highway time in an operational model, travel time needs to be separated into at least two components, where one measures the minimum travel time needed to reach a destination (assuming, for

example speeds close to the speed limit), and the second measures the additional time it takes due to traffic congestion. A more fine-grained treatment would further classify congested time by level of congestion, measured, for example, by the volume-to-capacity ratio. The travel demand model would then be specified so that congested travel time is perceived as *X* times more inconvenient than free-flow time, where the parameter *X* could increase with the volume-to-capacity ratio.

If the demand model is already set up to produce free-flow travel times, then there is very little additional overhead (in terms of computation time) required to implement this method. However, depending on the number of levels used to classify the degree of congestion, run time would increase proportionally to the number of highway assignments needed to produce the various time components. There would also be demands on storage space, since additional travel time matrices will need to be saved.

Section 5.0: Uncertainty, Systematic Bias, and Risk Analysis

The evaluation of model quality and capability is directly related to the degree of accuracy and likely sources of error. This section discusses the most likely sources of risk and uncertainty and methods developed to eliminate built-in optimistic biases and produce more realistic and conservative forecasts.

5.1. Sources of Risk and Uncertainty

While significant uncertainty in traffic forecasts clearly exists, the causes of such uncertainty vary. Numerous studies have identified and examined several sources of forecast error (see for example Flyvbjerg et al., 2006 and 2006; Bain & Wilkins, 2002; George et al., 2003; and George et al., 2007). For the most part, these sources of error are similar for tolled and non tolled highways, but differences do exist. A detailed and extensive survey of literature on sources of risk and uncertainty can be found in Technical Appendix 3.

Overall, the top drivers of forecast failure are:

- Poorly estimated VOTs, or reliance on a single VOT (as opposed to segmenting user groups);
- Economic downturns;
- Erroneous prediction of future land use conditions;
- Lower-than-predicted time savings;
- Added competition (e.g., improvements to competing roads or the addition of new roads);
- Lower-than-anticipated truck usage;
- Tolls being set at a different level than what was assumed in the T&R model;
- High variability in traffic volumes (by time of day or by day of the year);
- Complexity of the tolling regime;
- Underestimation of the duration and severity of the ramp-up period; and
- Use of a travel demand model developed for other planning purposes.

5.2. Relevant Risk Factors for Toll Projects in Oregon

The first step in formulating a risk mitigation plan is the identification of risk factors. While a full accounting of such factors in specificity can be accomplished only on a project basis, these factors generally fall within the following groups:

- *Population growth* in the relevant project corridor. This growth should be compared to the observed tendencies in the past in the entire region and the corridor. If the projected growth is significantly higher than the observed trends, it should be considered as a high risk factor. Creating “optimistic” and “pessimistic” scenarios, with estimated probability of each of these to occur is recommended.
- *Employment growth* in the relevant project corridor. As was with population growth, realistic comparisons of employment growth to the observed trends should be made. Each case where growth rates are higher than the observed trends should be carefully substantiated; otherwise, high risk is assigned to this factor. Creating “optimistic” and “pessimistic” scenarios, along with their estimated probability to occur, is recommended.

- *Special markets growth* in the relevant project corridor. This factor is important when a significant share of the toll traffic consists of travel to a destination external to the model area, such as weekend/holiday travel, airport travel, and other markets that are not well captured by the regional model.
- *Competing highway and transit projects* in the corridor. This factor is relevant for pricing projects located in corridors where another significant and competing project may take place (including a significant improvement of the existing free road or transit service). If this is a realistic option, the competing projects should be described, coded, and included in the "pessimistic" network scenarios.
- *Complementary (feeding) highway projects* in the corridor and beyond. This factor is relevant for the pricing projects that are located in such a way that a substantial share of travelers might use this facility in combination with some other future projects. It specifically affects such projects and policies as HOV/HOT lanes, where the network connectivity is essential. If this is a real factor, the complementary projects should be described, coded, and included in the "optimistic" network scenarios.
- *VOT* estimates and the related travel time and cost coefficients used in the traffic assignment, mode choice, time-of-day choice, and other models. This factor is a fundamental behavior parameter in the travel model that always represents a source of uncertainty simply because of the randomness inherent to travel behavior. All existing Oregon models use VOT estimated from surveys dating from the mid-1990s, or borrowed from other metropolitan areas in the state, and therefore, are considered high risk. First, it should be ensured that the average VOT values applied for each segment are reasonable. A high risk is assigned to this factor if the VOT value was not estimated but rather was assumed or borrowed (SWIM), or if it was estimated by pulling data from different metropolitan regions, as is the case for various Oregon MPO models. No matter how well structured and segmented the model system is, a ±20% variation in VOT (due to situational factors alone) should be considered as the minimum level of variation. For simple models with poor segmentation, the range should be extended to at least ±40%. Variation of VOT values also incorporates uncertainty associated with real income growth, possible economic recession, and other related factors if they are not considered explicitly.
- *Toll escalation* scenarios that may be affected by economic conditions or government intervention. Ability to escalate tolls over years represents a risk factor even if the toll escalation strategy is well defined in the contract between the toll road operator and the government. Normally, it is assumed that the toll rates will automatically grow every year with the gross domestic product, the Consumer Price Index, or other index (with some "floor" and "ceiling" thresholds). In reality, tolls might be frozen for several years and reconsidered only intermittently. A sensitivity test with tolls updated only every 10 years is recommended.
- *Ramp-up period*, especially for start-up projects and policies, represents a risk factor that can significantly affect the revenue stream for the most precious first years of the project that are the least discounted. It is recommended, depending on the project type, to establish a realistic ramp-up period, and then run a sensitivity test with a longer (at least two more years) ramp-up period. As discussed above, longer ramp-up behaviors are expected in regions where tolling is not ubiquitous, as is the case anywhere in Oregon. These situations are the most risky and have historically resulted in the largest toll traffic and revenue over-predictions.

5.3 Risk Analysis Methods

Several risk analysis methods have been proposed, and are discussed in detailed in Technical Appendix 3. The method described here combines the ability to measure the effect of individual factors and combinations of factors in a timely fashion. Timeliness is important, given the need to run the model multiple times to assess all the different effects within the typical timeframe of a feasibility study.

First, the risk factors should be identified and then measured on a one-at-a-time basis. For each of the factors, at least three possible scenarios, or states, should be defined, and probabilities assigned to them: optimistic, average, and pessimistic. The optimistic and pessimistic scenarios do not have to be the best and worst possible scenario, respectively. The absolutely worst and absolutely best scenarios are not extremely informative for the risk analysis, because they are normally characterized with a very low probability of occurring. Optimistic and pessimistic scenarios should rather capture an average of the region that yields approximately one-third in probabilistic terms. With respect to the model parameters, the average scenario should correspond to the model calibrated for the base year with a good level of fidelity.

Then, depending on the number of risk factors and the model run time, two strategies can be applied to assess the effect of likely combinations of factors on toll revenue and its associated probability:

- Run the model for *each possible combination* of the input factors and relate the results (T&R forecast) to the joint probability of the scenario to happen. The joint probability can be calculated as the product of assigned probabilities for each factor (assuming the factors are independent; otherwise a more complicated conditional calculation is needed). This method is a theoretically preferable, but it may result in an infeasible number of scenarios to test. For example, with five factors and three possible states (optimistic, average, and pessimistic) for each of them, the total number of scenarios to test will be $3^5 = 243$.

- Run the model for *several combinations* of the input factors and use auxiliary regression for interpolation of the results for the other (nonmodeled) combinations, as described above. It is important for each particular factor state to appear at least once in the modeled combinations. For example, with the same example of five factors (denoted as A, B, C, D, and E) and three possible states for each of them (denoted as 1=optimistic, 2=average, 3=pessimistic), the total number of scenarios to explore will be 5×3=15. All these scenarios can be covered in three model runs with the following combinatorial logic. The first run would combine A1, B2, C3, D1, E2; the second run would combine A2, B3, C1, D2, E3; the third run would combine A3, B1, C2, D3, E1. These three runs would normally provide enough information about possible interactions between the risk factors versus the base scenario of A2, B2, C2, D2, E2. In order to provide more variation for the auxiliary regression, the base run and three runs described above could be complemented by two extreme runs – optimistic (A1, B1, C1, D1, E1) and pessimistic (A3, B3, C3, D3, E3). The six combinations described above are normally enough to approximate all of the possible 243 combinations.

Section 6.0: Evaluation of Modeling Capability

6.1 Capability of Oregon's Travel Models to Analyze Tolling Projects

Our assessment of the capability of Oregon's models to adequately forecast toll traffic and revenue focuses on the structural characteristics of the models, more so than meeting specific requirements related to how the model is applied. The treatment of risk, for example, is largely a function of how the model is run - identification of risk factors, selection of risk scenarios, etc. An assessment of specific model run procedures can only be conducted on a project-by-project basis.

In terms of model structure, there are two considerations. The first is whether the model, as is, has the necessary characteristics in terms of modeled decisions and market segmentation, and whether it meets the requirements for the preparation of investment-grade forecasts. The second consideration is whether, in the absence of the first set of characteristics, the models could be improved to handle tolling applications without undertaking a large model development effort.

As currently designed and implemented, only SWIM and the Portland Metro model are configured to handle tolls. Both of these models have well-developed mode choice models, which are critical for the creation of generalized costs. Neither SWIM or Portland Metro, however, include a pre-route choice model. The choice of whether to use a toll road or not is left up to the network simulation. This considerably limits the simulation of diversion behavior at the route level, because the static assignment procedures represent the time/cost tradeoff only in a rather crude way, and completely ignore other factors known to influence the toll choice.

SWIM includes all the relevant first-order decisions, route choice (assignment level only) and time-of-day choice, and many of the relevant second-order decisions, including feedback to changes in land use due to its seamless integration with economic/spatial models. Due to its disaggregate nature, SWIM lends itself also to a more accurate representation of travelers' characteristics than is possible with a trip-based model. For example, a continuous distribution of VOTs could be used, instead of segmenting the population into three groups, each with its own VOT.

The Portland Metro model includes only one first order decision, route choice, though handled in the assignment process instead of as a discrete choice. The Metro time-of-day model is not sensitive to tolls or travel times. Time of day models based on invariant diurnal factors are the norm among state-of-the-practice MPO models. However the state-of-the-art has progressed enough that time-of-day models sensitive to level of service can be implemented in practical models. The Metro model is also capable of forecasting changes in trip destination due to tolls, an important second-order effect.

The other MPO models are not currently configured to handle tolls. However, their structure and implementation allows for the introduction of tolls in the trip distribution, mode choice, and highway assignment steps with a relatively modest effort. The only exception may be the Eugene-Springfield model, because of its use of the gravity model for trip distribution. Before this model could be used to evaluate tolls, development of a destination choice model to replace the gravity model would be highly desirable.

In terms of market segmentation, we find again that SWIM and the Portland Metro model already use the minimum recommended segmentation of the travel market by time of day, trip purpose, and income levels. However, in both models the VOTs that are currently specified do not distinguish between these various segments. For example, in the Metro model, home-based shopping, recreation, and other trips all share the same VOT, even though separate trip tables are generated at the distribution level. We also find that the VOTs are relatively low, which tends to make the models overly sensitive to cost. It is highly recommended that these VOTs be revised based on current, locally gathered data.

The models for the smaller MPOs use more aggregate market segmentation than SWIM or Portland Metro. For example, in the MPO models the nonwork purposes may not be segmented by income level. None of the models exhibit VOTs that vary by time of day. Again, this structure reflects the general state of the practice nationwide, but more disaggregate representation of the toll markets is essential for toll applications.

All of the models under study suffer from relatively aggregate representation of market segments at the highway assignment (route choice) step. The extent of this aggregation varies from a single vehicle class (in the case of the Medford, Corvallis, and Bend models) to five vehicle classes in the statewide model. Where segmentation is present, it is typically along vehicle type (autos versus trucks), which correlates with VOT only to some degree. This limited segmentation almost ensures a large degree of aggregation bias in the forecasts, because the number of classes currently available may not be sufficient to model both the full toll regime and differences in VOT.

We find, in summary, that all of Oregon's MPO models are state-of-the-practice models, when compared to models for metropolitan regions of similar size. SWIM goes beyond the state of the practice; it is in fact among the most advanced integrated land use/transport models worldwide, and incorporates many of the characteristics recommended for practical, advanced activity based models. Nonetheless, given the specific requirements placed upon travel demand models by the financial community, and recent advances in bringing travel behavior research into practice, there are several areas where the statewide and MPO models could be and should be improved before they are used to forecast toll traffic and revenue.

6.2 Recommended Travel Demand Model Improvements

Recommended model improvements are classified into those that would be required for any type of tolling study and those that would be desirable for specific types of studies, in reference to the requirements for the types of pricing applications shown in Table 5. It is understood that the project-specific improvements would be in addition to the general model improvements, unless otherwise indicated. Given the similarities between the various models, the various improvements are described together, rather than model by model. Table 6 indicates the recommended improvements for each model. In this table, the number indicates the level of priority (1 being the highest priority) for making the improvement, while a check mark indicates that the model already incorporates the corresponding feature.

6.2.1 Recommended improvements for all types of tolling applications:

- *Pre-route choice*. A pre-route choice model provides the ability to include attributes other than time and cost in the decision of whether to use a toll road or a free road. In many instances, a bias

constant in pre-route choice may be used instead of explicitly modeling travel time reliability. The importance attached to this modeling improvement is largely project-specific: It is critical when there is a real choice between a free road and a toll road, but considerably less critical when all likely routes are tolled. This model improvement is essential for all the types of tolling applications being considered for Oregon, with the possible exception of mileage-based and area-wide pricing.

- *Additional mode choice segmentation*. It is highly desirable to consider the following purposes separately, with purpose-specific VOTs: home-based work, home-based school, home-based shop, home-based recreation, home-based other, non-home-based work and non-home-based other. Aggregation into fewer purposes would ideally be guided by model estimation analysis. In addition, it is highly desirable to segment the travel market for each purpose by income group. This recommendation applies primarily to the small MPO models.

- *Distributed VOTs*. One significant advantage of the SWIM model is that it has the ability to vary VOT per person, as opposed to per travel market. Rather than assign VOT to each market, one can assign a VOT to each person, drawn from a distribution of VOTs. This feature has the potential to greatly reduce aggregation bias. The VOT distributions can be estimated from stated preference (SP) data, and would be conditional on trip purpose and income group, among other possible factors.

- *Additional vehicle class segmentation*. The designation of vehicle classes for highway assignment should be guided by differences in VOT and differences in (potential) toll fees, rather than simply by vehicle type (i.e., autos or trucks). All of the models reviewed here could be improved by the implementation of a well-designed vehicle class segmentation.

- *Model estimation*. Most of the current models were originally estimated with home interview data collected in the period of 1994 through 1996. Other models use parameters that were transferred from other metropolitan areas. Over the last 15 years, various model components and procedures have been updated, but VOT parameters have remained unchanged from their original estimation. Estimation that is based on more recent survey data would help update the VOTs to account for real income growth over the last 15 years. It would also be an opportunity to explore differences in VOT among the various metropolitan areas in the state and to better segment the travel market.

- *Speed validation*. In addition to traffic volume validation, it is highly desirable to validate the model's estimated speeds to observed speeds. Depending on the results of this validation, the volume-delay functions may need to be updated to better reflect congestion levels. Portland Metro has conducted speed studies and developed its volume-delay functions based on these data. A similar level of speed validation is desirable for SWIM and the small MPO models.

- *Model validation*. The level of model validation typical for regional models may be insufficient for tolling applications, particularly for the specific facility, corridor, or subarea under study. Therefore a critical step before initiating a road pricing or traffic and revenue study is ensuring that the model is well-validated at a geographic scale commensurate with the scale of the project. The validation should not be limited to a comparison of model output to daily traffic volumes, as is customary, but extended to examine how well the model reproduces diurnal traffic patterns. Another important

validation criteria is establishing that the model adequately captures the major travel markets in the project influence area. Sensitivity tests are often also used to ensure that the model responds adequately to changes in tolls and corresponding changes in other level of service attributes.

- *Incorporation of travel time reliability*. A practical method for incorporating travel time reliability has been proposed (see Section 4). This method relies on estimates of congested travel time, and therefore, a first step would be to ensure that the model adequately reproduces observed volume-to-capacity ratios.

- *Time-of-day choice model*. A time-of-day choice model that is sensitive to tolls and levels of service is highly desirable for projects that consider variable time-of-day tolls. Scheduling models similar to the one implemented in SWIM can be adapted for trip-based models. This method estimates time-of-day choice in one-hour increments, and therefore would also serve as a peak spreading model. A time-of-day choice model could be estimated with revealed preference (RP) data, or a combination of RP and SP data. Depending on where in the model chain this model is placed, it may be necessary to restructure the trip distribution model.

- *Assignment periods*. While the standard four periods (AM Peak, Midday, PM Peak, and Night) are typically sufficient for most planning applications, a more fine-grained segmentation of time periods for the assignment process may be needed in order to study peak spreading and time-of-day effects due to tolls. The additional information to be gained from increasing the number of assignment periods needs to be weighed against the additional model run time that would result. It should be noted that recent advances in computing procedures allow to distribute a single model run across several processors, significantly reducing model run times.

- *Trip distribution segmentation*. It would be desirable, though not critical, to segment the trip distribution models by time of day, for example peak versus off-peak trips. Alternatively, rather than using "blended" multimodal accessibilities (peak and off-peak combined into a single accessibility measure), the models could be based on "representative" multi-modal accessibilites (separate peak and off-peak accessibilities), with parameters derived through model estimation.

6.2.2 Recommended improvements for congestion/area pricing and mileage-based projects:

- *Flexible trip generation*. An important response to cordon/area pricing and ubiquitous mileage-based fees is the trip suppression effect, that is, forgoing to make a trip altogether. In order to measure this effect, the trip generation model needs to be sensitive to levels of accessibility. Currently SWIM is the only model with a flexible trip generation component, though its sensitivity is limited to home-to-work travel time.

- *Integrated land use model*. One likely response to cordon/area pricing schemes is for businesses to locate outside of the priced area. These effects are best captured with an integrated spatial or land use model. In the Metro region, these effects could potentially be modeled using Metroscope, the spatial economic model currently in use for Portland. At the statewide level, SWIM already provides this functionality. For the other MPOs, these effects can be modeled with the Land Use Scenario

Developer (LUSDR), a land use model developed by Oregon DOT (Gregor, 2007). LUSDR uses transportation accessibility measures obtained from travel demand models, and in turn provides estimates of household and employment at the TAZ level that can be fed back into the transport models. LUSDR can be coupled with any of the MPO models so that it would essentially function as an integrated land use / transport model.

6.2.3 Recommended improvements for HOT lane projects:

- *Car occupancy segmentation*. Explicit treatment of the costs incurred as a function of the number of vehicle passengers becomes critical if the toll regime differentiates by occupancy levels, as is typically the case for HOT lanes (as well as for projects in which carpools are allowed to bypass toll plazas). Both the mode choice and the highway assignment models would need to be segmented by occupancy levels.

- *Joint household travel*. A potential improvement for the statewide model would be to explicitly consider joint household travel. It has been shown that most carpools involve members of the same household, and that many carpooling instances are due to the need to serve passengers (such as taking a child to school or a spouse to work), and therefore involve substantial activity coordination among household members. This type of improvement is beyond the scope of a trip-based model; at most household size could be used to explain the likelihood of carpooling, as is done in the Metro model.

6.2.4 Recommended improvements for evaluating complementary transit and/or parking policies:

- *Corridor-level transit validation*. The specific structural components for evaluating complementary transit services as part of a tolling project are already in place in all Oregon models. However, additional data and effort is likely needed to achieve a rigorous corridor-level transit validation.

- *Parking costs and parking choice*. Additional attention would be needed to ensure that parking costs are adequately represented in the model. The model would need to include differentiation of daily and hour rates by zone, mode and destination choice models sensitive to parking costs, and, in the case of SWIM, possible segmentation of the model by free or discounted parking eligibility. A more advanced treatment, which can be left for the final stages of project development, would be the development of a parking location choice model that could explicitly account for lot capacity constraints and trade-offs between parking downtown, parking at the city boundary (for free), and commuting into the city by transit.

Table 6 – Recommended Oregon Model Improvements

Model Improvement	Priority Level *		
	SWIM	Portland Metro	Other MPO
All pricing studies			
Pre-route choice	1	1	1
Additional mode choice segmentation	✔	✔	1
Distributed VOTs	2		
Additional vehicle class segmentation	1	1	1
Model re-estimation	2	2	2
Speed validation	1	✔	1
Travel time reliability	4	4	4
Time-of-day choice	✔	3	3
Additional assignment period segmentation	3	3	3
Trip distribution segmentation	✔	3	3
Detailed model validation (project-specific)	1	1	1
Cordon/area pricing and mileage-based tolls			
Flexible trip generation	1	1	1
Integrated land use model	✔	✔	1
HOT lanes			
Car occupancy segmentation	1	1	1
Joint household travel	4		
Pricing with complementary transit and/or parking policies			
Corridor-level transit validation	1	1	1
Parking costs and parking choice	3	3	3

(*) Level 1 indicates the highest priority for model improvement. A check mark indicates an already existing model feature.

Section 7.0: Recommended Data Collection Efforts

7.1 Overview of Data Collection Techniques for Highway Pricing Studies

One of the major factors affecting model accuracy relates to the quality of the data used in model estimation, calibration, and validation. Tremendous progress has been made in recent years with respect to data collection technology and new types of surveys, to the point that it is cost-effective to consider such data collection efforts. This section will discuss the advantages of complementing traditional data sources (home interview surveys and annual average daily traffic counts) with sources that better target potential toll customers. These sources include GPS-assisted surveys, information available from electronic toll collection systems, combined revealed and stated preference surveys, and traffic choices experiments (like the one recently implemented in Seattle as part of the Traffic Choices Study). Techniques that significantly improve the quality and comprehensiveness of the data will improve the accuracy of the travel model.

The following major types of surveys are applied to support pricing studies and models developed for these studies:

- Travel Pattern Surveys (Revealed Preferences, or RP) including:
  - Household-Based Travel/Activity Surveys,
  - Origin-Destination Surveys on specific facilities and existing toll roads,
- Stated Preference (SP) Surveys that vary significantly across the following dimensions:
  - Choice Dimensions and Scenario Design,
  - Trip Attributes Relevant for Pricing Studies,
  - Choice Context,
  - Instrument Design,
  - Sampling,
- Special Survey Types including:
  - Surveys of Commercial Vehicles,
  - Behavioral Experiments and Follow-up Surveys,
  - Attitudinal/Public Opinion Surveys

7.1.1 Travel Pattern Surveys:

A comprehensive *Household Travel Survey* is generally needed to develop a regional transportation model that can serve as the source for VOT and other relevant model parameter estimates. However, there is a growing recognition that the household survey data must be supported by complementary, project-specific RP and/or SP surveys. These project-specific surveys are especially crucial for start-up projects in regions with no previous experience with highway pricing, where the RP survey cannot provide direct information about behavior under pricing conditions. SP surveys are typically designed to address willingness-to-pay factors relevant for road pricing (VOT savings, value of reliability) and are used to supplement the RP data. Survey data collection can also support other model development data needs, including HOV/HOT lane usage and payment media choice.

GPS-based supplements are included with some household surveys and these provide detailed route information for all recorded trips. Either vehicle-based or person-based GPS data collection can be used, but vehicle-based GPS data collection is generally more useful for collecting route information, assuming that tracking routes for transit and pedestrian/bicycle alternatives is not necessary.

Surveys that collect information about *origins, destinations,* and other details have been widely used to determine the characteristics of trips that are observed at selected locations (Hagen, 2006). These types of surveys are particularly useful for characterizing the trips that currently travel in particular corridors that are, or might be, served by a toll facility and the trips that cross into or out from a cordon that might be subjected to area pricing. This type of focused information is especially useful in estimating the numbers and types of trips that might be affected by facility or area pricing. Although regional travel forecasting models can also be used to provide this information synthetically, those models are typically not refined sufficiently to estimate these details as precisely as can be done with an origin-destination survey. Also, as the experience of several recent origin-destination surveys have shown, ETC registration can allow access to the current toll facility users, thus making sampling strategy, questionnaire distribution, and post-survey development of expansion factors easier and more accurate.

There are several objective *limitations associated with RP surveys*:

- First and foremost, they are not applicable for model estimation/calibration in new corridors located in regions where there are no current toll facilities.
- Another associated problem is that with the survey of existing toll facility users, a very specific choice-based sample is created, because it can be difficult to define and access nontoll users.
- It is difficult to collect data associated with time-of-day choice because generally only a single trip is observed and surveyed; otherwise the origin-destination survey would need to be extended into a Household/Person Interview Survey.
- With RP surveys, it is also difficult to support data that is necessary for measurement of travel time reliability and estimation of its impact on traveler's choices.
- Lastly, RP surveys are not very helpful for understanding and modeling mid-term choice, such as transponder acquisition.

7.1.2 Stated Preference Surveys:

For more than 20 years, *Stated Preference* surveys have been used to estimate values of travel time and other parameters related to the effects of tolls and road pricing (see, for example, Adler and Schaevitz, 1989). SP surveys include a set of hypothetical scenarios in which conditions (e.g., travel times, tolls) are varied and respondents are asked to indicate what they would most likely choose under those specified conditions. The conditions are varied according to an experimental plan that optimizes the information about the respondents' preferences that each scenario provides.

SP surveys are especially useful in applications in which an alternative, such as a toll facility, does not currently exist but is being planned for the future. In those types of applications, RP surveys are not useful for estimating price effects because road prices, which are the variables of interest, do not vary across trips within the region. While other cost elements such as operating costs do vary across trips, those variations are highly correlated with trip lengths and travel times and thus generally do not provide reliable indications of the effects of price on travel choices.

With respect to *choice dimensions*, the SP surveys that have been conducted to support road pricing projects have most often focused on the choice between tolled and toll-free routes. For conventional toll facility studies, these surveys would typically present two alternatives; a toll-free route with a given travel time and an alternative tolled route with a lower travel time and a toll at some level. However, many road pricing projects involve more complex effects beyond simply influencing route choice. Some projects, such as HOT lanes, affect occupancy and mode. Therefore, the stated preference scenarios should include other modes and occupancy levels as available choice alternatives. For projects that have time-varying prices, different travel periods should be included among the stated preference alternatives. For area pricing projects, the scenarios could allow alternative destinations. In some special cases, effects on trip frequency also may be included in the SP experiments.

Travel times and toll prices are the primary *attributes* in most road pricing SP experiments. However, there are other attributes that may also be significant in travelers' choices in the presence of road pricing. Some of the other attributes or features that have been tested in SP experiments for road pricing projects include:

- Travel time components – time in free-flow conditions and time in congested traffic;
- Travel time reliability;
- Occupancy-based toll levels;
- Fair lanes policy;
- Commercial vehicle restrictions;
- ETC discounts;
- Travel time variability;
- Driving distance along the route; and
- Nontoll "running" costs.

Recent advances in SP survey design and technology have made this tool significantly more attractive and practical, particularly in the following respects:

- Computer-based SP surveys customize choice experiments around specific contexts (choice of toll road/lanes versus non toll road/lanes, choice between toll road and transit, switching to other time-of-day periods in presence of congestion pricing, etc).
- The SP framework is extremely convenient for multiple/repeated experiments with the same person that can be effectively employed for screening inherent randomness in travelers' preferences.
- The SP framework is convenient for estimation of value of reliability (VOR), along with VOT and other possible impacts.
- SP allows for more efficient experimental design with multiple alternatives, while the RP sample structure is bound to the observed frequencies of different alternatives.
- SP surveys can be designed to include transponder acquisition in the model's choice hierarchy.
- SP surveys are an effective tool in capturing different price perceptions, for example, ETC users versus cash users.

SP surveys have their own limitations. Incorporating all relevant choices leads to complex designs that may confuse respondents. Thus, an SP survey is only effective as a focused tool. SP surveys also have inherent strategic biases. For these reasons, the most promising direction for model estimation is to use a

combination of SP and RP surveys that allows for elimination of strategic biases by statistical scaling procedures.

7.2. Recommended Data Collection Program for Model Improvement in Oregon

Together, the several survey and data collection methods described above constitute a suite of options that can be used to support the analysis of road pricing programs. The decision about which of these methods to employ depends on several factors, including the stage of decision-making that the analysis must support, the types of data and models available for use and, of course, the schedule and budget for the work. Table 7 below provides some general guidelines for the types of data that might be used to support the different stages of project development. In this table, the large check marks represent items that are generally required in some form to support the stage, and the small check marks represent items that may be appropriate depending on the project importance and complexity.

Table 7: Highway Pricing Survey and Data Collection Needs

Project Stage	Survey Type					
	Household Interview	Origin-Destination	Stated Preference	Opinion	Highway Speed	Traffic Counts
Exploratory screening	✔					✔
Preliminary feasibility	✔	✓	✓	✓		✔
Feasibility evaluation	✔	✔	✓	✓	✔	✔
Investment Grade	✔	✔	✔	✓	✔	✔

✔ *represents surveys required to support a given project stage;* ✓ *represents optional surveys.*

Specifically for Oregon, the recommended data collection program would include the following:

- *Home interview survey*. The most critical need to improve Oregon's models is an update of the home interview survey; the last one was conducted in the mid-1990s. A statewide survey is, in fact, already in the planning stages and nearing implementation. The survey should be used to update all the MPO models and the statewide model, and to explore additional market segmentation opportunities.

- *Traffic counts*. The need for up-to-date traffic counts is ongoing. All MPOs have traffic count programs in place, and they are expected to continue gathering these data on a continuous basis. One possible improvement would be to report observed vehicle volumes by time of day, and then validate the models separately for each time period. The Portland Metro model already performs time-of-day validations. For the other MPOs, the additional effort for gathering these data needs to be weighed against the potential uses of their models. To the extent that the evaluation of tolling projects, and in particular variable time-of-day tolls, is a realistic application, serious consideration

should be given to time-of-day highway validation. The trafic count database will need to include weekend data to support the prediction of weekend toll road usage, if weekend forecasts are desired.

- *Stated preference survey*. Given the absence of toll facilities in the state, which precludes directly observing how motorists respond to tolls, the need for SP surveys before starting preliminary feasibility studies of tolling projects is paramount. An SP survey would directly measure willingness to pay for tolls and identify markets and conditions under which tolling would be most successful.
- *Special market surveys*. More specific surveys, addressing special markets (visitor travel, truck travel) would need to be considered on a project-by-project basis.
- *Speed studies*. Speed studies are highly desirable to ensure that the model is adequately reproducing observed speeds. While a region-wide speed study effort may not be practical, at a minimum corridor-level speeds should be gathered as part of a tolling project, assuming, of course, that the facility already exists.

Section 8.0: Conclusions and Overall Recommendations for Model Applications

We find that all of Oregon's MPO models meet state-of-the-practice modeling standards, when compared to models for metropolitan regions of similar size. The Portland Metro model goes a step beyond the state-of-the-practice, by including advanced modeling features. SWIM is in a category all by itself; it is in fact among the most advanced integrated land use/transport models worldwide, and incorporates many of the characteristics recommended for practical, advanced activity based models. None of these models, however, was specifically developed for evaluating tolling applications, and therefore all of them lack to varying degree one or more of the essential modeling features described in this paper. Furthermore, given the requirements placed upon travel demand models by the financial community, and recent advances in bringing travel behavior research into practice, Oregon statewide and MPO models could and should be improved prior to using them to forecast toll traffic and revenue.

Equally as important as the improvement of the models in and of themselves is the undertaking of a fundamental shift in how models are used to produce toll traffic and revenue forecasts. A thorough analysis of the risks associated with the forecast needs to become an integral part of the forecasting process. Typical risks associated with toll projects are related to the model itself, to the model input data, and to specific circumstances associated with particular projects.

The development of better models and a more rigorous risk assessment approach will help increase the credibility of toll traffic and revenue forecasts, as well as better integrate the transportation modeling culture with the culture of the investment analysis community.

Overall recommendations for model and forecasting practice improvement cut across all of the state's models, at the MPO and statewide level. Given the disaggregate, probabilistic nature of the statewide model, there are opportunities to take advantage of it to better reflect recent advances in research related to travel behavior under pricing conditions, time-of-day choice, and travel time reliability. Our recommendations, which are detailed throughout the paper, fall into the following groups:

Improvement of the model structure and its parameters. This improvement includes better representation of first-order behavioral responses (route choice and time-of-day choice) and of the relevant second-order responses, which may vary depending on the tolling application. Re-estimation of the mode choice models is a critical need.

Improved market segmentation. Minimization of aggregation biases should be a driving concern. Additional segmentation, at the mode choice and route choice levels, and for the statewide and MPO models, is highly recommended.

Improvement of the model validation, particularly at the corridor level. We highly recommend that any toll application study begin with a thorough review of how well the model estimates traffic flows (and possibly

also transit ridership) in the corridor of interest. While all models are validated at a region-wide level, corridor-specific biases need to be addressed.

Implementation of a data collection program to support model improvements.

Identification and systematic analysis of risk factors, related to the model, the model's inputs, and the project. Several risk factors have already been identified in the literature. A comprehensive list of the most likely risks can only be prepared on a project-by-project basis. Risk analysis adds a layer of complexity to the forecasting process, but it is not beyond the modeling resources already available at the state and MPO levels. We specifically propose a method that would help to eliminate built-in optimistic biases and produce reliable and conservative forecasts.

References

- Abdelghany, A.F. and H.S. Mahmassani. (2003) Temporal-Spatial Microassignment and Sequencing of Travel Demand with Activity-Trip Chains. *Transportation Research Record* 1831, pp. 89-97.
- Adler, T., W. Ristau, and C. Falzarano. (1999) Traveler Reactions to Congestion Pricing Concepts for New York's Tappan Zee Bridge, *Transportation Research Record 1659*, pp.
- Adler, T., W. Olsen, and Y. Dehghani. (2004) A Facility-Level Model of Peak Spreading. Presented at the *83rd Annual Meeting of the Transportation Research Board*, Washington D.C. (CD-ROM).
- Adler, T., Y. Dehghani, M. Doherty, J. Klodzinski, and W. Olsen. (2005) A Multi-Period Toll Mode Choice Model for Florida's Turnpike Enterprise, *Proceedings of the 10th TRB Transportation Planning Applications Conference*, Portland, OR.
- Appiah, J. (2004) An Examination of Factors Affecting High Occupancy/Toll Lane Demand. Master's Thesis. Department of Civil Engineering. Texas A&M Univeristy.
- Axhausen, K., S. Hess, A. Konig, G. Abay, J. Bates, and M. Bierlaire (2007) State of the Art Estimates of the Swiss Value of Travel Time Savings. Presented at the *86th Annual Meeting of the Transportation Research Board*, Washington D.C. (CD-ROM).
- Bain, R. and M. Wilkins. (2002) Infrastructure Finance: Traffic Risk in Start-Up Toll Facilities, Standard & Poor's, McGraw-Hill International (UK) Ltd., September 2002.
- Bain, R. and J. .W. Plantagie (2003) Traffic Forecasting Risk: Study Update 2003, Standard & Poor's, McGraw-Hill International (UK) Ltd., November 2003.
- Bain, R. and J. W. Plantagie. (2004) Traffic Forecasting Risk: Study Update 2004, Standard & Poor's, McGraw-Hill International (UK) Ltd., October 2004.
- Bain, R. and L. Polakovic. (2005) Traffic Forecasting Risk Study Update 2005: Through Ramp-Up and Beyond, Standard & Poor's, McGraw-Hill International (UK) Ltd., August 2005.
- Bain, R., K. Forsgren, and P. B. Calder. (2006) Credit FAQ: Assessing the Credit Quality of Highly Leveraged Deep-Future Toll-Road Concessions, Standard & Poor's, McGraw-Hill International (UK) Ltd., February 2006.
- Bates, J., J. Polak, P. Jones, and A. Cook. (2001) The Valuation of Reliability for Personal Travel, *Transportation Research*, 37E, 191-229.
- Boyles, S., S. Ukkusuri, S. T. Waller, and K. Kockelman. (2006) A Comparison of Static and Dynamic Traffic Assignment Under Tolls: A Study of the Dallas-Fort Worth Network. *Proceedings of the 85th Annual Meeting of the Transportation Research Board*. Washington, D.C.
- Boyles, S., S. V. Ukkusuri, S. T. Waller, and K. Kockelman. (2006a) "Examining the Benefit of Accounting for Traffic Dynamics in Congestion Pricing Applications." *Meeting Compendium of the Transportation Research Board's 85th Annual Meeting*, Washington, DC.
- Boyles S., S. Ukkusuri, S. T. Waller, and K. Kockelman. (2006b) "A Comparison of Static and Dynamic Traffic Assignment under Tolls in the Dallas-Fort Worth Region." *Proceedings of the Transportation Research Board Specialty Conference: Innovations in Travel Modeling*, Austin, Texas.
- Bradley, M., and H. F. Gunn. (1991) A Stated Preference Analysis of Values of Travel Time in the Netherlands, *Transportation Research Record 1285*, 78-88, Washington D.C.

- Bradley, M., M. Ben-Akiva, and D. Boldic. (1993) Estimation of Travel Choice Models with Randomly Distributed Values of Time. *Transportation Research Record 1413*, 88-97.
- Brownstone, D., A. Chosh, T. F. Golob, C. Kazimi, and D. Van Amelsfort. (2003) Drivers' Willingness-to-Pay to Reduce Travel Time: Evidence from the San Diego I-15 Congestion Pricing Project, *Transportation Research*, 37A(4), 373-388.
- Brownstone, D., and K. A. Small. (2005) Valuing Time and Reliability: Assessing the Evidence from Road Pricing Demonstrations, *Transportation Research*, 39A, 279-293.
- Burris, M. W., and R. M. Pendyala. (2002) Discrete Choice Models of Traveler Participation in Differential Time of Day Pricing Programs, *Transport Policy*, Vol. 9, 241-251.
- Burris, M., and J. Appiah. (2004) An Examination of Houston's QuickRide Participants by Frequency of QuickRide Usage, *Transportation Research Record 1864*, 22-30.
- Cambridge Systematics, Inc., (2005). *Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation*. Final Report. Prepared for Federal Highway Administration by Cambridge Systematics, Inc. with Texas Transportation Institute.
- Cambridge Systematics, Inc., (2006) *Washington State Comprehensive Tolling Study. Final Report – Volumes 1 and 2*. Prepared for Washington State Transportation Commission.
- Cambridge Systematics, Inc., (2007). *The Future of Tolling in Oregon: Understanding How Varied Objectives Relate to Potential Applications*. Final Report. Prepared for the Oregon Department of Transportation.
- Clay, M. J. and R. A. Johnston. (2006) Multivariate Uncertainty Analysis of an Integrated Land Use and Transportation Model: MEPLAN. Transportation Research Part D, 11, 191-203.
- Dehghani, Y. and W. Olsen. (1999) Potential Pitfalls in Forecasting Travel Demand for Toll Roads: Experience in the U.S. and Overseas. Presented at the *78th Annual Meeting of Transportation Research Board*, Washington D.C.
- Dehghani, Y., T. Adler, T. Doherty, and R. Fox. (2003) Development of a New Toll Mode Choice Modeling System for Florida's Turnpike Enterprise, *Transportation Research Record 1858*, 9-17.
- Dial, R. B. (1997). Bicriterion Traffic Assignment: Efficient Algorithms plus Examples, *Transportation Research Part B,* 31, pp. 357-379
- Dornan, D. (2006) Moving Beyond the Interstate Era, *Tollways*, Spring 2006, 47-64.
- Duthie, J., A. Voruganti, K. Kockelman, and S. T. Waller. (2008) Uncertainty Analysis and its Impacts on Decision-Making in an Integrated Transportation and Gravity-Based Land Use Model. Paper submitted for presentation to the *88th Annual Meeting of the Transportation Research Board*, January 2009, Washington, D.C., and for publication in *Transportation Research Record*.
- Duthie, J. (2008) Implications of Uncertain Future Network Performance on Satisfying Environmental Justice and Tolling. Doctoral dissertation, Department of Civil, Architectural, and Environmental Engineering, University of Texas at Austin.
- Erhardt, G. D., F. S. Koppelman, J. Freedman, W. A. Davidson, and A. Mullins. (2003) Modeling the Choice to Use Toll and HOV Facilities, *Transportation Research Record 1854*, 135-143.
- Fitch Ratings. (2003) Project Finance Special Report. Bliss, Heartburn, and Toll Road Forecasts.

- Flyvbjerg, B., M. K. Skamris Holm, and S. L. Buhl. (2005) How (In)accurate Are Demand Forecasts in Public Works Projects: The Case of Transportation, *Journal of the American Planning Association*, 71 (2), 131-146.
- Flyvbjerg, B., M. K. Skamris Holm, and S. L. Buhl. (2006) Inaccuracy in Traffic Forecasts. *Transport Reviews*, 26 (1), 1-24.
- George, C., W. Streeter, and S. Trommer. (2003) Bliss, Heartburn, and Toll Road Forecasts. Project Finance Special Report, Fitch Ratings, November 2003.
- George, C., S. Trommer, M. McDermott, G. Zurita, C. Lewis, L. Monnier, W. Streeter, E. Lopez, and C. Fuenalida. (2007) Global Toll Road Rating Guidelines. Criteria Report, Fitch Ratings, March 2007.
- Golob, J. M. and T. F. Golob. (2001) Studying Road Pricing Policy with Panel Data Analysis: The San Diego I-15 HOT Lanes. In *Travel Behavior Research: The Leading Edge*, Pergamon, Oxford, 869-883.
- Golob, T. F. (2001) Joint Models of Attitude and Behavior in the Evaluation of the San Diego I-15 Pricing Project, *Transportation Research Part A*, 35, 495-514.
- Golob, T. F., R. Kitamura, and J. Supernak. (1997) A Panel-Based Evaluation of the San Diego I-15 Carpool Lanes Project. Chapter Four in T. F. Golob, R. Kitamura, and L. Long, eds., *Panels for Transportation Planning: Methods and Applications*, Boston, Kluwer Academic Publishers, 97-128.
- Gregor, B. (2007). The Land Use Scenario Developer, LUSDR: A Practical Land Use Model Using a Stochastic Microsimulation Network. Submitted for Publication by Transportation Research Record.
- Hensher, D. A. and P. Goodwin. (2003) Using Values of Travel Time Savings for Toll Roads: Avoiding Some Common Errors, *Transport Policy*.
- Hess, S., M. Bierlaire, and J. Polak. (2005) Estimation of Value of Time Using Mixed Logit Models, *Transportation Research*, 39A, pp.
- HLB Decision Economics, Inc. (2003) S.R. 125 South Toll Road Project: Risk Analysis of Traffic and Toll Revenue Forecasts. Draft Final Report, Washington, D.C.
- HLB Decision Economics, Inc. (2004) Toll Road Project Risk Analysis. Presentation for MBIA Insurance Corporation.
- Holguin-Veras, J., K. Ozbay and de Cerreno, A. (2005). Evaluation Study of the Port Authority of New York and New Jersey Time of Day Pricing Initiative. Final Report. In cooperation with the New Jersey Department of Transportation Division of Research and Technology and the U. S. Department of Transportation Federal Highway Administration. Report No. FHWA/NJ-2005-005.
- Humphrey Institute of Public Affairs, University of Minnesota, and NuStats. (2005) I-394 MnPass Project Evaluation Attitudinal Panel Survey – Wave 1: Final Report. Prepared for the Minnesota DOT.
- Humphrey Institute of Public Affairs, University of Minnesota, and NuStats. (2006) I-394 MnPass Project Evaluation Attitudinal Panel Survey – Wave 2: Final Report. Prepared for the Minnesota DOT.
- Kim, H., J.-S. Oh, and R. Jayakrishnan. (2006) Activity Chaining Model Incorporating Time Use Problem and Its Application to Network Demand Analysis. Presented at the *85th Annual Meeting of the Transportation Research Board*, Washington D.C. (CD-ROM).
- Kitamura, R., and J. Suparnak. (1997) Temporal Utility Profiles of Activities and Travel: Some Empirical Evidence. In Stopher, P., Lee-Gosselin, M., eds., *Understanding Travel Behavior in Era of Change*, Elsevier, 339-350.

- Kockelman, K. and Charles River Associates. (2006) Safety Impacts and Other Implications of Raised Speed Limits on High-Speed Roads. National Cooperative Highway Research Program (NCHRP) Final Report 17-23. Transportation Research Board, Washington, D.C.
- Kockelman, K., T. Waller, P. Gulipalli, S. Kalmanje, A. Karoonsoontawong, and S. Ukkusuri. (2005) Application of Credit-Based Congestion Pricing in Texas: Operational Considerations and Impacts. Research Report 0-4634-1, Texas Department of Transportation, Center for Transportation Research, The University of Texas at Austin, Austin, TX.
- Kriger, D. (2005) Traffic and Revenue Forecasting for Roads and Highways: Concerns, Methods and a Checklist for Practitioners. Resource paper presented at the Expert Forum on Road Pricing and Travel Demand Modeling, United States Department of Transportation, Washington D.C.
- Kriger, D., S. Shiu, and S. Naylor. (2006) Estimating Toll Road Demand and Revenue: A Synthesis of Highway Practice. NCHRP Synthesis 364, Transportation Research Board, Washington, D.C.
- Krishnamurthy, S. and K. M. Kockelman. (2003) Propagation of Uncertainty in Transportation-Land Use Models: Investigation of DRAM-EMPAL and UTPP Predictions in Austin, Texas. *Transportation Research Record 1831*, 219-229.
- Lam, W. H. K. and M. L. Tam. (1998) Risk Analysis of Traffic and Revenue Forecasts for Road Investment Projects. Journal of Infrastructure Systems, 4 (1), 19-27.
- Lam, T. C. and K. A. Small. (2001) The Value of Time and Reliability: Measurement from a Value Pricing Experiment, *Transportation Research*, 37E (2-3), 231-251.
- Lam, W., and Y. Yin. (2001) An Activity-Based Time-Dependent Traffic Assignment Model, *Transportation Research B*, 35B, 549-574.
- Land Transport New Zealand (2006) Risk Analysis. Appendix A13 of 'Economic Evaluation Manual: Volume 1,' Land Transport New Zealand. Available online at: http://www.ltsa.govt.nz/funding/economic-evaluation-manual/eem1-1.pdf.
- Levinson, D., K. Harder, J. Bloomfield, and K. Winiarczyk. (2004) Weighting Waiting: Evaluating Perception of In-Vehicle Travel Time under Moving and Stopped Conditions, *Transportation Research Record 1898*, 61-68.
- Litman, T. (2005) *London Congestion Pricing: Implications for Other Cities*, Victoria Transport Policy Institute.
- Lu, C-C and H. S. Mahmassani. (2007) Heterogeneous Users and Variable Road Pricing: Model and Algorithm for the Bi-Criterion Dynamic User Equilibrium Problem on Large Networks, Accepted for *TRISTAN VI*, Phuket Island, Thailand.
- Lu, C-C., H. S. Mahmassani, and X. Zhou. (2006) Variable Toll Pricing and Heterogeneous Users: Model and Solution Algorithm for Bicriterion Dynamic Traffic Assignment Problems, *Transportation Research Record: Journal of the Transportation Research Board,* No. 1964, pp. 19-26.
- Mahmassani, H. S., X. Zhou, and C. Lu. (2005) Toll Pricing and Heterogeneous Users: Approximation Algorithms for Finding Bi-Criterion Time-Dependent Efficient Paths in Large-Scale Traffic Networks. T*ransportation Research Record: Journal of the Transportation Research Board,* No. 1923, pp. 28-36.
- Marcotte, P. (1999) Reformulations of a Bi-criterion Equilibrium Model. In M. Fukushima, L. Qi, ., *Reformulation – Nonsmooth, Piecewise Smooth, Semismooth and Smoothing Methods*. Kluwer Academic, Dordrecht, The Netherlands, 269-292.

- Marcotte, P. and D. L. Zhu. (1997) Equilibria with Infinitely Many Differential Classes of Customers. In *Complementarity and Variational Problems. State of the Art*, Proceedings of the 13th International Conference on Complementarity Problems, Jong-Shi Pang and Michael Ferris, eds., SIAM, Philadelphia, 234-258.
- Mastako, K. A. (2003) Choice Set as an Indicator for Choice Behavior when Lanes are Managed with Value Pricing, Ph.D. dissertation, Texas A & M University. College Station.
- McCormick Rankin Corporation (MRC) and Parsons Brinckerhoff (PB). (2008) *TRANS Model Redevelopment*, Technical Report.
- Metro Planning Department, Transportation Research and Modeling Services. (2007). Metro Travel Forecasting 2008 Trip-Based Demand Model Methodology Report.
- Metro Planning Department, Transportation Research and Modeling Services. (2008). Addendum to Metro Travel Forecasting 2008 Trip-Based Demand Model Methodology Report: Transportation Demand Modeling as it relates to Tolling in the Columbia River Crossing Corridor.
- National Cooperative Highway Research Program [NCHRP] (1999). Valuation of Travel-Time Savings and Predictability in Congested Conditions for Highway User-Cost Estimation. Report 431. Transportation Research Board, Washington D.C.
- NCHRP (2006). Estimating Toll Road Demand and Revenue: A Synthesis of Highway Practice. NCHRP Synthesis 364, Transportation Research Board, Washington D.C.
- NCHRP (2008). Improved Framework and Tools for Highway Pricing Decisions. Project 08-57. Interim Report.
- National Federation of Municipal Analysts (NFMA). (2005) Recommended Best Practices in Disclosure for Toll Road Financings. Available online at:. http://www.nfma.org/disclosure/rbp_toll_road.pdf.
- New Jersey Department of Transportation. (2005) Evaluation Study of Port Authority of New York and New Jersey's Time of Day Pricing Initiative: Final Report, New Jersey DOT.
- Ortiz, I. N., J. N. Buxbaum, and R. Little. (2008) Protecting the Public Interest: The Role of Long-Term Concession Agreements for Providing Transportation Infrastructure. Proceedings of the *87th Annual Meeting of the Transportation Research Board*, Washington, D.C.
- Parsons Brinckerhoff, Inc (1999). Development and Calibration of the First Generation Integrated Land Use-Transport Model for Oregon," technical report prepared for the Oregon Department of Transportation, http://www.odot.state.or.us/tddtpau/modeling.html.
- Parsons Brinckerhoff Inc., HBA Specto Incorporated, and EcoNorthwest. (2008). Oregon Statewide Model Description. Draft Report.
- PBQD and MW Consulting (2001). Transportation and Land Use Model Integration Program: Overview of the First Generation Models. Prepared for Oregon Modeling Improvement Program, Oregon Department of Transportation.
- PB Consult (2003) Travel Demand Model Development for Traffic and Revenue Studies for Public-Private Partnership Highway Projects in the Montreal Region. Prepared for the Ministry of Transportation of Quebec.
- PB Consult (2004) NYMTC Transportation Model and Data Initiative: New York Best Practice Model. General Final Report. Prepared for the New York Metropolitan Transportation Council.
- Pendyala, R. (2005) Modeling Pricing in the Planning Process. Resource paper presented at the Expert Forum on Road Pricing and Travel Demand Modeling, United States Department of Transportation.

- Perez, B. G. and G. C. Sciara. (2003) A Guide for HOT Lane Development. Report prepared by Parsons Brinckerhoff with the Texas Transportation Institute (TTI) for the Federal Highway Administration (FHWA), Publication Number FHWA-OP-03-009.
- Pickrell, S., Cambridge Systematics, Inc. (2007) Cost-Effective Measures and Planning Procedures for Travel Time, Delay, and Reliability, NCHRP Project 7-15, Transportation Research Board, Washington, D.C.
- Poole, R. W. (2007) Tolling and Public-Private Partnerships in Texas: Separating Myth from Fact. Reason Foundation Working Paper, May 2007. Retrieved August 2007 from www.reason.org/TX_toll_roads_working_paper.pdf.
- Pradhan, A. and K. M. Kockelman. (2002) Uncertainty Propagation in an Integrated Land Use-Transportation Modeling Framework: Output Variation via UrbanSIM. *Transportation Research Record 1805*, 128-135.
- Redmond, L., Mokhtarian, P. (2001) The Positive Utility of the Commute: Modeling Ideal Commute Time and Relative Desired Commute Amount, *Transportation*, Vol. 28, pp.
- Rodier, C. J. and R. A. Johnston. (2002) Uncertain Socioeconomic Projections Used in Travel Demand Model and Emissions Models: Could Plausible Errors Result in Air Quality Nonconformity?, *Transportation Research Part A*, 36, 613-631.
- Rodier, C. J. (2003) Verifying the Accuracy of Regional Models Used in Transportation and Air Quality Planning. Mineta Transportation Institute (MTI) Report 02-03, College of Business, San Jose State University. Retrieved June 2008 from http://transweb.sjsu.edu/mtiportal/research/publications/documents/02-03.pdf.
- Rodier, C. J. (2005) Verifying the Accuracy of Land Use Models Used in Transportation and Air Quality Planning: A Case Study in the Sacramento, California Region. Mineta Transportation Institute (MTI) Report 05-02, College of Business, San Jose State University. Retrieved June 2008 from http://transweb.sjsu.edu/mtiportal/research/publications/documents/05-02.pdf.
- Rodier, C. J. (2007) Beyond Uncertainty: Modeling Transportation, Land Use, and Air Quality in Planning. Mineta Transportation Institute (MTI) Report 07-01, College of Business, San Jose State University. Retrieved June 2008 from http://transweb.sjsu.edu/mtiportal/research/publications/documents/07-01.pdf.
- Sevcikova, H., A. E. Raftery, and P. A. Waddell. (2007) Assessing Uncertainty in Urban Simulations Using Bayesian Melding, *Transportation Research Part B*, 41, 652-669.
- Small, K. A. (1982) The Scheduling of Consumer Activities: Work Trips, *American Economic Review*, 72 (3), 467-479.
- Small, K. A., C. Winston, and J. Yan. (2005) Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability, *Econometrica*, 73(4), 1367-1382.
- Small, K. A., R. Noland, X. Chu, and D. Lewis. (1999) Valuation of Travel-Time Savings and Predict-ability in Congested Conditions for Highway User-Cost Estimation, National Cooperative Highway Research Program Report 431, National Academy Press.
- Sorensen, P. A., and B. D. Taylor. (2005) Innovations in Road Finance: Examining the Growth in Electronic Tolling. Presented at the *84th Annual Meeting of the Transportation Research Board*, Washington D.C.

- Spear, B. D. (2005) A Summary of the Current State of the Practice in Modeling Road Pricing. Resource paper presented at the Expert Forum on Road Pricing and Travel Demand Modeling, United States Department of Transportation.
- Standard & Poor's. (2002) Traffic Risk in Start-Up Toll Facilities, McGraw-Hill International (UK) Ltd., September 2002.
- Standard & Poor's. (2003) Traffic Forecasting Risk: Study Update 2003. McGraw-Hill International (UK) Ltd., November 2003.
- Standard & Poor's. (2004) Traffic Forecasting Risk: Study Update 2004. McGraw-Hill International (UK) Ltd., October 2004.
- Stefan, K., J. McMillan, C. Blaschuk, and J. Hunt. (2007) Estimation of a Weekend Location Choice Model for Calgary. Presented at the *11th Transportation Planning Application Conference*, Transportation Research Board, Daytona Beach, FL.
- Steimetz, S. C., and Brownstone, D. (2005) Estimating Commuters' Value of Time with Noisy Data: A Multiple Imputation Approach, *Transportation Research Part B*, 39, 865-869.
- Stockton W., P. Hughes, M. Hickman, D. Pucket, Q. Brown, A. Miranda, and S. Woong. (2000) An Evaluation of the Katy Freeway HOV Lane Pricing Project, TTI Report E 205001, Texas Transportation Institute.
- Stockton W., R. Benz, L.., Rilett, D. Skowronek, S. Vadali, and G. Daniels. (2000) Investigation of General Feasibility of High Occupancy/Toll Lanes in Texas, TTI Report 4915-1, Texas Transportation Institute.
- Sullivan, E. C. (2000) Continuation Study to Evaluate the Impacts of the SR 91 Value-Priced Express Lanes, Final Report, State of California, Department of Transportation.
- Sullivan, E. C. (2002) State Route 91 Value-Priced Express Lanes: Update Observations, *Transportation Research Record 1812*, 37-42.
- Supernak, J. (1992) Temporal Utility Profiles of Activities and Travel: Uncertainty and Decision Making, *Transportation Research B*, 26(B), 549-574.
- PB Consult, Inc. (2005) The MORPC Travel Demand Model. Validation and Final Report. Prepared for the Mid-Ohio Regional Planning Commission.
- Tillman R., J. Smolley, K. Massarelly, A. Goldberg, A. Prott, and P. Eshelman. (2006) Long-Term Projections of Traffic and Revenues for Equity Analysis, *Tollways*, Autumn 2006, 29-40.
- Tseng, Y. and E. Verhoef. (2008) Value of Time by Time of Day: A Stated Preference Study, *Transportation Research Part B* (in press).
- Texas Turnpike Authority. (2005a) Technical memorandum 2005-1. TTA Toll Feasibility Analysis Process. Austin, Texas.
- Texas Turnpike Authority. (2005b) Technical memorandum 2005-2. Guidelines for Conducting TTA Traffic and Revenue Studies. Austin, Texas.
- University of Washington et al. (1999). Longitudinal Calibration of Urbansim for Eugene-Springfield. Transportation and Land Use Model Integration Program. Prepared for the Transportation Development Branch, Oregon Department of Transportation.

- Ukkusuri, S., A. Karoonsoontawong, S. T. Waller, and K. M. Kockelman. (2005) Congestion Pricing Technologies: Synthesis and an Evaluation Framework. Presented at the *84th Meeting of the Transportation Research Board*, Washington, D.C.
- Urban Analytics. (2004) Estimating Demand for Value Pricing Projects: State of the Practice. Prepared for the NCTCOG by Urban Analytics, Inc and URS Corporation.
- Vassallo, J. M. and Baeza, M. A. (2007) Why Traffic Forecasts in PPP Contracts Are Often Overestimated? Research Paper, Final Draft, EIB University Research Sponsorship Programme. European Investment Bank, Luxembourg.
- Verhoef, E. T., and K. A. Small. (2004) Product Differentiation on Roads: Constrained Congestion pricing with Heterogeneous Users, *Journal of Transport Economics and Policy*, 38, 127-156.
- Vollmer Associates. (2001) Northwest Parkway Traffic and Revenue Study. Prepared for Northwest Parkway Public Highway Authority, Denver, Colorado, May 2001.
- Vovsha, P., M. Bradley, and J. Bowman. (2005) Activity-Based Travel Forecasting Models in the United States: Progress Since 1995 and Prospects for the Future. In *Progress in Activity-Based Analysis*, H. Timmermans (ed.), Elsevier, 389-414.
- Vovsha, P. and M. Bradley. (2004) Hybrid Discrete Choice Departure-Time and Duration Model for Scheduling Travel Tours, *Transportation Research Record 1894*, 46-56.
- Vovsha, P., W. Davidson, and R. Donnelly. (2005) Making the State of the Art the State of the Practice: Advanced Modeling Techniques for Road Pricing. Resource paper presented at the Expert Forum on Road Pricing and Travel Demand Modeling, United States Department of Transportation.
- Vovsha P., E. Petersen, and R. M. Donnelly. (2003) Explicit Modeling of Joint Travel by Household Members: Statistical Evidence and Applied Approach. In *Transportation Research Record 1831*, 1-10.
- Vovsha P. and E. Petersen. (2005) Escorting Children to School: Statistical Analysis and Applied Modeling Approach, *Transportation Research Record 1921*, 131-140.
- Waddell, P. et al. (1998). Development and Calibration of the Prototype Metropolitan Land Use Model. Transportation and Land Use Integration Program. Final Report Phase II. Prepared for the Transportation Development Branch, Oregon Department of Transportation.
- Wardman, M. (1998) The Value of Travel Time: A Review of British Evidence, *Journal of Transport Economics and Policy*, 32(3), 285-316.
- Wilbur Smith Associates. (2001) Traffic and Revenue Study. Proposed SR 125 South Tollway. Prepared for California Transportation Ventures, Inc. , San Diego, California, October 2001.
- Yan, J., K. A. Small, and E. C. Sullivan. (2001) Choice of Route, Occupancy, and Time-of-Day with Value Priced Tolls. Presented at the *81st Annual Meeting of the Transportation Research Board*, Washington D.C.
- Yan, J., and K. A. Small. (2002) Choice Models of Route, Occupancy, and Time of Day with Value Priced Tolls. *Transportation Research Record 1812*, 69-77.
- Yang, H., W. H. Tang, W. M. Cheung, and Q. Meng. (2002) Profitability and Welfare Gain of Private Toll Roads in a Network with Heterogeneous Users. *Transportation Research A*, 36, pp. 537-554.
- Zhao, Y. and K. M. Kockelman. (2002) The Propagation of Uncertainty through Travel Demand Models: An Exploratory Analysis. Annals of Regional Science, 36 (1), 145-163.

- Zhou, X., H. S. Mahmassani, and K. Zhang. (2007) Dynamic Micro-Assignment Modeling Approach for Integrated Multimodal Urban Corridor Management, presented at the *86th Annual Meeting of the Transportation Research Board*, Washington, D.C.
- Zmud, J. (2005) Data Requirements to Support Road Pricing Analysis. Resource paper presented at Expert Forum on Road Pricing and Travel Demand Modeling, United States Department of Transportation.
- Zmud J., M. Bradley, F. Douma, and C. Simek. (2007) Panel Survey Evaluation of Attitudes and Willingness to Pay for Tolled Facilities. Proceedings of the *87th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Tolling White Paper 3

Travel Demand Model Sufficiency

Technical Appendices:

Appendix 1 - Representation of Travel Costs in Travel Demand and Network Simulation Models
Appendix 2 - Incorporating Travel Time Reliability in Travel Demand Models
Appendix 3 - Methods to Evaluate Uncertainty, Systematic Biases and Risk Associated with Pricing Projects

Prepared for the Oregon Department of Transportation

by

Parsons Brinckerhoff
and
David Evans and Associates Inc.
Stantec Consulting Services, Inc.

February 2009

Appendix 1: Representation of Travel Costs in Travel Demand and Network Simulation Models

Before examining the impact of tolling or pricing on travel decisions, it is necessary to model a representation of the total cost of going from one place to another. Highway pricing should be first incorporated in network assignments using generalized cost functions. Then, through generated travel time and cost origin-destination matrices (i.e., "skims"), pricing will affect all other choice dimensions, specifically mode choice, time-of-day choice, trip/tour distribution, and other upper level choices. This appendix provides detail on how various components of travel costs are formulated in travel demand and network simulation models.

1.1 Representation of Generalized Costs in Highway Assignment and Route Choice

In highway assignment generalized cost is defined for each network link and further calculated for each origin-destination pair. Generalized cost consists of two cost elements: travel time and out-of-pocket cost. Typically the out-of-pocket cost consists only of tolls, but it may also include a portion of vehicle operating costs (that typically vary with the distance traveled) and other monetary costs, if pertinent. The generalized cost function can be written in the following general way:

$$G_k = a_k \times T_k + b_k \times C_k \qquad (1)$$

where:

k	=	vehicle class, typically defined by vehicle types (auto, truck) and auto occupancy,
T_k	=	travel time,
C_k	=	travel cost,
a_k	=	travel time coefficient,
b_k	=	travel cost coefficient.

The marginal rate of substitution between time and money (in this case the ratio of the travel time to cost coefficients, a_k / b_k), is the value of time (VOT). The time and cost coefficients could be obtained from the estimation of a route choice model; for example a binary toll/no-toll choice embedded in a nested mode choice model. Another critical consideration is the definition of the vehicle classes. There should be enough classes to keep aggregation bias to a minimum, yet not so many as to negatively impact model run times in a significant way. For highway tolling and pricing projects the vehicle classes should comprehend vehicle type (private auto, light truck, heavy truck, taxi, etc.), and auto occupancy classes (single occupant, two person carpool, three person carpool, etc.) for the following reasons:

- Different vehicle types and occupancy classes may have very different *values of time (VOTs)*. For example, commercial trucks tend to exhibit higher VOTs than personal vehicles.

- *Toll rates might be differentiated* by vehicle types and/or occupancy classes, for example, such as when a high occupancy toll (HOT) lane allows three-person carpools to travel for free, allows two-person carpools to pay half of the toll, and single occupant vehicles pay a full toll.
- General *prohibitions and eligibility* rules can be applied for certain vehicle types on certain facilities (for example, trucks prohibited on expressways or truck-only toll (TOT) lanes) or auto occupancy classes (for example, HOT lanes).

In order to satisfy all these conditions, traffic assignment should be implemented as a multi-class procedure with 6 to 12 or even more classes, depending on the model structure. While this is a certain complication, it is essential for proper modeling of all related choices. If different vehicle types and auto occupation classes are mixed together (with some average VOT) it is not only a source of bias in the route choice, but it will also distort mode choice, time-of-day choice, and all other choices that rely on the skimmed level-of-service (LOS) variables.

Equation 1 corresponds to the general expression of *highway utility* in its most common form. This expression constitutes a key component in all travel choice models. In the context of traffic assignment when choice is modeled between alternative routes, the travel time coefficient is normally set to 1.0. This convention does not affect the all-or-nothing choice embedded in the conventional Static User Equilibrium assignment[1]. With this simplification, the highway generalized cost function can be written in the following way:

$$G_k = T_k + b_k \times C_k = T_k + \frac{1}{VOT_k} \times C_k \qquad (2)$$

While the all-or-nothing route choice embedded in the conventional assignment procedure is frequently applied in practice to distinguish between free and tolled routes, it has been recognized that this is not an adequate tool in itself, because highway utility is not a simple linear combination of time and cost. In particular, toll roads or managed lanes represent a more attractive option than free roads because of their enhanced reliability and other considerations that are not directly measured by average time and cost. Explicit inclusion of travel time reliability in the highway generalized cost function represents a technical challenge; possible ways to accomplish this are discussed in Appendix 3. A simpler but useful (and common) approach is to estimate an additional *bias constant associated with priced facilities*. This bias can be most effectively incorporated in a binary choice model frequently referred to as pre-route choice, and placed between mode choice and route choice. It can also be included as the lower-level sub-nest in the mode choice nested structure. An additional argument is favor of this binary choice model is that its probabilistic nature helps to avoid the "lumpiness" of all-or-nothing assignment associated with unstable routes.

[1] Stochastic assignment methods are sensitive to the values of both time and cost parameters, and therefore when using these assignment methods the time coefficient should not be arbitrarily set to any value. The values of these coefficients are instead determined by statistical estimation based on observed data.

With the addition of the toll bias constant, the highway generalized cost function can be written in the following way, where γ_k represents the toll bias:

$$G_k = \begin{cases} a_k \times T_k^{free}, & if \quad C_k = 0 \\ \gamma_k + a_k \times T_k^{toll} + b_k \times C_k, & if \quad C_k > 0 \end{cases}, \qquad (3)$$

Since in a discrete choice framework only the difference between utilities matters, the expressions in Equation 3 can be rewritten in terms of *relative travel time savings* where the generalized cost of the free route is set to zero, as a reference point:

$$G_k = \begin{cases} 0 & if \quad C_k = 0 \\ \gamma_k + a_k \times \left(T_k^{toll} - T_k^{free}\right) + b_k \times C_k, & if \quad C_k > 0 \end{cases}. \qquad (4)$$

Equation 4 constitutes the essence of many models applied in practice for T&R forecasting. This cost function can be modified in several different ways, oftentimes to overcome the limitation of assuming a linear disutility with respect to time and/or cost. One alternative non-linear specification, adopted for many pricing studies in Texas and Colorado, takes the following form (Wilbur Smith Associates, 2001; Vollmer Associates, 2001):

$$G_k = \begin{cases} 0 & if \quad C_k = 0 \\ \gamma_k + a_k \times \ln\left(1 + T_k^{toll} - T_k^{free}\right) + b_k \times \left(C_k\right)^2, & if \quad C_k > 0 \end{cases} \qquad (5)$$

1.2 Representation of Generalized Costs in Mode Choice

The generalization of Equation 4 for *mode choice* is achieved by including the generalized highway cost in the mode choice utility for highway modes, as follows:

$$U_m^p = \gamma_m^p + a_m^p \times T_m + b_m^p \times C_m + \sum_v \lambda_{vm}^p S_v, \qquad (6)$$

where:

m	=	mode (including auto occupancy classes),
p	=	travel purpose (work, school, shopping, etc) and other possible segments,
v	=	person, household, and zonal variables,
T_m	=	travel time by mode,
C_m	=	travel cost by mode,
S_v	=	values of the person, household, and zonal variables,
γ_m^p	=	mode-specific constant for each purpose/segment,
a_m^p	=	coefficient for travel time by mode and purpose/segment,

b_m^p = coefficient for travel cost by mode and purpose/segment,

a_m^p / b_m^p = VOT,

λ_{um}^p = coefficients for person, household, and zonal variables for each mode by purpose.

The most frequently used person, household, and zonal variables in 4-step models include income, car ownership, household size and urban density. In research works, AB models and a few advanced trip-based models (such as Portland Metro), the set of explanatory variables and also possible dimensions for segmentation has been significantly extended, and may include gender, age, worker status, electronic vs. manual toll collection, and accessibility to mixed or retail land uses, among others. Travel time and cost variables in themselves include many components. In particular, for auto modes, travel time can include parking search and parking time as well as additional time for collecting and dropping-off passengers (for carpool modes) while travel cost can include toll, parking cost, and vehicle operating cost (fuel and some fraction of maintenance cost that depends on the mileage).

An important issue that is difficult to fully resolve in practice relates to maintaining *consistency* between the *segmentation applied in traffic assignment* (vehicle and occupancy classes k) and the *segmentation applied in the mode choice model* (modes m and purposes/segments p). While it is comparatively straightforward to use the same auto modes (occupancy classes) in both procedures, the additional segmentation by travel purpose, income group, and other possible dimensions pertinent to mode choice is difficult to preserve in the assignment procedure since it would result in an infeasible number of vehicle classes. Possible reasonable compromises are discussed below.

Table 1 illustrates an ideal segmentation structure that maintains consistency across the mode choice and assignment model components. The VOT estimates shown for each segment are meant primarily to illustrate approximate relative differences observed among these segments. The market segmentation shown in Table 1 is typically simplified in practice because of assignment/skimming run time constraints. The mode choice models may also use additional segmentation, for example further classifying non-mandatory purposes into shopping, eating out, recreation or other discretionary activities. The network simulation models rarely include more than three to six vehicle classes.

.

Table 1: Coordinated Segmentation of Mode Choice and Assignment Procedures

Time of Day/Mode Choice Segments		Assignment Vehicle Classes	
Trip / Tour Purpose	Vehicle Occupancy	Vehicle Occupancy	Approximate VOT ($2008)
Commuting – low income workers	SOV	SOV	$10
	HOV2	HOV2	$10× O_2
	HOV3+	HOV3+	$10× O_3
Commuting – medium income workers	SOV	SOV	$15
	HOV2	HOV2	$15× O_2
	HOV3+	HOV3+	$15× O_3
Commuting – high income workers	SOV	SOV	$20
	HOV2	HOV2	$20× O_2
	HOV3+	HOV3+	$20× O_3
Work-based sub-tours	SOV	SOV	$30
	HOV2	HOV2	$30× O_2
	HOV3+	HOV3+	$30× O_3
University / school tours	SOV	SOV	$6
	HOV2	HOV2	$6× O_2
	HOV3+	HOV3+	$6× O_3
Non-mandatory tours – low income	SOV	SOV	$8
	HOV2	HOV2	$8× O_2
	HOV3+	HOV3+	$8× O_3
Non-mandatory tours – medium income	SOV	SOV	$10
	HOV2	HOV2	$10× O_2
	HOV3+	HOV3+	$10× O_3
Non-mandatory tours – high income	SOV	SOV	$12
	HOV2	HOV2	$12× O_2
	HOV3+	HOV3+	$12× O_3

The scaling parameters to account for vehicle occupancy, O_2 and O_3, should be statistically estimated along with other mode choice model parameters. More often, these parameters are not estimated but assumed equal to the actual occupancy because of the lack of good quality data to support model estimation. Recent statistical evidence suggests that VOT is not directly proportional to vehicle occupancy, and that the actual coefficient values stand lower than 2 and 3.

The logic behind the market segmentation structure shown in Table 1 is to treat VOT consistently across all choices while avoiding an excessive proliferation of travel segments and vehicle classes. Additional segmentation of the behavioral choice models in the AB framework is less onerous than in 4-step models, but issues associated with the multiplication of vehicle classes in the assignment procedure are shared by both AB and 4-step models.

The choice of the number of vehicle occupancy categories in the assignment procedure should be based on the expected nature of carpool and/or pricing policies. If projects that give preferential treatment to three+ person carpools (HOV3+) are anticipated (whether exclusive lanes or free/discounted tolls) then the model may require explicit segmentation of trip tables by single occupant, two person carpool, and three or more person carpool classes. Otherwise all carpools may be collapsed into a single class. However, even in the absence of specific traffic restrictions or pricing policies, segmentation by vehicle occupancy may be desirable to capture VOT differences.

Market segments with similar VOT may be combined prior to highway assignment to reduce the impact of the proliferation of segments on assignment runtimes. This aggregation should also consider additional vehicle classes associated with non-passenger travel such as heavy and light commercial trucks. Table 2 shows a possible aggregation of vehicle classes based on the values of time shown in Table 1 and assuming scaling coefficients equal to occupancy. For simplicity, a value of 3.0 for occupancy of the HOV3+ category is used, although in reality the average occupancy of these carpools is approximately 3.2. In the assignment and skimming procedures, each vehicle class table is assigned based on the weighted average VOT across all components. In this example the 24 demand trip tables are collapsed into 6 vehicle classes, with minimal VOT aggregation. It is possible to make the VOT weighting specific to each assignment time-of-day period to ensure a better reflection on the differential mix of purposes across time of day.

Table 2: Example of Vehicle Class Aggregation

Purpose	Vehicle Occupancy	Approximate VOT	Trip Tables by Occupancy and VOT					
			SOV $6-12	SOV $15-30	HOV2 $12-24	HOV2 $30-60	HOV3+ $18-36	HOV3+ $45-90
Commuting – low income workers	SOV	$10	X					
	HOV2	$10×2=$20			X			
	HOV3+	$10×3=$30					X	
Commuting – medium income workers	SOV	$15		X				
	HOV2	$15×2=$30				X		
	HOV3+	$15×3=$45						X
Commuting – high income workers	SOV	$20		X				
	HOV2	$20×2=$40				X		
	HOV3+	$20×3=$60						X
Work-based sub-tours	SOV	$30		X				
	HOV2	$30×2=$60				X		
	HOV3+	$30×3=$90						X
University / school tours	SOV	$6	X					
	HOV2	$6×2=$12			X			
	HOV3+	$6×3=$18					X	
Non-mandatory tours – low income	SOV	$8	X					
	HOV2	$8×2=$16			X			
	HOV3+	$8×3=$24					X	
Non-mandatory tours – medium income	SOV	$10	X					
	HOV2	$10×2=$20			X			
	HOV3+	$10×3=$30					X	
Non-mandatory tours – high income	SOV	$12	X					
	HOV2	$12×2=$24			X			
	HOV3+	$12×3=$36					X	

1.3 Representation of Generalized Costs in Time of Day and Destination Choice

Mode utility functions that include travel time savings and costs associated with highway pricing (Equation 6) represent the basis of a theoretically consistent formation of impedance functions for destination choice (trip distribution) and/or time-of-day choice. Specifically, the logsums of the lower-level choices (mode choice, for example) are used as explanatory variables on the utility functions in the upper-level choices (destination or time-of-day choice). We will illustrate the basic representation of generalized costs assuming a model system where trip distribution is the upper level choice, followed by time of day choice and then mode choice.

The *time-of-day choice* utility can be formed using mode choice logsums in the following way:

$$V_t^p = \mu \times ln\left[\sum_m exp\left(U_{mt}^p\right)\right] + \sum_v \lambda_{vt}^p S_v, \qquad (7)$$

where:

t	=	time of day periods (TOD),
$0 < \mu \leq 1$	=	scaling coefficient that should be in the unit interval,
λ_{vt}^p	=	coefficients for person, household, and zonal variables for each TOD.

In 4-step model systems, TOD choice models normally operate with broad 3-4 hour periods. An additional peak spreading or peak-hour factoring sub-model may be required to adequately capture time savings and/or toll differentials between the peak hour and the shoulders of the peak. In disaggregate AB model systems, TOD choice models operate with a temporal resolution of 60 or even 30 minutes, which is usually fine enough for all applications of a regional model (Vovsha & Bradley, 2004). Variables such as income, occupation, industry, gender, presence of school-age children in the household and density (especially at the destination end) have proven to be significant. When utilities are constructed as shown in Equation 7, the mode choice logsums provide the appropriate and desired TOD choice sensitivity to tolls and associated travel time savings.

The *destination choice* utility (or trip distribution impedance functions) can be formed using a logsum over all TOD periods. While it is possible to calculate this logsum and it would represent the most consistent impedance measure, it is computationally very intensive since it should be implemented for each origin-destination pair. A more practical approach for a 4-step model (also adopted for some AB models) is to use the mode choice logsum of representative TOD periods for each travel purpose in order to economize on calculations. For example, for work trips/tours AM peak period and PM peak period mode choice logsums can be used, while for non-work trips the midday (off-peak) period mode choice logsum is assumed. Weighted linear interpolations of LOS variables between several periods can also be used. The destination choice utility can be generalized in the following way:

$$W_{od}^p = \eta \times ln\left[\sum_m exp\left(U_{odmt(p)}^p\right)\right] + ln\left(A_d^p\right), \qquad (8)$$

where:

o, d	=	origin and destination TAZs,
$0 < \eta \leq 1$	=	scaling coefficient that should be in the unit interval,
$t(p)$	=	representative TOD period for each purpose,
A_d^p	=	destination TAZ attraction (size variable) for each purpose.

The size variables represent destination TAZ attractions for each purpose. The most frequently used attraction size variables are total employment for work purpose, enrollment for school purpose, and retail employment for non-work purposes. Advanced trip-based models and AB models provide examples of more complicated size variables that mix several employment and population variables as well as segmented by urban type and density. Size variables are not added to the impedance function in doubly-constrained gravity models of trip distribution since they are applied directly as constraints on the destination side. The destination choice utility is sensitive to tolls and associated travel time savings through the mode choice logsum variables.

When the transit share is very low, the highway generalized cost itself (Equation1) can be used instead of the mode choice logsum in the utility function of time-of-day or destination choice models.

1.4. Representation of Generalized Costs in Other Upper-Level Choices

When the destination choice utilities are sensitive to highway pricing and travel time savings, zonal accessibility indices can be calculated and used as an explanatory variable for trip generation, activity pattern, car ownership, and land-use development models. Accessibility indices essentially represent mode destination choice logsums calculated by trip purpose in the following way:

$$Z_o^p = ln\left[\sum_d exp\left(W_{od}^p\right)\right] \qquad (9)$$

If Equation 9 is directly applied in combination with Equation 8 it may result in very intensive calculations. For this reason, in most model systems the destination choice utilities used in accessibility calculations are simplified in such a way that they could be pre-calculated based on a limited number of origin-destination skims and for a limited number of modes, purposes, and population segments. Even with these simplifications accessibility measures represent useful explanatory variables, and allow upper-level choices to be sensitive to highway pricing and travel time savings.

Appendix 2: Incorporating Travel Time Reliability in Travel Demand Models

Measurement of highway time reliability and its impact on travel choices is now considered one of the most important strategic directions for travel model improvement. Several published and ongoing research

projects (NCHRP 8-57, NCHRP 8-64, NCHRP Report 618, SHRP2 CO4, SHRP2 LO4) as well as FHWA guidance are devoted to reliability issues. This appendix provides details on the different ways to incorporate reliability into travel demand models.

3.1 Perceived Highway Time

Perceived *transit* time has been long recognized and used in travel models. For example, in most mode choice models and transit assignment algorithms, out-of-vehicle transit time components like wait time and walk time are weighted compared to in-vehicle travel time. It is not unusual to apply weights in the range of 2.0 - 3.5 reflecting the fact that the travelers' perceive out-of-vehicle time as more onerous than in-vehicle time.

Contrary to the transit modeling practice, practically all travel models include a generic highway time coefficient; that is, the same coefficient is applied for each minute of highway time regardless of the travel conditions. There is however compelling statistical evidence indicating that highway users perceive travel time in congested conditions as more onerous than free-flowing travel time (National Cooperative Highway Research Program [NCHRP], 1999; Axhausen et al, 2007; Levinson et al, 2004; McCormick Rankin Corporation [MRC] & Parsons Brinckerhoff [PB], 2008). Also, recent analyses of RP travel surveys have found that the respondents' perception of time saved is about twice the actual measured time saved (Small et al., 2005; Sullivan, 2000). The larger disutility associated with increasing congestion levels that these studies have found can be interpreted in two ways: as a negative psychological perception (similar to the walk or wait time weight associated with a transit trip), or as a proxy for travel time reliability.

Two examples of estimated perceptions of travel time are discussed below in order to illustrate the magnitude of the congestion level time weights as well as possible approaches to differentiate travel time by congestion levels. It should be noted that in both cases the approaches are very simple on the supply side and could be easily applied with both AB and 4-step models.

The first example was documented in NCHRP Report 431 (1999). The study examined route choice in a SP survey context. Travel time was broken into two parts:

- Time in uncongested conditions (LOS A-D), T_1
- Time in congested conditions (LOS E-F), T_2.

Highway utility included total time, cost, and the percentage of total time spent in congestion, as follows:

$$U = a \times (T_1 + T_2) + b \times C + c \times \frac{T_2}{T_1 + T_2}. \qquad (10)$$

where a, b and c are the coefficients for total time, cost and percentage of congestion time, respectively.

The coefficient on percentage of congestion time exhibited high significance, confirming that travelers perceive congestion time as more onerous than free-flow time. The authors translated it into a recommended mark-up value of 2.5 to VOT savings under congested conditions compared to uncongested

conditions. More detailed estimation results are summarized in Table 3. By virtue of the specified utility function, the cost of shifting one minute from uncongested to congested time is dependent on the total travel time. For an average time of 30 minutes, the VOT equivalent of the additional perceived burden associated with congestion itself is about $15/hour, or roughly equal to the average commuting VOT applied in most models.

Table 3: Cost of Shifting Time from Uncongested to Congested Conditions

Total Travel Time (min)	Cost of Shifting 1 minute from Uncongested to Congested Time	VOT Equivalent ($/hour)
10	$0.77	$46.2
15	$0.51	$30.6
20	$0.30	$18.0
30	$0.26	$15.6
45	$0.17	$10.2
60	$0.13	$7.8

The second example is taken from the recently completed travel demand model for the Ottawa-Gatineau, Canada, region (MRC & PB, 2008). The model framework, choice context, and utility formulation were different from those used in the 1999 NCHRP report. However, the bottom line results are in many respects similar. In the Ottawa-Gatineau study, a mode choice model was estimated for 5 travel purposes and 2 time-of-day periods (AM and PM) based on RP data from a large household travel survey (approximately 23,870 households, representing 5% of the population). Travel time and cost variables were obtained from modeled static assignment equilibrium skims.

The highway utility included travel cost with one generic coefficient and travel time broken into the following two components (note that this breakdown of travel time is different from the one adopted in NCHRP (1999):

- Free-flow (minimal) time, T_1
- Extra delay, calculated as congested time minus free-flow time for the entire origin-destination path, T_2.

The highway utility function had the following form:

$$U = a_1 \times T_1 + a_2 \times T_2 + b \times C + \sum_s (d_s \times h_s) \qquad (11)$$

where:

s = additional mode-specific constants and household/zonal variables,

h_s = values of additional variables,

d_s = estimated coefficients.

The estimation results are shown in Table 4 expressed in terms of free-flow and congested VOT. These results confirm that for several segments, specifically AM and PM work trips, as well as PM discretionary trips, each minute of congestion delay is perceived as about twice as onerous as the free-flow (minimal)

time component. For the other segments the statistical tests did not show a significant difference between free-flow and congestion time components, thus the two coefficients were pooled together.

Table 4: VOT Estimates for Free-Flow Time and Congestion Delay

Trip Purpose	VOT ($/hour)			
	AM		PM	
	Free-flow time	Congestion delay	Free-flow time	Congestion delay
Work	22.2	42.7	19.4	40.0
University	10.0	10.0	11.0	11.0
School	5.1	5.1	5.1	5.1
Maintenance	10.7	10.7	12.1	12.1
Discretionary	9.0	9.0	11.4	29.3

3.2 Time Variability

Time variability can be measured by any statistic of a travel time distribution (for example any combination of the mean, standard deviation, skewness, and higher moments). Taking into account such considerations as behavioral realism and simplicity of the model estimation (specifically, formulation of SP alternatives), as well as application, three main measures of time variability have been proposed and tested so far:

- Standard Deviation. This is a symmetric reliability measure that assumes that being early or late is equally undesirable; it is unlikely to be a realistic assumption for many trips and underlying activities.
- Buffer Time. This reliability measure is defined as the difference between 80-95th and 50th travel time percentile. Buffer time is asymmetric and therefore more behaviorally appealing than the standard deviation because it specifically targets late arrivals and is less sensitive to early arrivals.
- Delay Probability. This asymmetric reliability statistic simply states the probability of given delays, for example the likelihood of incurring a 15 minute delay or a 30 minute delay.

The following example illustrates the Standard Deviation approach, applied in the context of binary route choice [*NCHRP Report 431, 1999*]. The following utility function was adopted:

$$U = a \times T + b \times C + c \times SD(T) \qquad (12)$$

where $SD(T)$ is the standard deviation of travel time.

The standard deviation of travel time was calculated based on the set of 5 travel times presented in the SP questionnaire for each highway route alternative. The estimation results showed that highway users assign a very high value on each minute of standard deviation. The value of standard deviation is comparable with or even higher than the VOT associated with average travel time itself (i.e. $c \geq a$). Also a certain logical variation across trip purposes and income groups was captured. Table 5 summarizes the results for one of the several reported model specifications.

Table 5: Value of Reliability Measured as Standard Deviation of Time

Trip Purpose and Income Group	Value of Reliability	
	$ per min SD	$ per hour SD
Work trips, high income	0.258	15.5
Work trips, low income	0.215	12.9
Non-work trips, high income	0.210	12.6
Non-work trips, low income	0.167	10.0

A good example of the Buffer Time measure was used in a study of binary route choice between the managed (tolled) lanes and general purpose (free) lanes on SR-91 in Orange County, CA (Small et al., 2005). The adopted quantitative measure of variability was the upper tail of the distribution of travel times, such as the difference between the 80th and 50th percentile travel times (see Figure 1). The authors argue that this measure is better than a symmetric standard deviation, since in most situations being "late" is more crucial than being "early", and many regular travelers will tend to build a "safety margin" into their departure times that will leave them an acceptably small chance of arriving late (i.e. planning for the 80th percentile travel time would mean arriving late for only 20% of the trips).

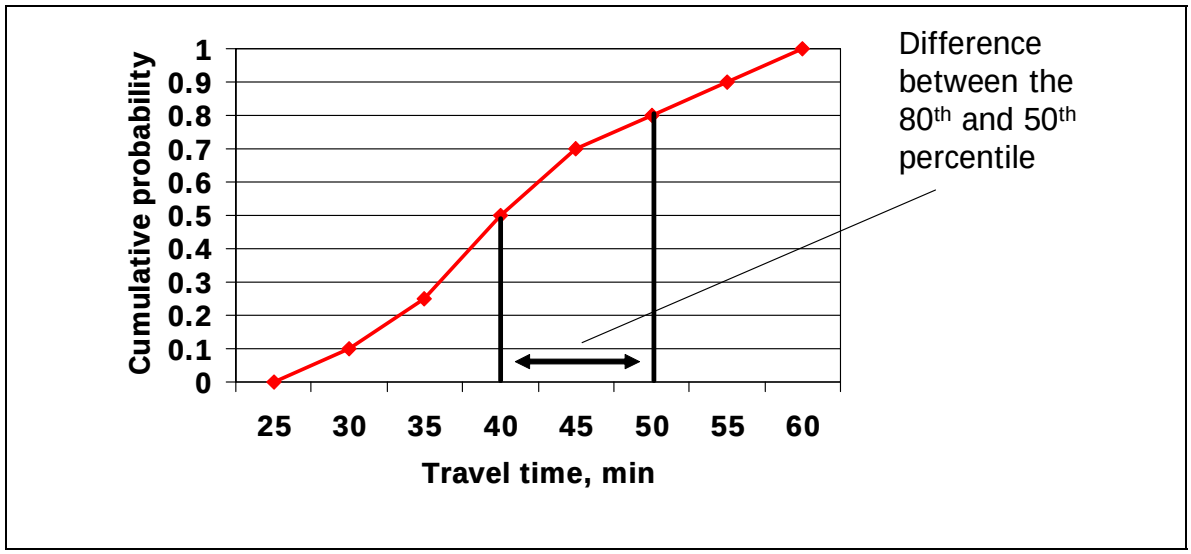


Figure 1: Buffer Time

The binary route choice model was estimated using a mix of RP and SP data. The variation of travel times and tolls was significantly enriched by combining RP data from actual choices with SP data from hypothetical situations. The distribution of travel times was obtained from field measurements on SR-91 taken at many times of day, on 11 different days. It was assumed that this distribution was known to the travelers because they are habitual SR-91 users. The utility function was specified as follows:

$$U = a \times T + b \times C + c \times R(T) \qquad (13)$$

where $R(T)$ is the difference between the 80th and 50th travel time percentile.

Reliability, as defined above, proved to be valued by travelers as highly as the average travel time; that is VOT was approximately equal to VOR, or $a \approx c$. This condition of equal VOT and VOR could be exploited

to obtain a simplified model form. If the willingness to pay for saving one minute of average travel time (the 50th percentile) is equal to the willingness to pay for one minute of reduction in the difference between the 80th and 50th percentile, then Equation 13 reduces to Equation 14. In this case, the underlying decision-making variable is the travel time value at the 80th percentile.

$$U = a \times T^{80th} + b \times C \qquad (14)$$

Rather than estimating two separate terms (average travel time and additional time associated with 80th-50th percentile), a single travel time statistic could be used, whether the 80th percentile or any other percentile larger than the 50th that yields the best statistical fit. For example, the 90th travel time percentile was used in a similar choice context (Brownstone & Small, 2005).

The approach suggested by Equation 14 is illustrated in Table 6. In this example, motorists have to choose between two roads for commuting that are characterized by different time distributions. Road A is longer but more reliable – its travel time varies from 41 minutes to 50 minutes. Road B is shorter but its travel time is less predictable and varies from 29 minutes to 52 minutes. Motorists are familiar with both roads and make their choice based on a rational consideration of the known time distributions.

Table 6: Illustration of Travel Time Reliability Impact on Route Choice

Percentile	Travel time (minutes)		Road Preference
	Road 1	Road 2	
10	41	29	
20	42	30	
30	43	35	
40	44	39	
50	45	40	Road B (better average travel time)
60	46	41	
70	47	45	
80	48	50	Road A (better 80th percentile travel time)
90	49	51	
100	50	52	

While Road B has a shorter average travel time and would be the preferred road in most conventional modeling procedures, Road A has a better 80th travel time percentile. Therefore motorists would probably prefer Road A, because it offers more reliable service than Road B.

This simplified buffer time framework is based on the plausible assumption that travelers under congestion conditions characterized by travel time uncertainty behave so as to rationally minimize risk. They do not base their decisions on average values. However, they do not adopt the extreme mini-max approach (minimize risk and choose according to the worst possible case) either. The decision point probably lies somewhere between 80th and 90th percentile.

It is important to note that making this approach operational within the framework of regional travel models requires explicit modeling of travel time distributions, as well as making assumptions about how travelers

acquire information about the uncertain situation they are about to experience. Dynamic traffic assignment (DTA) and traffic microsimulation tools are crucial for the application of models that include explicit travel time variability, since static assignment can only predict average travel times.

There are other approaches similar in concept to the one described above, but that use a different technique in both the estimation and the application stages. For example, in a T&R study in Montreal (PB Consult, 2003), the probability of experiencing delays longer than 15 minutes and 30 minutes was introduced in the SP questionnaires for truckers. The subsequent estimation of the choice model revealed that the coefficient on this variable was highly significant. The magnitude of the delay probability coefficient was comparable with the total trip time coefficient, as found in the VOR estimation for SR-91 motorists (Small et al., 2005). The application of the Montreal model required developing probability-of-delay skims. These skims were calculated based on the observed statistics of delay as a function of the modeled volume-to-capacity (V/C) ratio. Although this technique requires a multi-day survey of travel times and speeds, it can be applied in combination with the static assignment method. Many regions with continuous traffic monitoring equipment now have such data available for important highway segments. There is a problem yet to be resolved however: when calculating the travel time reliability measure over the entire origin-destination path, the highway links cannot be considered independent.

Reliability is closely intertwined with VOT. In RP models, if variability is not measured explicitly and included as a variable, this omission will tend to inflate the estimated value of average time savings. In reality, variability in travel time tends to be correlated with the mean travel time. When choosing a toll road, people are paying for changes in both variables – a reduction of the average travel time, and increased reliability, so omitting one variable will tend to attribute the total effect to the included variable.

The principal conceptual drawback of the reliability approaches based on travel time variability is that they do not explicitly consider the nature of the underlying activities and mechanisms that create the travel disutility. Needless to say, the largest part of the disutility associated with unreliable travel time is due to being late (or too early) at the activity location and consequently losing a part (or all) of the planned activity participation. The practical advantage of the time variability approaches is however, in its relative simplicity and exclusive reliance on the data supplied by the transportation networks.

3.3 Schedule Delay Cost

This approach has been widely accepted by the research community since it was first proposed in 1982 by Small. According to this approach, the impact of travel time (un)reliability is measured by the explicit cost associated with the delayed or early arrival at the activity location. This approach considers a single trip at a time and assumes that the preferred arrival time that corresponds to zero schedule cost is known. The essence of the approach is that the trip cost (i.e. disutility) can be calculated as a combination of the following three components:

α = value of travel time and cost,

β = cost of arriving earlier than the preferred schedule,

γ = cost of arriving later than the preferred schedule.

By definition, only one of the schedule cost can have a non-zero value in each particular case depending on the actual arrival time versus the preferred one. There can be many analytical forms for the schedule cost as a function of the actual time difference (delay or early arrival). Both functions should be monotonically increasing with respect to the time difference. It is also expected in most cases that the schedule delay function should be steeper than the early arrival function for most activities, because being late is more onerous than being earlier.

The most frequently used forms, shown in Figure 2, include a simple linear function (i.e. constant schedule delay cost per minute), non-linear convex function (assuming that large delays are associated with growing cost per minute), and various piece-wise functions accounting for fixed cost associated with any delay along with a variable cost per minute.

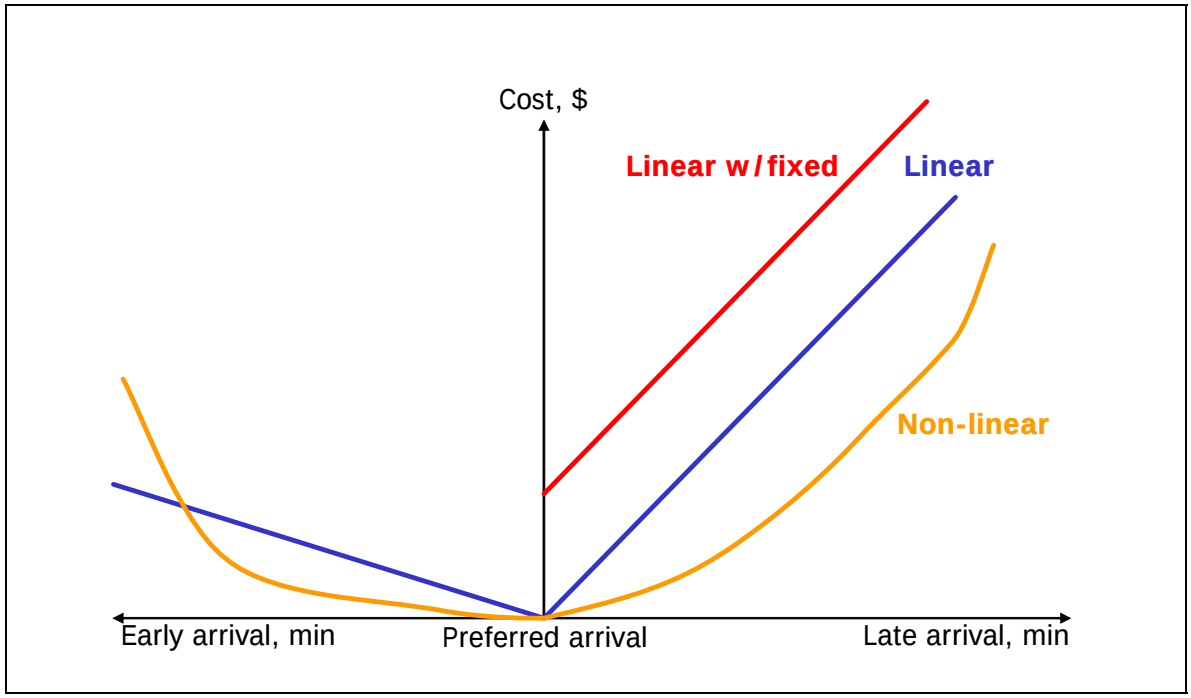


Figure 2: Schedule Delay Cost Functions

An example of a schedule delay model estimated in a highway route choice context with a specially designed SP survey is given in NCHRP (1999). The utility function was specified in the following way:

$$U = a \times T + b \times C + c \times SD(T) + \beta(\Delta t) + \gamma(\Delta t) \qquad (15)$$

where:

Δt = time difference between the actual and preferred arrival time,

$\beta(\Delta t)$ = early arrival cost specified as a non-linear convex function,

$\gamma(\Delta t)$ = late arrival cost specified as a linear function with a fixed penalty for any delay and another fixed penalty for extra late arrival.

The schedule delay cost estimation results are summarized in Table 7, for one of the tested model specifications. Interestingly, as reported by the authors, in the presence of explicit schedule delay cost the travel time variability measure (standard deviation) lost its significance. The authors concluded that in models with a fully specified set of schedule cost, it is unnecessary to include the additional cost of unreliability of travel time.

Table 7: Schedule Delay Cost Estimation Results

Schedule Delay Component	Marginal Values
Early arrival (non-linear):	
- by 5 min	$0.028/min
- by 10 min	$0.078/min
- by 15 min	$0.128/min
Late arrival dummy:	
- work trips	$2.87
- non work trips	$1.80
Late arrival (linear)	$0.310/min
Extra late arrival dummy	$0.98

Schedule delay cost should be distinguished from TOD choice and the associated disutility of shifting the planned (preferred) trip departure time or trip arrival time. In practical estimation analysis the data might mix these two factors. To clearly distinguish between the planned schedule and schedule delay, the person should explicitly report actual and preferred arrival time for each trip. Schedule delay cost assumes that the person has planned a certain schedule, but in the implementation process on the given day the delay occurs to disturb this plan. TOD choice relates to the stage of schedule planning. The outcome of this process is the preferred arrival time.

The difference between these two measures become even less clear if the schedule adjustments are modeled pivoting off of the observed (preferred) arrival time; that is, the travelers are asked about their willingness to shift the arrival time if the preferred arrival time would be associated with an additional toll. An example of a model of this type that was recently estimated based on a SP survey of highway users traveling to the downtown area of San Francisco is shown in Figure 3.

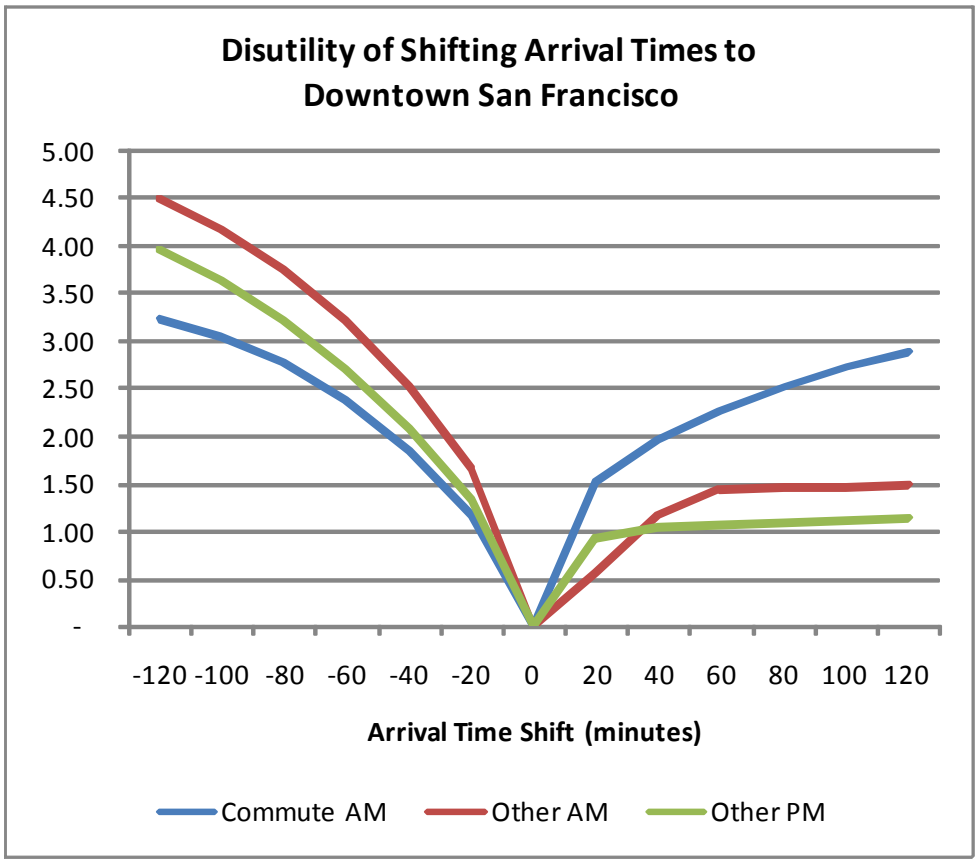


Figure 3: Estimated Schedule Adjustment Cost

The disutility of schedule adjustment is presented unitless as it comes out of the logit model estimation process. It can be scaled in monetary units by dividing by the cost coefficient, which roughly corresponds to $3.0 per unit. Thus, for example, to induce AM travelers to shift their trips one hour earlier, an incentive of $7-$10 is needed. In this model formulation commuters are less willing than non-commuters to switch their planned arrival time to later periods. This may be explained by the longer duration of work trips; later arrivals may imply less discretionary evening time. Interestingly and contrary to the schedule delay models, the associated disutility of making a trip earlier is larger than the disutility of making a trip later. This shows that the choice framework for planning/scheduling trips is different from the framework of schedule delays. In the model formulation and estimation, these frameworks should be clearly distinguished and separated.

Comparing schedule delay to time variability as two different measures of time reliability, it should be noted that the schedule delay approach provides a better behavioral insight than travel time variability. It explicitly states the reasons and attempts to quantify the factors of the disutility associated with unreliable travel time, specifically real or perceived penalties associated with not being at the activity location on time. The schedule delay approach, however, has its own theoretical limitations:

- The approach is applied separately for each trip made by a person during the day and it assumes that the schedule delay cost for each subsequent trip is independent of the previous trip. Technically this approach is based on a fixed departure time and a preferred arrival time for each trip. This is in

general not a realistic assumption, since the activity duration requirements would create a dependence of the departure time for the next trip on the arrival time for the previous trip.

- This approach does not consider activity participation explicitly, though it makes a step towards such a consideration compared to the travel time variability approach.
- If applied for the evaluation of user benefits from travel time savings, this approach must incorporate TOD choice, i.e. travelers' reconsideration of departure time in response to the changed congestion. Otherwise, travel time savings can result in early arrival penalties out-weighting the value of saved travel time.

On the practical side, in order to be implementable, the schedule delay approach imposes several requirements that are not easy to meet, especially with conventional RP surveys:

- For each trip, in addition to the actual arrival time, the preferred arrival time should be identified. While it is generally known to the traveler (or perceived subconsciously), it is generally not observed in RP-type data. To explore this phenomenon and estimate models that address it, the SP framework has proven to be very effective, since the preferred arrival time and schedule delays can be stated in the design of alternatives. Simplified assumptions about the preferred arrival time have been adopted. For example in (Tseng & Verhoef, 2008), the preferred arrival time was calculated as a weighted average between the actual departure time and would-be arrival time under free-flow traffic conditions.
- Application of this model for forecasting would again require input in the form of preferred arrival times. This can be accomplished either by means of external specification of the usual schedules on the activity-supply side (that would probably be possible for work and fixed non-work activities), or by means of a planned schedule model on the demand side. The latter would generate individual schedule plans (departure times) based on the optimal activity durations conditional upon the average travel times. The subsequent simulation (plan implementation) model would incorporate schedule delay cost based on the simulated travel times.

3.4 Loss of Activity Participation Utility

This approach to incorporating travel time reliability in travel demand models is based on a concept of time-dependent utility profiles (Supernak, 1992; Kitamura & Supernak, 1997). Recently this approach was adopted for research into integrating DTA formulations with activity scheduling analysis (Kim at al., 2006; Lam & Yin, 2001). The essence of the of loss of activity participation utility approach is that each individual has a temporal utility profile for any given activity, characterized by function $U(t)$. This utility profile can be estimated either as parametric or non-parametric functions of time, and time itself can be modeled in either continuous or discrete form. The utility profile represents an instant utility of participation in the activity at any given point in time (or during the discrete time unit that starts at the given point in time). The total utility of participation in the activity can be calculated by integrating the utility profile from the arrival time (τ) to departure time (π):

$$U(\tau,\pi)=\int_{\tau}^{\pi}U(t)dt \qquad (16)$$

Simple utility profiles are independent of the activity duration. In this case, it is assumed that the marginal utility of each activity at each point of time is independent of the time already spent on this activity. This might be too simplifying an assumption, at least for certain activity types like household maintenance needs where the activity loses its value after the errands have been completed. More complicated utility profiles can be specified as two-dimensional functions $U(t,d)$ where d denotes the activity duration until moment t. In this case, the total utility of activity participation can be written as:

$$U(\tau,\pi)=\int_{\tau}^{\pi}U(t,t-\tau)dt \qquad (17)$$

Hypothetical, but typical temporal utility profiles specified in a discrete space with an hourly resolution are shown in Figure 4. The work activity profile is adjusted to reflect the fixed schedule requirements (higher utility to be present at 8.00 AM and 5:00 PM points). The shopping activity profile is much more uniform, with an additionally assumed convenience to undertake this activity after usual work hours.

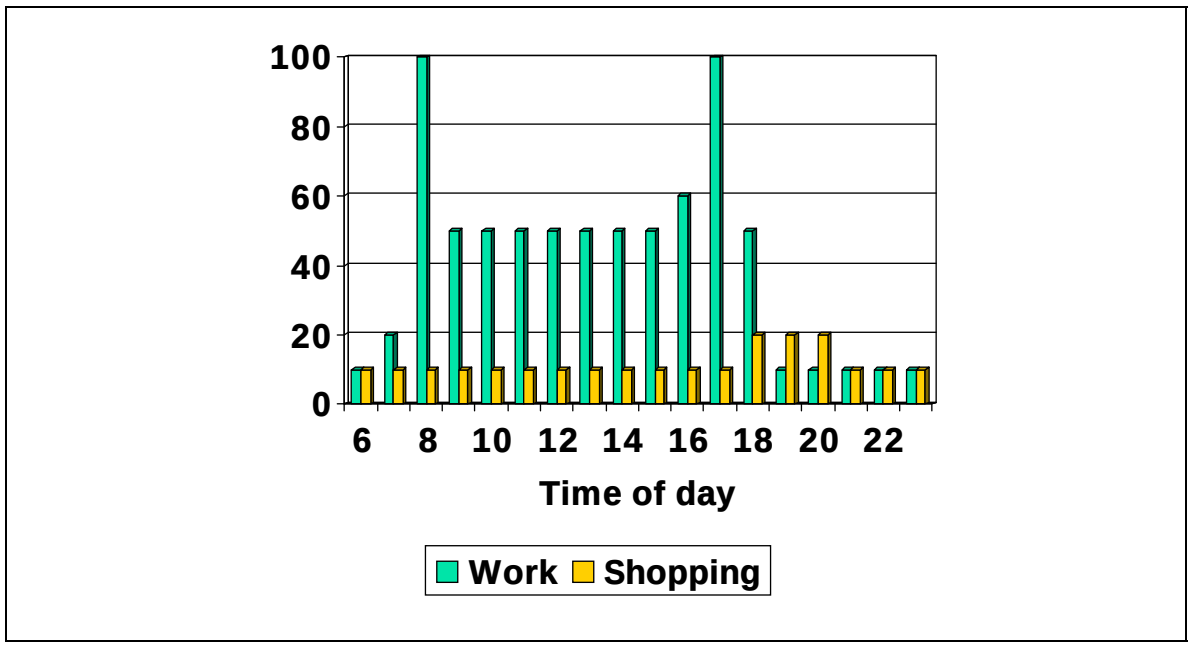


Figure 5: Activity Participation Utility Profiles

The concept of utility profiles helps in understanding how individuals construct their daily activity schedules. According to this concept, each individual maximizes a total daily utility of activity participation. If we consider a predetermined sequence of activity episodes, it can be said that individuals switch from activity to activity when the utility derived from participating in the second activity exceeds the utility from continuing the previous activity. Travel episodes are placed between activity episodes in such a way that the whole individual daily schedule represents a continuous sequence of time intervals as shown in Figure 5.

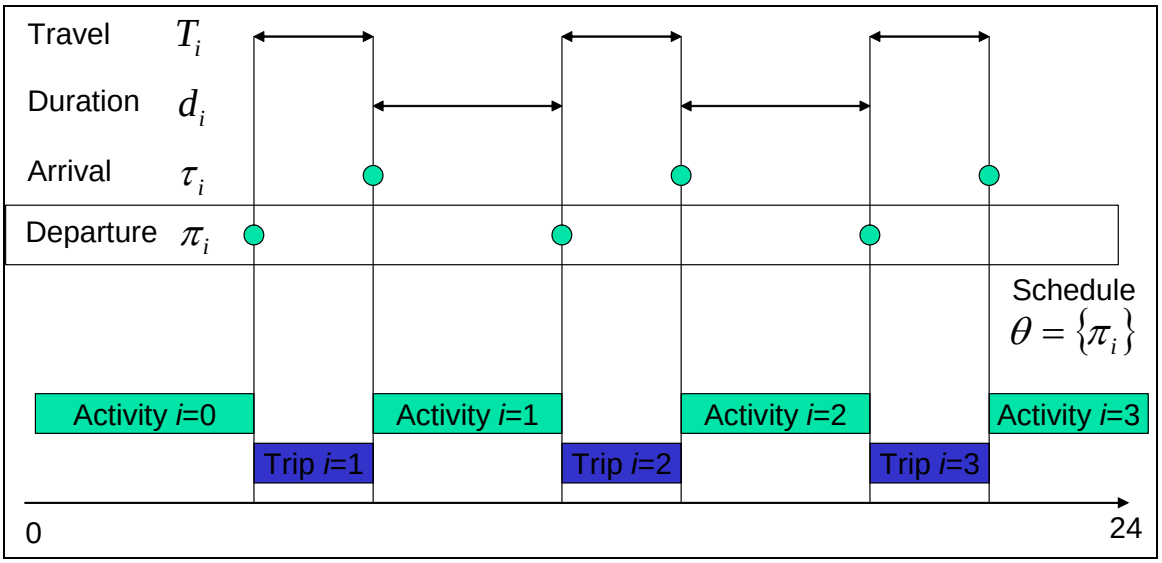


Figure 5: Individual Daily Schedule

The effect of unreliable travel times can be directly measured by comparing the planned and actual total daily activity and travel schedule utility. For simplicity, but without loss of generality, we assume that the sequence of activity episodes and trip departure times are fixed. We will also assume that a travel time delay never exceeds the planned duration of the subsequent activity, thus no activity is cancelled as a result of unreliable travel times. In other words, unreliability affects only travel times and arrival times. In this context, the reliability measure can be expressed as the loss of activity participation in the following way:

$$L = \sum_i \left(U_i^P - U_i^A\right) \qquad (18)$$

where:

L	=	total user loss (disutility) over the whole schedule,
U_i^P	=	utility of the trip and subsequent activity with planned (preferred) arrival time,
U_i^A	=	utility of the trip and subsequent activity with actual arrival time,

The planned and actual utilities can be expressed as:

$$U_i^P\left(\tau_i^P\right) = a \times T_i^P + b \times C_i^P + \int_{\tau_i^P}^{\pi_{i+1}} U_i(t)dt \qquad (19)$$

and

$$U_i^A\left(\tau_i^A\right) = a \times T_i^A + b \times C_i^A + \int_{\tau_i^A}^{\pi_{i+1}} U_i(t)dt \qquad (20)$$

where $T_i^P = \tau_i^P - \pi_i$ and $T_i^A = \tau_i^A - \pi_i$.

Substituting expressions *(19)* and *(20)* into Equation 18 we obtain:

$$L = \sum_i \left[a \times \left(\tau_i^P - \tau_i^A\right) + b \times \left(C_i^P - C_i^A\right) + \int_{\tau_i^P}^{\tau_i^A} U_i(t)dt \right] \qquad (21)$$

The integral term of Equation 21 represents activity participation utility loss resulting from the unreliable travel times, while the first two terms represent the loss resulting from the extra travel time and cost.

It can be shown that the activity participation utility loss and the schedule delay cost approaches are not independent (Tseng & Verhoef, 2008). The schedule delay cost functions can be derived from the temporal utility profiles. Thus the schedule delay approach can be thought of as a particular transformation of the temporal utility profile approach. The opposite is not true; that is, the temporal utility profiles could be fully restored from the schedule delay cost functions only under some specific assumptions.

To illustrate the relationship between temporal utility profile and schedule delay cost, consider two adjacent activities in the daily schedule with a trip between them as shown in Figure 6. In this fragment of the daily schedule, we assume that the temporal utility profile of the first activity is monotonically decreasing, while the utility of the second activity is monotonically increasing with time. We also number the trip between the two activities as T_2, to be consistent with the numbering shown in Figure 5. With an (ideal) zero trip time between the activities, the rational individual would switch from the first activity to the second activity at the intercept point of the two utility profiles, to ensure a maximum total utility. We can assume that the intercept point is the preferred arrival time, so that no schedule delay would be incurred when this point is realized as the activity start time. With a non-zero trip time, the optimal strategy would be to depart at such time that the departure time utility of the first activity would be equal to the arrival time utility of the second activity.

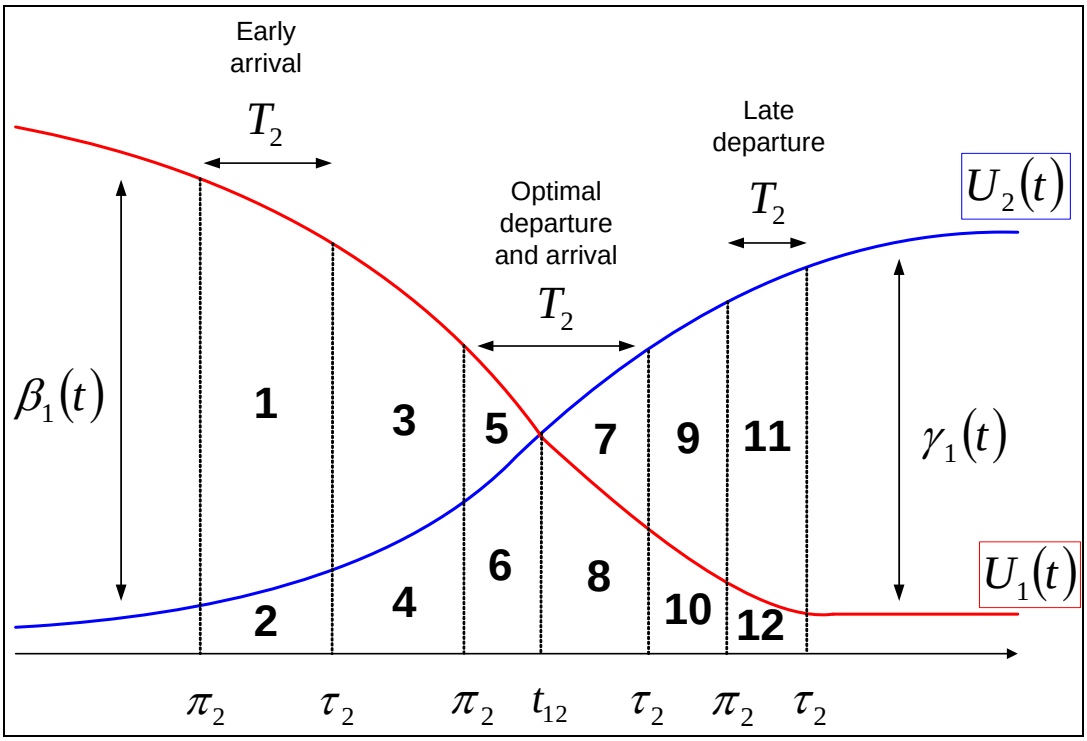


Figure 6: Temporal Utility Profiles for Two Adjacent Activities

Since the maximum utility would be realized when there is no trip between the activities, then the loss of utility associated with a trip can be calculated as the sum of the travel cost itself and the cost of the necessary schedule delay:

$$C_2(\pi_2,\tau_2) = \alpha_2(\pi_2,\tau_2) + \beta_2(\pi_2,\tau_2) + \gamma_2(\pi_2,\tau_2) \qquad (22)$$

where:

$\alpha_2(\pi_2,\tau_2)$	=	travel cost,
$\beta_2(\pi_2,\tau_2)$	=	cost of arriving early,
$\gamma_2(\pi_2,\tau_2)$	=	cost of departing/arriving late.

The travel cost can be understood as the lost utility that results from spending time on travel instead of in activity participation; this travel-related loss is incurred from the activity that would provide the most utility at the time of the trip:

$$\alpha_2(\pi_2,\tau_2) = \int_{\pi_2}^{\tau_2} \alpha_2(t)dt = \int_{\pi_2}^{\tau_2} \max[U_2(t), U_1(t)]dt \qquad (23)$$

The cost of arriving early ($\tau_2 < t_{12}$) or late ($\pi_2 > t_{12}$) is simply the utility lost from both activities due to their sub-optimal schedules:

$$\beta_2(\pi_2,\tau_2)=\int_{\tau_2}^{t_{12}}\beta_2(t)dt=\int_{\tau_2}^{t_{12}}[U_1(t)-U_2(t)]dt \qquad (24)$$

and

$$\gamma_2(\pi_2,\tau_2)=\int_{t_{12}}^{\pi_2}\gamma_2(t)dt=\int_{t_{12}}^{\pi_2}[U_2(t)-U_1(t)]dt \qquad (25)$$

While this derivation is intuitive, the resulting schedule delay expressions are a function of both departure and arrival times, which is rather inconvenient. An alternative way of deriving these cost components results in functions expressed solely in terms of activity arrival time. To do so, the travel cost is expressed as the loss of utility due to traveling instead of participating in the first activity:

$$\alpha_2(\pi_2,\tau_2)=\int_{\pi_2}^{\tau_2}\alpha_2(t)dt=\int_{\pi_2}^{\tau_2}U_1(t)dt \qquad (26)$$

The cost of early arrival remains equal to the cost due to sub-optimal activity scheduling, as in Equation 24. The cost of late arrival is also the cost due to sub-optimal activity scheduling, plus the opportunity cost of traveling instead of participating in the second activity:

$$\gamma_2(\pi_2,\tau_2)=\int_{t_{12}}^{\tau_2}\gamma_2(t)dt=\int_{t_{12}}^{\tau_2}[U_2(t)-U_1(t)]dt \qquad (27)$$

To verify that both cost derivation approaches produce the same total cost and also highlight the differences between them, all cost components are shown in Table 8, related to the areas 1-12 of integration under the temporal utility curves shown in Figure 6. It is clear that the only difference between the two derivation methods is in the formulation of the travel cost function and the area of integration for the schedule delay cost for a late arrival. In the second method the extra utility of the second activity over the first activity at the time of traveling (areas 7 and 11 in Figure 6) is transferred from the travel cost component to the late arrival schedule delay component.

Table 8: Trip Cost Components

Case	Component	Areas of Integration in Figure 6	
		First Derivation	Second Derivation
$\pi_2 \le t_{12} \le \tau_2$: departure earlier than the intercept and arrival later	$\alpha_2(\pi_2,\tau_2)$	5,6,7,8	5,6,8
	$\beta_2(\pi_2,\tau_2)$		

than the intercept	$\gamma_2(\pi_2, \tau_2)$		7
$\pi_2 < \tau_2 < t_{12}$: arrival earlier than the intercept	$\alpha_2(\pi_2, \tau_2)$	1,2	1,2
	$\beta_2(\pi_2, \tau_2)$	3,5	3,5
	$\gamma_2(\pi_2, \tau_2)$		
$t_{12} < \pi_2 < \tau_2$: departure later than the intercept	$\alpha_2(\pi_2, \tau_2)$	11,12	12
	$\beta_2(\pi_2, \tau_2)$		
	$\gamma_2(\pi_2, \tau_2)$	7,9	7,9,11

It is possible to restore the temporal utility profiles from estimated travel cost and schedule delay functions in the following way, as long as the intercept (preferred arrival time) is known and the temporal utility functions exhibit the monotonicity properties depicted in Figure 6:

$$U_1(t) = \alpha(t) \tag{28}$$

and

$$U_2(t) = \begin{cases} \alpha_2(t) - \beta_2(t), & \text{for } t < t_{12} \\ \alpha_2(t), & \text{for } t = t_{12} \\ \alpha_2(t) + \gamma_2(t) & \text{for } t > t_{12} \end{cases} \tag{29}$$

Thus, for a simple case under the assumptions explained above, there is no essential difference between the schedule delay cost approach and temporal utility profile approach. The direct analogy does not hold however, when more than two activities are considered (and not necessarily in a fixed order) or when the underlying utility profiles are more complicated and the preferred arrival times cannot be established for each trip (pair of adjacent activities) independently. In this case, utility profiles still provide a comprehensive framework for calculation of the loss of activity participation, while schedule delay cost components are bound to a particular order of activities and trips with predetermined preferred arrival time.

As long as the daily schedule can be understood as a sequence of fixed activities taking place in discrete time periods, with only two activities feasible at any given time period and preferred arrival times known, then the analogy described above between schedule delay cost and temporal utility profiles can be extended to multiple activities. The equations above can be applied recursively to any pair of activities to derive the schedule delay cost, and from it, restore the temporal utility profiles. This technique however is extremely “fragile” and fails if any of the simplifying assumptions does not hold.

The concept of temporal utility profiles, where travel time unreliability effects are considered as the loss of the activity participation utility, is the most holistic among the four possible approaches to incorporating travel time reliability outlined above. One important theoretical limitation of this concept is the assumption of independence among the temporal utility profiles, needed so that the daily schedule utility can be constructed as the sum of the individual activity utilities. In reality, the utility of one activity may be dependent on the participation and duration of the other activities. Effects related to substitution, saturation, satiation, and time-space budget constraints make the utility profiles interdependent across

activity episodes. A microeconomic framework that distinguishes between direct and indirect utility functions holds promise; however, it has not yet resulted in operational structures for travel demand modeling.

For practical applications, this approach requires estimation of the temporal utility profiles on the demand side. This is a realistic task using econometric methods, although it might result in quite complicated structures and would require a large (household type) survey. Application of such a model would require explicit modeling of a planned daily schedule based on expected travel times for each individual. The network simulation would provide actual travel times, so that the calculation of the utility loss would result from the difference between the actual and expected travel times.

Appendix 3: Methods to Evaluate Uncertainty, Systematic Biases and Risk Associated with Pricing Projects

Considerable uncertainty exists in traffic forecasts for new highway projects. A review of forecasts using data from highway and transit projects across the globe found that the different between forecasted and actual traffic is more than 20% for about one half of the highway projects examined, and about 40% for approximately one-quarter of all highway projects (Flyvbjerg et al., 2005 and 2006). While such uncertainty is not unexpected, it is often largely ignored by designers and transportation planners. This appendix provides more detail on this discussion.

Even greater uncertainty characterizes forecasts of the demand for *tolled* roadways, compared to other roadways, because of the presence of additional unknown variables, such as the toll schedule and motorists' willingness to pay for using the road. Yet gaining a good understanding of this uncertainty can be critical, since private investment generally depends on cost recovery through toll collection, which in turn is a function of the realized roadway demand. In order to address this clear gap in the literature, Standard & Poor's (S&P's) produced a series of studies that examine the risk and uncertainty of tolled highway projects. This appendix summarizes key elements of these studies and investigates methods for accommodating (or at least recognizing) uncertainty in the traffic forecasting process. The first section of this appendix describes the observed frequency and magnitude of traffic volume mispredictions, while the second section explains the various sources of risk and uncertainty in traffic forecasts and how these relate to project financing. The third section describes methods for recognizing and incorporating uncertainty in models of travel demand.

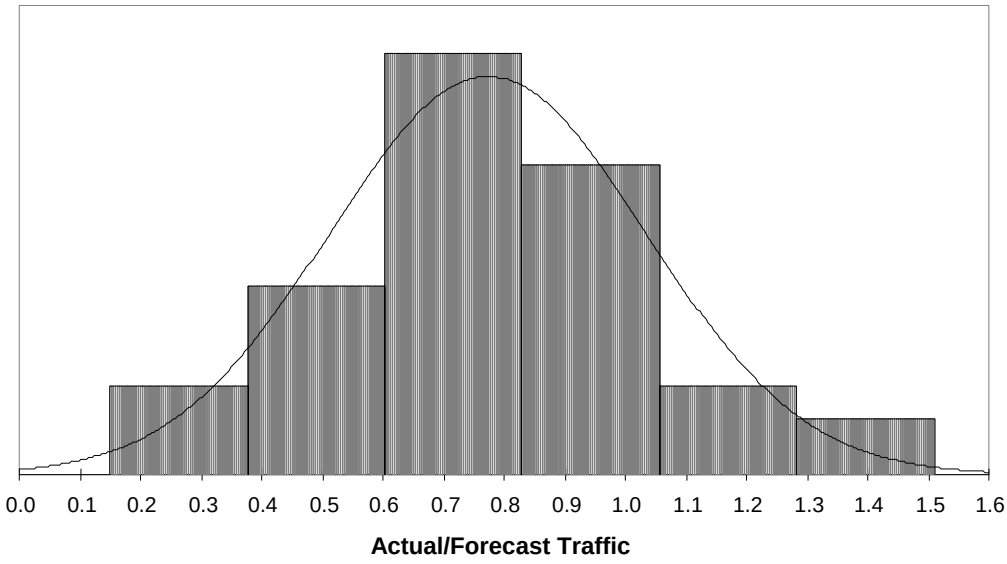
3.1 Frequency and Magnitude of Traffic Demand Misprediction

S&P's study of traffic forecasts began in 2002 with data on 32 toll road projects from around the world. The sample was then increased to 68 and 87 projects in 2003 and 2004, respectively. However, in both updates the conclusions remained largely the same.

In the first study, Bain and Wilkins (2002) found that traffic forecasts for new toll roads suffer from substantial optimism bias, a finding that is supported by the subsequent studies. The average ratio of actual-to-forecast traffic volumes in the first year of operation was about 0.73 (versus 0.74, 0.76, and 0.77 in the 2003, 2004, and 2005 studies). Figure 7 shows the distribution of forecasting errors in the 2005 update. Due to the nature of averaging ratios such as these, traffic forecasts for toll roads may be over-predicting actual volumes by even more than 33% (implied by an actual-to-forecast ratio of 0.75).[2] The 2002 study found that 78% of actual-to-forecast traffic volume ratios were less than 0.9 while only 12% were over 1.05; that is, the forecasts for approximately three-quarters of the tolled facilities overestimated demand by more than 10%. In the 2003 study, 63% of the facilities exhibited actual-to-forecast ratios less

[2] A volume-weighted average of ratios (essentially the sum of predicted values over the sum of actual values) yields a much more robust indicator of the average percentage error, reflecting whether an investor will win (average >1) or lose (<1) – on average, across projects. Essentially, the issue is that the ratios are non-negative and bounded by zero, leaving a right-side skew that can tends to bias averages high.

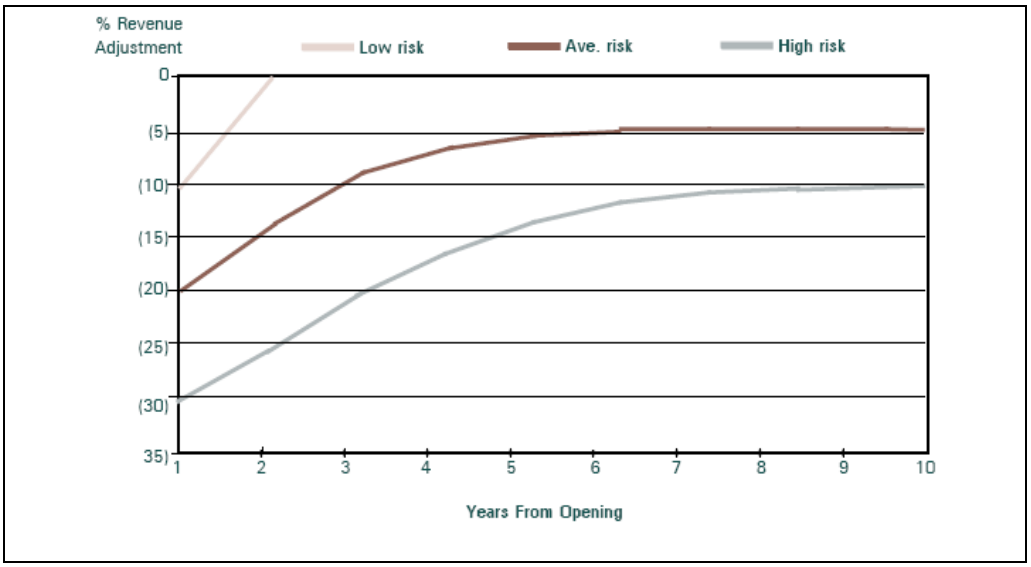
than 0.85, and 12% of the facilities had a ratio over 1.05. This evidence clearly suggests that travel demand modelers need to improve their forecasting methods.



Source: Bain and Polakovic, 2005

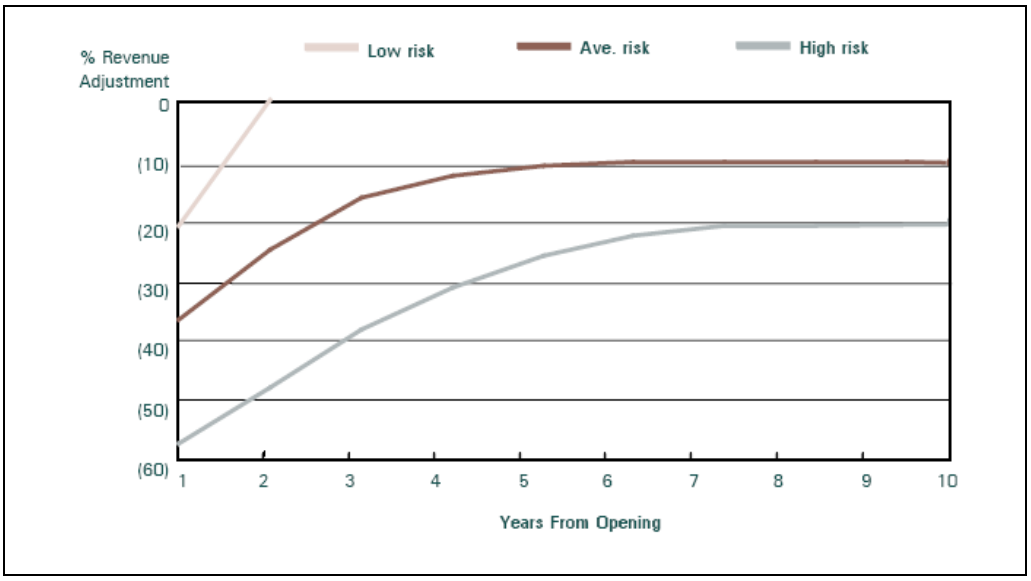
Figure 7: Actual-to-Forecast Traffic Volume Ratio Distribution

One of the main diagnostics to come out of the 2002 study was S&P's Traffic Risk Index (TRI). While the exact details for its estimation are proprietary in nature (and thus not provided), the index attempts to predict the amount of project risk based on many project attributes. Based on the TRI, Bain and Wilkins (2002) determined a risk level (low, average, or high) for each project, and divided its discussion by forecast source: those commissioned by banks versus those commissioned by others. Figure 8 and Figure 9 show the TRI profiles.



Source: Bain and Wilkins, 2002

Figure 8: Estimated Error in Tolled Highway Project Forecasts Commissioned by Banks



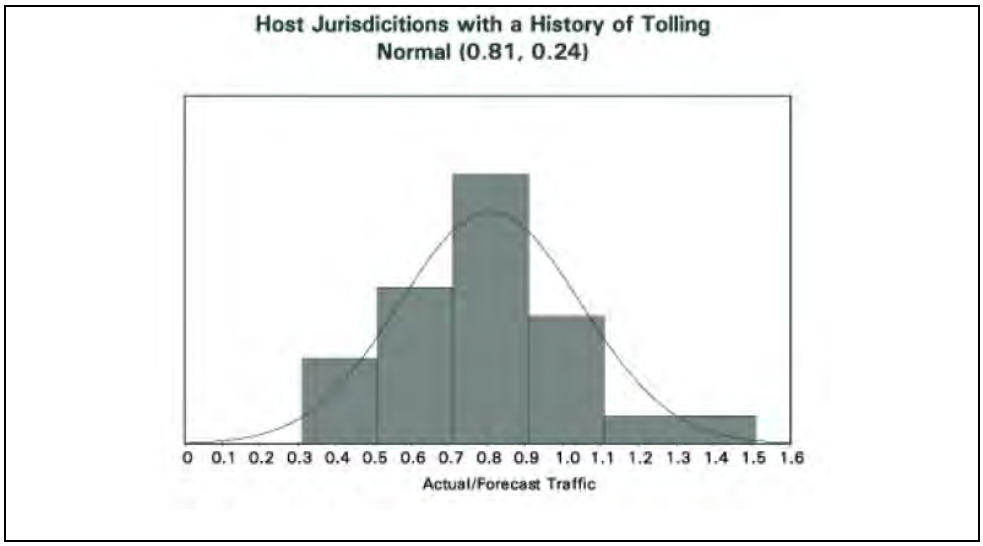
Source: Bain and Wilkins, 2002

Figure 9: Estimated Error in Tolled Highway Project Forecasts Commissioned by Others (Non-Banks)

These findings suggest that actual-to-forecast traffic volume ratios in the first year of operation average about 0.9 for low-risk bank-commissioned projects, and 0.8 for low-risk projects commissioned by others. Both types of low-risk projects had average ramp-up durations[3] of about 2 years (after which actual volumes closely matched forecasts). For average-risk projects, year one volume ratios were found to be 0.8 and 0.65 for bank- and non-bank-commissioned projects, respectively. The ramp-up duration was about 5 years in both cases. However, projects commissioned by banks ramped up to about 95% of forecast volumes over the first five years, while projects commissioned by others ramped up to only 90%. For high-risk projects, the volume ratios were just 0.7 and 0.45, respectively, and ramp-up durations were about 8 years. After the ramp-up period, bank-commissioned high-risk projects reached about 90% of forecast volumes while other projects reached approximately 80% of forecast. This suggests that projects with greater uncertainty (and thus risk) underestimate initial traffic volumes by a greater amount, on average, experience a longer ramp-up duration (to reach stable volumes), and stabilize at lower final traffic volumes (versus predictions). Moreover, the risk magnitude is greater for projects not commissioned by banks, suggesting that non-bank project commissioners (public agencies, interest groups, and bidders) may have interests that are better served when predicted traffic volumes are high, and are typically less accountable than banks for investors' monies (Bain & Wilkins, 2002).

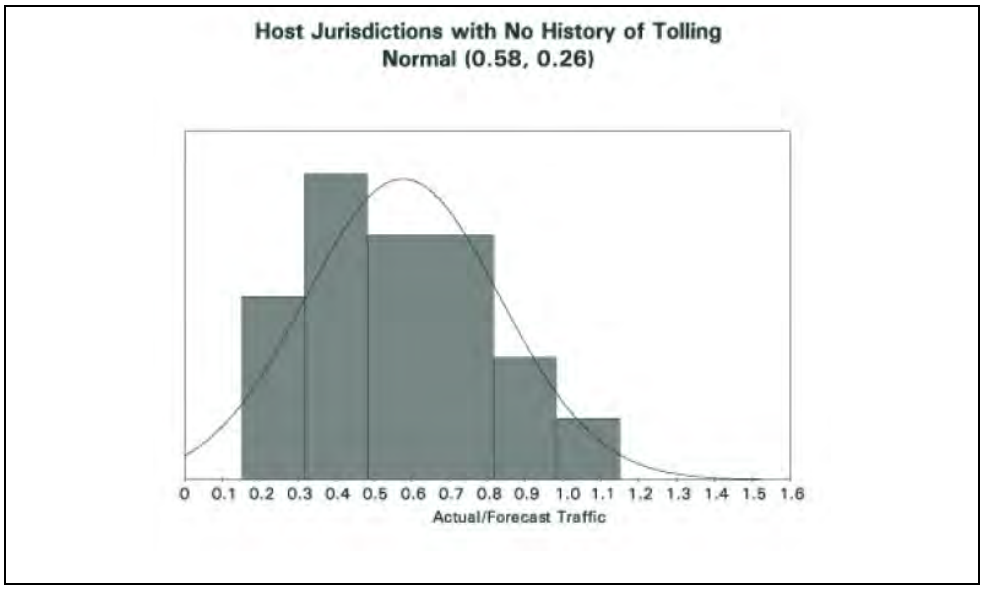
The 2003 study provided sufficient observations to conduct several less aggregate analyses. It was found that projects developed in countries with a history of toll facilities exhibited significantly higher actual-to-forecast ratios than projects in countries unaccustomed to highway tolling. Actual-to-forecast volume ratios in the first year of operations averaged 0.81 in countries with a history of tolling, but just 0.58 in other countries (see Figure 10 and Figure 11). Thus, forecast risks appear much higher in countries without a history of tolling. This is intuitive, given that user adoption will be much faster (thanks to existing toll tag and manual payment experiences), and that contractors and operators would be expected to be more familiar with tolling operations. In U.S. regions where flat-rate tolling is already well-established (e.g., Florida, Southern California, New York, and Houston), it may be reasonable to expect first-year ratios in the neighborhood of 0.8. However, most other U.S. regions are unfamiliar with tolling, and therefore forecasts may be overly optimistic if appropriate modeling assumptions are not used, particularly for the ramp-up period.

[3] The ramp-up period is the period in which traffic volumes rise to a relatively stable or equilibrium level. This period may require several years.



Source: Bain and Plantagie, 2003.

Figure 10:
Distribution of Actual-to-Forecast Traffic Volume Ratios in Year One of Operation for Projects in Countries with a History of Tolling

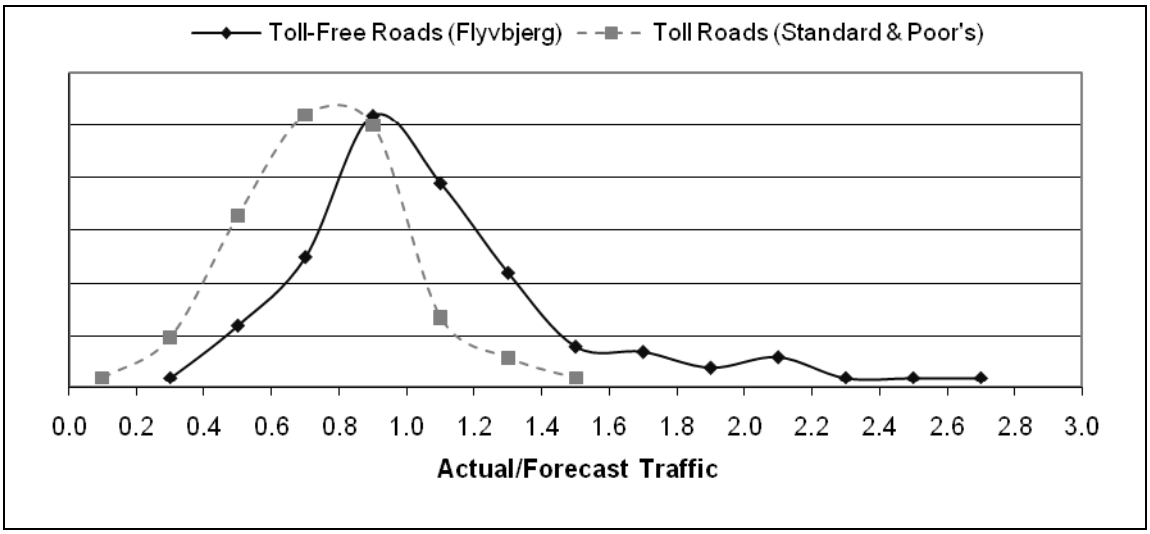


Source: Bain and Plantagie, 2003.

Figure 11:
Distribution of Actual-to-Forecast Traffic Volume Ratios in Year One of Operation for Projects in Countries with No History of Tolling

Traffic forecasts for new tolled highways were compared to forecasts for new non-tolled facilities (Bain & Plantagie, 2004). The comparison suggests that new non-tolled roadways exhibit little optimism bias,

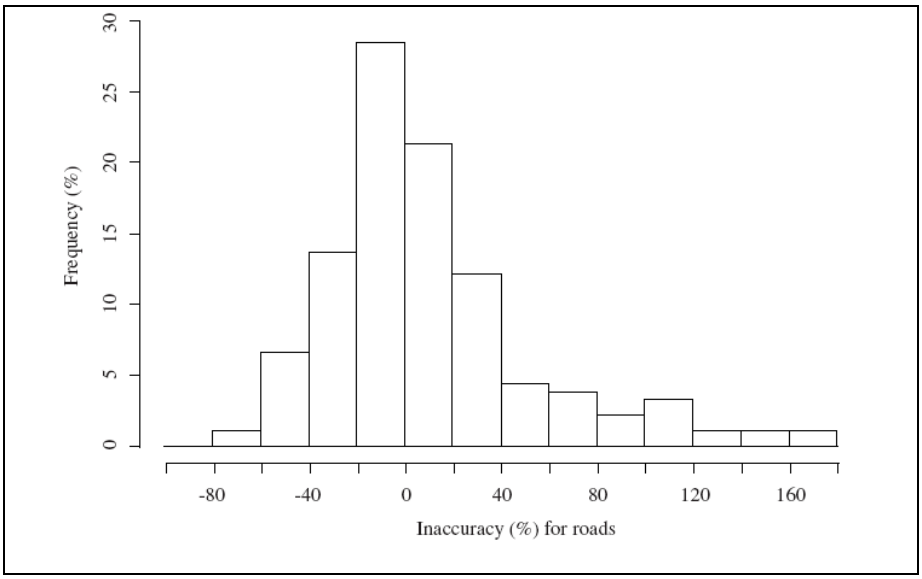
though the same amount of forecast uncertainty remains. Figure 12 shows that the two actual-to-forecast ratio distributions exhibit approximately the same shape, but with an added -20% optimism bias shift in the distribution of tolled road ratios. This suggests that after controlling for the added optimism bias of tolled projects, there may be little difference in the accuracy of traffic forecasts for tolled and non-tolled projects.



Source: Bain and Plantagie, 2004.

Figure 12: Distribution of Actual-to-Forecast Traffic Volume Ratios for Tolled and Non-Tolled Projects

Independent studies of the forecast performance for non-toll roads have found that the average actual-to-forecast ratio for these roads is 1.09, with 95% confidence that this value lies between 1.03 and 1.16 (Flyvbjerg et al., 2005 and 2006). As discussed previously, this average ratio is higher than if a weighted average were taken. A weighted average ratio would likely be very close to zero since there appears to be approximately the same number of projects falling above and below the break even ratio of 1.0. This situation corresponds to the 0% difference in forecast inaccuracy shown in Figure 13.



Source: Flyvbjerg et al., 2006.

Figure 13: Distribution of Actual-to-Forecast Traffic Volume Ratios for Non-Tolled Road Projects

In Standard & Poor's 2005 update the uncertainty in project ramp-up years was investigated in greater depth. The expectation was that uncertainty would fall slightly from opening year forecasts, because traffic demand would have an opportunity to stabilize, as drivers learn of route alternatives and obtain toll accounts, for example. The sample size was just 25 projects for years one through five, and the hypothesis was not supported (Bain & Polakovic, 2005). The mean ratio of actual-to-forecast traffic volumes was 0.77 in year one, and 0.79 (negligibly higher) in year five. Table 9 shows the average uncertainty ratios for each of the first five years of traffic operation. The difference in ratios is just 0.02, and thus, not significant. These results suggest that traffic demand generally remains well below the forecast, even into the fifth year of operation. Conversely, while a much smaller sample of Spanish toll roads identified similar optimism biases, it also showed that forecast ratios generally improved following year one (Vassallo & Baeza, 2007).

Table 9: Average Ratio of Actual-to-Forecast Traffic Volumes

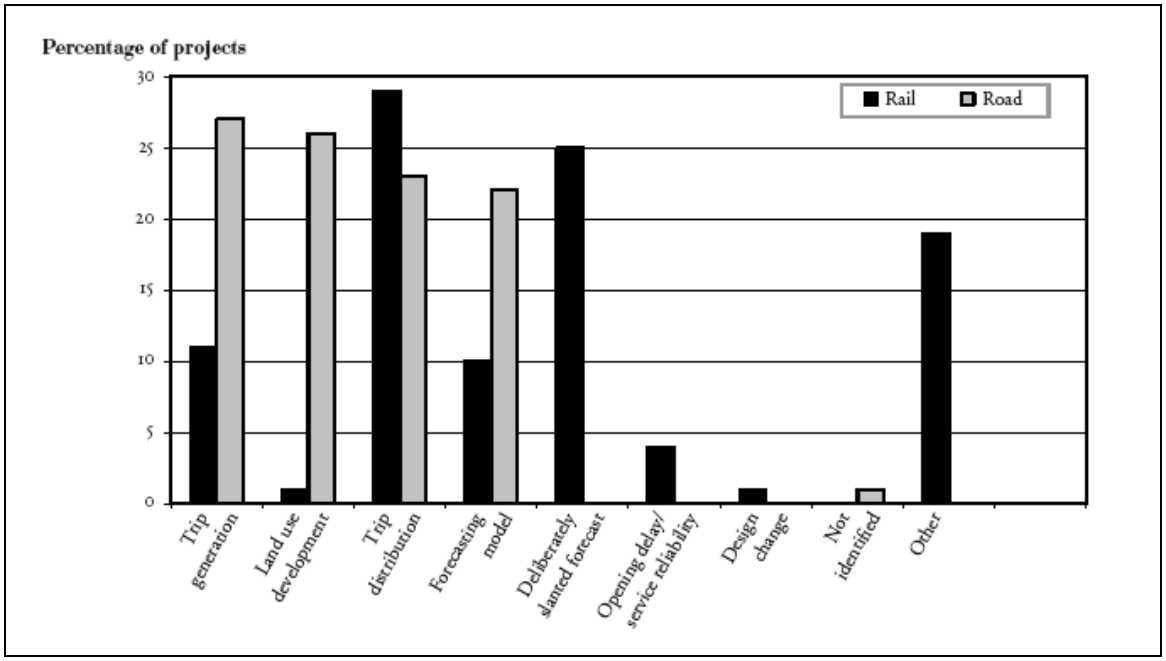
Years from Opening	Average Actual-to-Forecast Traffic Volume Ratio
1	0.77
2	0.78
3	0.79
4	0.80
5	0.79

Source: S&P's, 2005.

4.2 Sources of Risk and Uncertainty in Traffic Forecasts

While significant uncertainty in traffic forecasts clearly exists, the causes of such uncertainty vary. Numerous studies have identified and examined several sources of forecast error (see for example Flyvbjerg et al., 2005 and 2006; Bain & Wilkins, 2002; George et al., 2003 and 2007). These studies indicate that there are differences between tolled and non-tolled highways in terms of the sources of forecast error.

Figure 14 provides the percentage of projects with stated sources of traffic forecasting error, as reported by project managers, for both passenger rail and road projects (Flyvbjerg et al., 2005 and 2006). The two top-stated sources of error for toll-free road projects are estimates of trip generation and land development, though trip distribution and the forecasting model are close runners-up. The authors attribute much of the modeling uncertainty to dated data used in model calibration. Land Transport New Zealand (2006) also notes the importance of quality and relevance of data used in the forecasting model. This is a common problem with travel survey data. However, with forecasts at 10 years out, more of the error may stem from uncertainty in how land will develop (Flyvbjerg et al., 2005 and 2006). Such forecasts are based on development plans, which emerge and evolve over time.

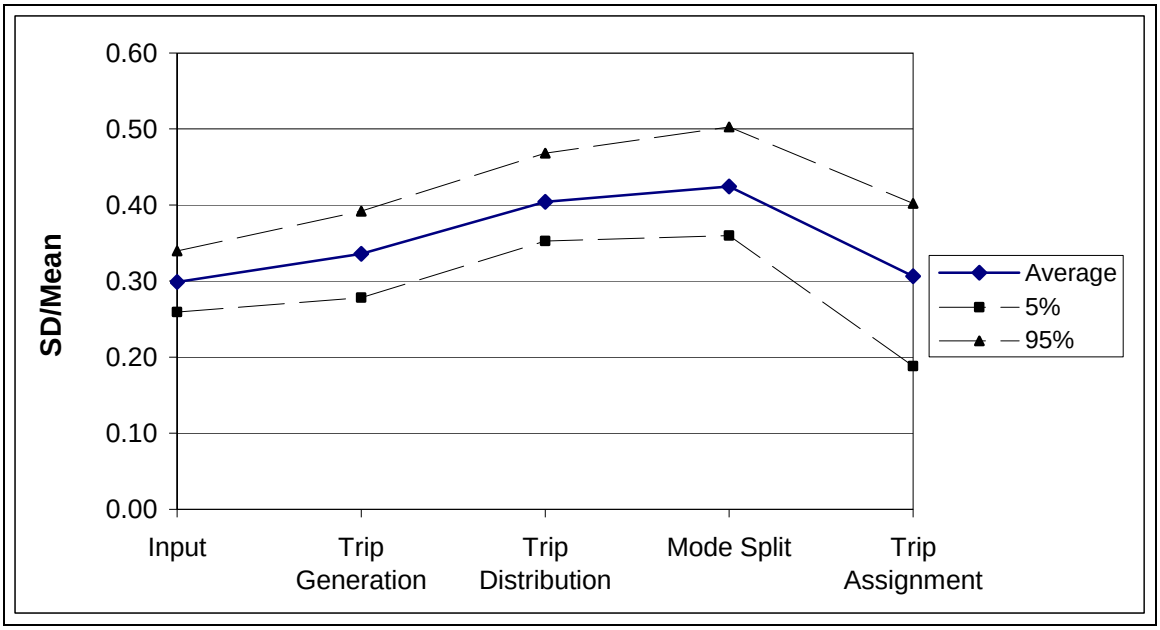


Source: Flyvbjerg et al., 2005.

Figure 14: Project Manager-Stated Sources of Forecast Error for Non-Tolled Facilities

Zhao and Kockelman (2002) tracked the propagation of uncertainty through a four-step travel demand model. They controlled the uncertainty of model inputs and parameters, and performed 100 simulations of the model. Figure 15 illustrates the range of coefficients of variation (CoVs) in intermediate and final model outputs (across the 100 simulations), given CoVs of 0.3 for all model inputs. These results suggests that

modeling error in effect "grows" through the application of trip generation, trip distribution, and mode choice models (as one's scale of resolution gets finer, essentially – to the number of trips by mode between each origin-destination pair). However, the final step of traffic assignment enjoys a drop in uncertainty (at the link-flow level), thanks to overlap in different trips' routings and mode and trip distribution choices across all travelers, along with congestion feedbacks (which moderate the presence of high link-demand values). Overall, Zhao and Kockelman's (2002) work suggests that link-flow estimates enjoy the same level of uncertainty as inputs and parameters. Consequently, simple regressions of outputs on inputs (and aggregations of inputs) should offer very high predictive power, suggesting that prime sources of forecast uncertainties can be rather quickly deduced – and exploited, for better prediction.



Source: Zhao and Kockelman, 2002

Figure 15: Uncertainty Propagation Through a Four-Step Travel Demand Model

Zhao and Kockelman (2002) also point out that models are abstractions of reality and the entire modeling paradigm is a source of error in traffic forecasts. While their study did not consider tolled roads, one can imagine that output variability may rise, as toll-technology adoption rates and heterogeneity in value of travel time savings introduce more uncertainty. In fact, for tolled roads, Bain and Wilkins (2002) noted the importance of data used to calibrate travel demand models, both in terms of currency (more recent is better) and the ease with which data were collected (affecting data quality and quantity).

Network attributes can also play a key role in forecast reliability. Analysts do not know the actual future network, and coded networks are significant simplifications of actual networks (generally ignoring local streets, signal timing plans, turning lane presence and lengths, etc.). Forecasts that depend on future network changes (such as nearby highway extensions) tend to be less reliable (Bain & Wilkins, 2002). The level of traffic congestion is also a key source of forecast error. As noted by Bain and Wilkins (2002) and Zhao and Kockelman (2002), it is more difficult to predict traffic flows on uncongested than congested

networks, because congestion feedbacks distribute traffic more evenly over space and time while establishing something like a volume upper bound on all links, associated with a link capacity.

Another key source of error in traffic forecasts comes from uncertainty in land development patterns (Rodier, 2003; Flyvbjerg et al., 2005 and 2006; Land Transport New Zealand 2006). Rodier's (2003) application of the Sacramento, California travel demand model for year 2000 conditions found that about half of the 11-percent overestimation of VMT was due to demographic and employment projections, which serve as inputs to the demand models. The other half was due to the model itself. With forecasts anticipating demand ten or more years out, Flyvbjerg et al. (2005 and 2006) suggest that more of the error may stem from uncertainty in future land development patterns. For tolled roads, Bain and Wilkins (2002) argue convincingly that land development forecasts are regularly critical, and that the more stable a region's economy, the better its land use (and, thus, its travel demand) forecasts. Such forecasts are generally based on land use plans and expert judgment, which are simply educated guesses and tend to evolve over time. Another option is land use modeling, which, of course, is also fraught with a variety of uncertainties (see for example Pradhan & Kockelman, 2002; Rodier & Johnston, 2002; Krishnamurthy & Kockelman, 2003; Rodier, 2005; Clay & Johnston, 2006; Sevcikova et al., 2007; and Duthie et al., 2008).

While the sources of error described above apply for projects of any type, there are many other error sources that are specific to tolled roads. One such source identified by Bain and Wilkins (2002) and George et al. (2007) is tolling design – that is, whether shadow tolls or user-paid tolls[4] are used. With shadow tolls, the government pays the concessionaire an amount based on toll road use. So from the user perspective, it is very similar to a toll-free road. With user-paid tolls, the toll charge is quite obvious to the user. Since driver willingness to pay is complex and varies with observed and unobserved driver attributes, projects with user-paid tolls carry more forecasting risk than free roads or shadow-priced roads. Moreover, George et al. (2007) suggest that user fees make a tolled road more susceptible to changes in demand caused by economic downturns and recessions, toll rate increases, and escalating fuel costs. Other special or relatively rare events, such as natural disasters or acts of terrorism, are often key sources of uncertainty as well (George et al., 2007). While such events are difficult to predict, HLB Decision Economics (2004) suggests that the number and duration of recessions in the forecast period should be considered in investment grade studies.

Another important consideration in understanding project risk is the "tolling culture" of a region (Bain & Wilkins, 2002). This is essentially the degree to which tolls have been used in the past. In nations and regions where tolling has not previously been used, there is greater uncertainty surrounding traffic forecasts. If travelers are accustomed to paying tolls for other road facilities, forecasts tend to be much more reliable. As noted earlier, the absence of a "tolling culture" appears to result in 20% greater average optimism bias (Bain & Plantagie, 2003).

Of course, over-simplifications embedded in the travel demand model are also sources of error in traffic forecasts. For instance, the robustness and heterogeneity (across travelers and trip types) of value of travel time (VOT) estimates are generally ignored, but may be crucial in producing accurate forecasts. The

[4] Only 4 of the 32 projects investigated in the 2002, Bain and Wilkins study had shadow tolls.

use of imported parameters (calibrated for other regions or even other countries) can also cause much error (Bain & Wilkins, 2002). Another important modeling issue is related to the actual representation of tolls. Models that recognize the full complexity of certain tolling regimes (such as variable tolls or HOT lanes that are free at certain hours) can be quite difficult to specify and calibrate (Bain & Wilkins, 2002), introducing further uncertainty.

Facilities enjoying a competitive advantage of some sort also tend to offer more reliable forecasts (Bain & Wilkins, 2002; George et al., 2007). For instance, forecasts for projects in dense, urban networks (with many alternative routes) generally will be less certain than those for projects with a clear competitive advantage over alternatives (for example a corridor with the only river crossing in a region). Moreover, many privately financed projects rely on protection against competition in the future. If protection is provided (via non-compete clauses, for example), long-run traffic forecasts tend to be more reliable (Bain & Wilkins, 2002). Of course, such clauses may be contentious, as discussed in Perez and Sciara (2003), Poole (2007), and Ortiz et al. (2008). However, non-compete clauses generally do not ban planned improvements (Ortiz et al. 2008) and typically do not prohibit new free roads. But they may allow for compensation when toll revenues fall due to improvements on nearby non-tolled facilities (Poole 2007).

Meaningful distinctions can also arise in the context of user attributes. Bain and Wilkins (2002) assert that toll facilities serving mostly a small market segment of travelers allow for more reliable traffic forecasts. This is because smaller markets are easier to model than more heterogeneous populations. For example, beltways (orbital style facilities) are likely to carry more forecasting risk than radial facilities (which typically carry a high share of commuters into and out of the city center, for work purposes). In addition, if there is a single origin-destination pair that constitutes the majority of trips made on the facility, forecasts errors fall, as a result of the relatively homogeneous makeup of such travelers. However, George et al. (2007) warn that when only a small market segment constitutes the majority of toll road users, road traffic and revenues will be more susceptible to any form of downturn affecting that small segment.

Of course, road location and configuration also affect levels of forecast error. When the preferred alignment of a new toll road is constrained by external factors (for example land use patterns, nature and location of existing development, land/right-of-way availability, topography, geological sensitivities, engineering limitations, and/or politics), traffic forecasts become more uncertain (Bain & Wilkins, 2002). Bain and Wilkins (2002) also assert that facilities with proper connectors to the rest of the network have more reliable estimates. If the toll road terminates in the downtown area and long queues await travelers joining the local network and/or if travelers must take circuitous routes to enter the toll road, the competitive advantage of the toll road can be compromised, and greater forecast errors can emerge. Demand variations over times of day and days of the year also affect forecast reliability. If a road serves a stable demand profile, forecasts tend to be more reliable (Bain & Wilkins 2002). Commercial users of the tolled facility also can play an important role. In particular, if most commercial vehicles are independent truckers, there is added risk in traffic forecasts since their behavior is less well understood. However, if most commercial truckers work for fleet owners, the opposite is true. (Bain & Wilkins, 2002) Moreover, dependence on commercial travel carries more risk since commercial travel is more susceptible to economic downturns (George et al., 2007)

Overall, Bain and Wilkins (2002) indicate seven top drivers of forecast failure: poorly estimated VOTTs, economic downturns, mis-prediction of future land use conditions, lower-than-predicted time savings, added competition (e.g., improvements to competing roads or the addition of new roads), lower than anticipated truck usage, and high variability in traffic volumes (by time-of-day or day of the year). Bain and Plantagie (2003) added several other top drivers: complexity of the tolling regime, underestimation of the duration and severity of the ramp-up period, and reliance on a single VOT (as opposed to segmenting user groups). Another rating agency, Fitch Ratings, also suggested several of these same drivers, but added that the use of a regional travel demand model developed for other planning purposes also can cause great error in traffic forecasts (George et al., 2003). This suggests, to some extent, that a comprehensive, regional model may not perform as well as simpler estimation techniques (e.g., OD pair trend analysis), if the regional model lacks appropriate specification for the toll road scenario. Clearly, there is a great deal of uncertainty in traffic and revenue forecasts of tolled roads stemming from various sources. The next section discusses methods that can be used to measure and evaluate this uncertainty in forecasting models.

3.2 Methods for Accommodating Risk in Travel Demand Modeling and Revenue Estimation Analyses.

Accommodating risk and uncertainty in demand and revenue forecasts is an important component of any toll road study. While a single "best" statistical forecast is useful, it lacks the information needed for making long-term financial decisions. Given the great number of assumptions, inputs, and estimated parameters entering travel demand models, model outputs can be highly uncertain and inaccurate. Neglecting this uncertainty (or equivalently, assuming determinism) can invite scrutiny from stakeholders, since not all will agree with assumed inputs and parameter values (Duthie, 2008). As noted in the previous sections, the magnitude of error in demand forecasts (and, thus, revenue forecasts) can be substantial, and tends to be biased in favor of toll road projects. Even with advances in model designs over the past couple decades, a review of the data suggests that forecast accuracy has not improved and may have worsened (Flyvbjerg et al., 2006). Most analysts, policy-makers, and investors agree that it is imperative that modelers quantify forecasting risk in a meaningful way (Rodier, 2007), and while the financial community has understood the need to address risk in toll road studies, Kriger et al. (2006) believe that very few practitioners conduct any sort of risk assessment. Some simply verify results by use of "reality checks" (for example comparing to older forecasts and using simple intuition to verify whether results seem reasonable) while others use no verification methods at all.

One key component of risk assessment in model outputs lies in explicitly stating all modeling assumptions (Kriger et al., 2006), making the model specification as transparent as possible. If modelers and users understand the implications of alternative assumptions, the uncertainty in the forecasting process will be better understood. Of course, other options for understanding and communicating forecast uncertainty also exist, as discussed here now.

A relatively common and reasonably effective method for accommodating risk in demand and revenue forecasts is the use of sensitivity analyses or "stress tests" (Kriger et al., 2006). Most sensitivity analyses rely on the exploration of a very limited set of different values for key variables, such as a region's or neighborhood's population growth rate, values of travel time, and planned tolls (Kriger et al., 2006).

Though such analyses can provide key insights, many practitioners and financial analysts feel that they do not adequately reveal the range of possible outcomes (see for example HLB Decision Economics, 2003 and Kriger et al., 2006). As their name implies, stress tests seek to understand the outcomes of relatively extreme conditions – generally to anticipate worst- (and best-) case investment scenarios. In this way they help analysts anticipate lower (and upper) bounds on project outcomes, but certainly not a distribution of outcomes, or probability of financial loss.

Model validation studies offer another method for quantifying uncertainty, by examining how well model forecasts match observed data not used in model calibration (Rodier, 2007). Such studies measure forecast uncertainty directly from observed data, and thus require data from two points in time: the older data set is used for model estimation and calibration while the newer one is used for validation. It can be impossible to conduct such tests of models developed from recent data, but at least one obtains a sense of the magnitudes of errors that can emerge from transferring behavioral parameters calibrated on old data to current-year contexts. Such validation tests are a valuable complement to sensitivity tests. And such results assist analysts in communicating the size and relevance of uncertainty to decision makers and the public (Rodier, 2007).

Of course, sensitivity testing and model validation studies have their limitations. For example, sensitivity tests are constrained to typically three or four scenarios. In contrast, Monte Carlo simulation techniques more fully explore the range of possible outcomes, by defining and drawing from probability distributions for key inputs. Such techniques also exhibit limitations: they require assumptions of input distributions (and their covariances) when these are often unknown, and generally more sophisticated programming techniques (to ensure rapid run times for testing a high number of scenarios).

Monte Carlo techniques are at the heart of the four-step risk analysis process (RAP) used by HLB Decision Economics (2003). In step 1, HLB defines a “structure and logic” model, in order to forecast traffic and revenue on the basis of an array of inputs and parameters. In step 2, central estimates and probability ranges are assigned to each relevant input and parameter. In step 3, expert opinions regarding the results of step 2 are obtained, and probability ranges and central estimates are revised. In the final step, Monte Carlo simulation techniques are employed, drawing inputs and parameters from their respective probability distributions, and traffic and revenue probability ranges are derived based on the simulation outcomes. This approach allows firms like HLB to determine the likelihood that revenue cannot cover the debt service, an important criteria for issuance of debt.

As discussed earlier, Zhao and Kockelman (2002) performed a similar analysis (for a non-tolled case), using a four-step travel demand model for a sub-network of the extensive Dallas-Fort Worth region with 118 variable input and parameter values. Although only 100 runs were performed, the analysis by Zhao and Kockelman provides useful insights into the degree of uncertainty in link- and region-level traffic forecasts. They assigned density functions to 18 random model parameters (13 in trip generation, 1 in trip distribution, 2 in mode choice, and 2 in assignment) and four major model inputs for each of 25 zones (forecasts of households and jobs per zone). Each of the uncertain parameters and inputs were assumed to follow log-

normal distributions with coefficients of variation[5] (CoVs) of 0.3, 0.1, and 0.5. After performing 100 simulation runs (for each of the 3 CoVs), two network links were examined in detail for the case of CoVs equal to 0.3. On both links, flows ranged from around 400 vehicles per hour to over 2000, with CoVs of 0.31 and 0.32. Zhao and Kockelman (2002) also performed a regression analysis of standardized input and parameter values on system-level VMT results. This analysis indicated that inputs and trip generation parameter values were the most important factors in forecasts of total VMT. It seems evident that traffic forecasts can exhibit a great deal of variation and depend greatly on parameter and input assumptions used in model calibration and application. When tolls are present, results could exhibit even greater variation. However, Zhao and Kockelman (2002) observed similar uncertainty levels in model inputs and outputs suggesting that opportunities for errors in one part of the model to offset errors in another can have a dampening effect on overall uncertainty. Thus, adding more uncertain inputs and/or parameters may not amplify forecast uncertainty.

Lam and Tam (1998) also performed a study of uncertainty using Monte Carlo draws in traffic and revenue forecasts for a toll road project connecting Hong Kong to an adjacent region separated by a body of water. No actual travel demand model was used, however, since only one other reasonable route existed between the two regions and a detailed travel study was deemed unnecessary. Instead, trip generation and routing shares were assigned distributions, and allowed to vary across simulation runs in order to quantify forecast uncertainty. A total of 10,000 simulations were performed, and overall revenues were found to hit or exceed the base forecast approximately 52% of the time. This is not so surprising, since the base forecast represents a simulation based on the mean values for all 12 unknowns input parameters. They also estimated that the standard deviation of forecast revenues rose from just 17% of the mean in the first forecast year to 28% of the mean after 20 years (Lam & Tam, 1998). It is useful to note the smaller coefficients of variation found here, in comparison to Zhao and Kockelman's (2002) study. For instance, the total population and trip generation rates were both assumed to have CoVs of 0.05. Lam and Tam investigated a particular scenario with arguably much less risk. Since their bridge facility enjoyed a clear advantage over competing routes, there was a specific traveler group being serviced, and a single origin-destination pair making up the majority of travel.

More recently, Sevcikova et al. (2007) compared Bayesian melding techniques and standard sampling approaches to analyze uncertainty in projections of household counts using UrbanSim, a land use simulation model. They found that Bayesian melding techniques produced wider ranges in output values than standard approaches, and the ranges suggested by the standard approaches were too narrow. Duthie et al. (2008) used an antithetic sampling technique to analyze uncertainty in an integrated land use-transportation setting. Methods like these, for sampling thoughtfully and performing estimation rapidly, can be invaluable in obtaining output distributions from complex models relatively quickly.

Consistent with such analyses, the National Federation of Municipal Analysts (NFMA 2005) formally recommends that a range of possible road project and policy outcomes should be explored based on different scenarios (or assumptions), and that varying variables or parameters one at a time is insufficient. By assigning realistic probability distributions to parameter values and inputs, the probability of a given

[5] The coefficient of variation is defined as the ratio of the standard deviation to the mean.

scenario can be understood. The NFMA's (2005) guidelines for traffic and revenue studies include several highlights: a no-build traffic forecast should be produced, a baseline traffic and revenue forecast should be produced, sensitivity analyses should be performed on inputs (including population, employment, and income growth, toll elasticity by consumers, and acceleration of the planned transportation network), and debt service analysis should be performed.

Of course, just as neglecting uncertainty is equivalent to assuming determinism, neglecting covariance in inputs is equivalent to presuming their independence. Thus, it is important to recognize the co-dependence of input distributions due to correlated response under various conditions and as introduced in parameter distributions via the estimation process. For example, economic boom/bust cycles can affect land development and thus population and job growth across zones similarly, along with trip generation rates, vehicle ownership, and income levels. This can result in wider uncertainty bounds than univariate input and parameter distributions would indicate. For example, Zhao and Kockelman (2002) used multivariate distributions for their population and employment input values with +0.30 correlations, but relied on independent distributions for all model parameters.

Another approach is "reference class forecasting," as described by Flyvbjerg et al. (2005). This method essentially relies on past experiences with a sample of similar projects in order to estimate outcome distributions and thus the probability of various events occurring. By comparing the forecasts with past experience, judgments can be made regarding the validity of results. Of course, this is difficult to do without good data on a variety of reasonably comparable projects. But it is a useful strategy when such data exist.

To determine an investment's credit rating, credit agencies and financial analysts use varied approaches to account for revenue forecast risk. For example, Fitch Ratings (George et al., 2003, George et al., 2007) claims to study the key assumptions and inputs of the travel demand model used in creating future forecasts, and then considers a range of possible outcomes associated with each factor in order to develop a "stress" scenario alongside a base scenario (essentially sensitivity testing, but with relatively extreme scenarios). The base case is generally more conservative than the base case developed by the project sponsor, eliminating any evident forecast optimism. The stress case is developed to determine the project's ability to withstand rather severe (but not unreasonable) circumstances in which the ability to pay debt service is stressed. Based on the results of the stress scenario, an investment rating is assigned to the project. For credit analysis of longer-term traffic forecasts, Bain et al. (2006) suggest taking a conservative approach, reducing growth rate expectations and carefully examining future toll schedule increases. They also suggest that long-term growth rates exceeding 1% and toll increases beyond those suggested by reasonable correction for inflation should be viewed with caution. While these techniques simplify uncertainty testing dramatically and help investors understand the real possibility of loss, they do not illuminate the variety (and likelihood) of futures that truly exist, and associated investment risk cannot be fully understood using such methods.

3.3 Summary and Recommendations

As discussed in this appendix, a great deal of uncertainty exists in traffic forecasts. Flyvbjerg's analyses (2005 and 2006) suggest that traffic forecast errors exceed 20% roughly half the time across all roadway

projects and more than 40% of the time for a quarter of projects. This situation is compounded when traffic forecasts of *tolled* projects are considered, since more unknowns exist. S&P's analysts (Bain & Wilkins, 2002; Bain & Plantagie, 2003 and 2004) found that, on average, tolled traffic volumes are well below forecasts (on the order of 25% or more) in their first year of operation, suggesting considerable optimism bias, and that this bias does not fade over time. As transportation agencies look more closely at tolling options as a way to fund highway capacity expansion and manage demand, it becomes even more important that models provide reliable traffic forecasts.

Traditionally, travel demand models have been used to provide a single projection of future conditions. Though the models become more sophisticated, the future remains unknown, and model forecasts should be presented as such. It is critical that the uncertainty implicit in travel demand models be communicated to planners and policy makers. Of course, quantifying such uncertainty is not a trivial task. While the sources of misprediction vary, designers and transportation planners have found a number of methods to accommodate forecast uncertainty (or at least quantify it).

Sensitivity testing allows for greater understanding of the magnitudes of uncertainty in the model. By allowing key model inputs and parameters to vary simultaneously, creating multiple possible scenarios, uncertainty in traffic and revenue forecasts can be better bounded. Indeed, this appears to be the most common method for dealing with uncertainty by credit agencies. However, sensitivity testing generally does not provide a probability of particular outcomes occurring. Therefore, it can be difficult for policy makers to truly understand inherent risks. When feasible, comparisons with similar, past projects is a meaningful tool for anticipating potential outcomes.

Monte Carlo simulation may be most appropriate to identify a more comprehensive set of possible futures. By drawing parameters and inputs from reasonable sets of distributions, the probability of particular outcomes can be understood. Of particular importance for projects where financial backing is dependent on toll revenues is the probability that toll revenues will cover debt service, and whether additional revenues will remain (over and above debt service). Moreover, since most toll road studies use rather streamlined model systems, computing time is typically not an issue. Thus, the recommended best practice for dealing with uncertainty in toll road projects is the use of Monte Carlo simulation. Sensitivity testing is valuable in some cases where simulation may be too computationally expensive, though more thoughtful sampling methods, such as Bayesian melding and antithetic sampling, can reduce such computational burden in many cases.

REFERENCES

- Bain, R. and M. Wilkins (2002) Infrastructure Finance: Traffic Risk in Start-Up Toll Facilities, Standard & Poor's, McGraw-Hill International (UK) Ltd., September 2002.
- Bain, R. and J.W. Plantagie (2003) Traffic Forecasting Risk: Study Update 2003, Standard & Poor's, McGraw-Hill International (UK) Ltd., November 2003.
- Bain, R. and J.W. Plantagie (2004) Traffic Forecasting Risk: Study Update 2004, Standard & Poor's, McGraw-Hill International (UK) Ltd., October 2004.
- Bain, R. and L. Polakovic (2005) Traffic Forecasting Risk Study Update 2005: Through Ramp-Up and Beyond, Standard & Poor's, McGraw-Hill International (UK) Ltd., August 2005.
- Bain, R., K. Forsgren, and P.B. Calder (2006) Credit FAQ: Assessing the Credit Quality of Highly Leveraged Deep-Future Toll-Road Concessions, Standard & Poor's, McGraw-Hill International (UK) Ltd., February 2006.
- Clay, M.J. and R.A. Johnston (2006) Multivariate Uncertainty Analysis of an Integrated Land Use and Transportation Model: MEPLAN. *Transportation Research Part D*, 11, 191-203.
- Duthie, J., A. Voruganti, K. Kockelman, and S.T. Waller (2008) Uncertainty Analysis and its Impacts on Decision-Making in an Integrated Transportation and Gravity-Based Land Use Model. Paper submitted for presentation to the 88th Annual Meeting of the Transportation Research Board, January 2009, Washington, D.C., and for publication in Transportation Research Record.
- Duthie, J. (2008) Implications of Uncertain Future Network Performance on Satisfying Environmental Justice and Tolling. Doctoral dissertation, Department of Civil, Architectural, and Environmental Engineering, University of Texas at Austin.
- Flyvbjerg, B., M.K. Skamris Holm, and S.L. Buhl (2005) How (In)accurate Are Demand Forecasts in Public Works Projects: The Case of Transportation. Journal of the American Planning Association, 71 (2), 131-146.
- Flyvbjerg, B., M.K. Skamris Holm, and S.L. Buhl (2006) Inaccuracy in Traffic Forecasts. Transport Reviews, 26 (1), 1-24.
- George, C., W. Streeter, and S. Trommer (2003) Bliss, Heartburn, and Toll Road Forecasts. Project Finance Special Report, Fitch Ratings, November 2003.
- George, C., S. Trommer, M. McDermott, G. Zurita, C. Lewis, L. Monnier, W. Streeter, E. Lopez, and C. Fuenalida (2007) Global Toll Road Rating Guidelines. Criteria Report, Fitch Ratings, March 2007.
- HLB Decision Economics, Inc. (2003) S.R. 125 South Toll Road Project: Risk Analysis of Traffic and Toll Revenue Forecasts. Draft Final Report, Washington, D.C.
- HLB Decision Economics, Inc. (2004) Toll Road Project Risk Analysis. Presentation for MBIA Insurance Corporation.
- Kriger, D., S. Shiu, and S. Naylor (2006) Estimating Toll Road Demand and Revenue: A Synthesis of Highway Practice. NCHRP Synthesis 364, Transportation Research Board, Washington, D.C.
- Krishnamurthy, S. and K.M. Kockelman (2003) Propagation of Uncertainty in Transportation-Land Use Models: Investigation of DRAM-EMPAL and UTPP Predictions in Austin, Texas. Transportation Research Record No. 1831, 219-229.

- Lam, W.H.K. and M.L. Tam (1998) Risk Analysis of Traffic and Revenue Forecasts for Road Investment Projects. Journal of Infrastructure Systems, 4 (1), 19-27.
- Land Transport New Zealand (2006) Risk Analysis. Appendix A13 of 'Economic Evaluation Manual: Volume 1,' Land Transport New Zealand. http://www.ltsa.govt.nz/funding/economic-evaluation-manual/eem1-1.pdf.
- NFMA (2005) Recommended Best Practices in Disclosure for Toll Road Financings. National Federation of Municipal Analysts. http://www.nfma.org/disclosure/rbp_toll_road.pdf.
- Ortiz, I.N., J.N. Buxbaum, and R. Little (2008) Protecting the Public Interest: The Role of Long-Term Concession Agreements for Providing Transportation Infrastructure. Proceedings of the 87th Annual Meeting of the Transportation Research Board, Washington, D.C., January 13-17.
- Perez, B.G. and G.C. Sciara (2003) A Guide for HOT Lane Development. Report prepared by Parsons Brinckerhoff with the Texas Transportation Institute (TTI) for the Federal Highway Administration (FHWA), Publication Number FHWA-OP-03-009.
- Poole, R.W. (2007) Tolling and Public-Private Partnerships in Texas: Separating Myth from Fact. Reason Foundation Working Paper, May, 2007. Retrieved August 2007 from www.reason.org/TX_toll_roads_working_paper.pdf.
- Pradhan, A. and K.M. Kockelman (2002) Uncertainty Propagation in an Integrated Land Use-Transportation Modeling Framework: Output Variation via UrbanSIM. Transportation Research Record No. 1805, 128-135.
- Rodier, C.J. (2003) Verifying the Accuracy of Regional Models Used in Transportation and Air Quality Planning. Mineta Transportation Institute (MTI) Report 02-03, College of Business, San Jose State University. Retrieved June 2008 from http://transweb.sjsu.edu/mtiportal/research/publications/documents/02-03.pdf.
- Rodier, C.J. (2005) Verifying the Accuracy of Land Use Models Used in Transportation and Air Quality Planning: A Case Study in the Sacramento, California Region. Mineta Transportation Institute (MTI) Report 05-02, College of Business, San Jose State University. Retrieved June 2008 from http://transweb.sjsu.edu/mtiportal/research/publications/documents/05-02.pdf.
- Rodier, C.J. (2007) Beyond Uncertainty: Modeling Transportation, Land Use, and Air Quality in Planning. Mineta Transportation Institute (MTI) Report 07-01, College of Business, San Jose State University. Retrieved June 2008 from http://transweb.sjsu.edu/mtiportal/research/publications/documents/07-01.pdf.
- Rodier, C.J. and R.A. Johnston (2002) Uncertain Socioeconomic Projections Used in Travel Demand Model and Emissions Models: Could Plausible Errors Result in Air Quality Nonconformity?" Transportation Research Part A, 36, 613-631.
- Sevcikova, H., A.E. Raftery, and P.A. Waddell (2007) Assessing Uncertainty in Urban Simulations Using Bayesian Melding. Transportation Research Part B, 41, 652-669.
- Vassallo, J.M. and Baeza, M.A. (2007) Why Traffic Forecasts in PPP Contracts Are Often Overestimated? Research Paper, Final Draft, EIB University Research Sponsorship Programme. European Investment Bank, Luxembourg.
- Zhao, Y. and K.M. Kockelman (2002) The Propagation of Uncertainty through Travel Demand Models: An Exploratory Analysis. Annals of Regional Science, 36 (1), 145-163.

• *Glossary of Tolling Terms*

Amortization – A financial term referring to terms of a loan where the provision is made in advance for the gradual reduction of an amount owed over time.

Area pricing – A tolling approach where vehicles are charged a fee to travel within a high activity center, such as a downtown or business district. Prices may vary by time of day to encourage motorists to enter the zone during less busy times or to use transit. An example is Fareless Square in Portland, where transit is available for free to discourage short-term and short-distance auto travel within the business district.

Bus rapid transit (BRT) – High-frequency bus service on dedicated lanes that are separate from general travel. BRT combines the advantages of rail transit – exclusive right-of-way to improve punctuality and frequency – with the advantages of a bus system – low implementation costs and flexibility to serve lower density areas.

Congestion pricing – An overarching term used to describe measures that reduce congestion by charging drivers tolls that vary by time of day or traffic volumes.

Consumer surplus – In economics, the difference between the price a consumer pays for an item and the price she would be willing to pay rather than do without it.

Cordon pricing – A pricing scheme where vehicles entering a high activity area are charged a fee when they cross the boundary line into the activity center. Motorists are charged each time they cross the cordon line. Prices could vary by time of day, to encourage motorists to enter the cordon zone during non-peak periods or to make peak trips using transit. This is similar to area pricing, distinguished by the toll being charged for crossing the cordon rather than for driving within the cordon zone.

Cost-benefit analysis (CBA) – An analytic technique used in determining the economic value of a project or plan. Costs and benefits are typically denominated in dollars and include the money, time, resources, and consequences associated with a project or activity.

Distance-based tolls – Fixed toll rates based on distance traveled and vehicle type.

Diversion – The result of people making different travel choices, in this case as a result of a toll. Diversion can refer to taking different routes, or changing modes, travel time or destination.

Dynamic congestion pricing – Tolls that change based on real-time travel conditions. For example, when traffic volumes go up, so do the tolls. Rates are lowered as demand eases.

Elasticity – The price elasticity of demand measures the nature and degree of the relationship between changes in quantity demanded of a good and changes in its price. High elasticity implies high sensitivity to changes in price while low elasticity, often referred to as inelasticity, means low sensitivity to price changes.

Electronic toll collection (ETC) – Using technology to collect tolls from drivers without requiring them to stop and make cash payments.

Equity – The idea that all travelers are of equal standing, and should be considered in the development of toll policy. Social, geographic and income equity are examples of equity issues that arise in toll policy development and implementation.

Express toll lanes – Limited access, normally barrier-separated highway lanes requiring drivers of all vehicles to pay tolls in order to use the facility. All tolls are collected electronically.

Fixed tolls – Toll rates that don't change. They are typically used to pay for the bridge or road on which they are charged. Trucks pay more than cars.

Fixed-schedule congestion pricing – Tolls charged at predetermined rates reflective of demand levels at different times of day; rates can be based on hour of the day, day of the week, direction of travel and vehicle type.

Gas tax – A state levied tax on the consumption of gasoline. The primary means currently of financing highways in Oregon.

Greenhouse gas emissions – The generation and emission of gases, such as carbon dioxide, methane, nitrous oxide and halocarbons, which accumulate in the atmosphere and have a long residence time, leading to a surface warming of the land and oceans.

High occupancy vehicle (HOV) – A vehicle containing more than one person.

High occupancy vehicle (HOV) lane - A travel lane restricted to transit and carpool vehicles meeting occupancy requirements of two or three people per car. HOV lanes are meant to carry more people in less space than general purpose lanes.

High occupancy toll (HOT) lanes – Travel lanes restricted to either qualifying HOVs or solo drivers willing to pay a toll. The toll typically varies by time of day or traffic levels and is collected electronically.

Investment grade – The top four rating categories for bonds. Important to tolling as special, independent analysis of the revenue generating capacity of a particular toll project may be required for bond issuance.

Managed toll lanes – Any toll lane that uses variably priced tolls to maintain superior, less congested travel conditions.

Mileage-based fee or mileage tax – A tax on vehicle use based upon miles driven rather than fuel consumption.

Non-recurrent delay – A type of travel delay that occurs because of incidents, and is therefore not as predictable as recurrent delay caused by traffic exceeding capacity, bottlenecks, other infrastructure problems.

Open road tolling – Use of electronic toll collection methods to keep traffic moving, as opposed to making people stop at toll booths to pay the toll.

Opportunity cost – In economics, the value of the next-highest-valued alternative use of a given resource.

Parking policies –Adopted means of managing access to a particular locale by changes in the price of parking.

Peak period – The busiest travel times of the day, also known as commute time or rush hour. There are typical two peak periods each weekday – the morning and afternoon commute times.

Public-Private Partnerships (PPPs) – Contractual agreements formed between a public agency and private sector entity, which expand on the traditional private sector role in the delivery of transportation projects. PPPs are particularly prevalent for tolling projects.

Pricing – A tolling concept where the level of toll (price) is used to change travel behavior.

Public good – In economics, a good that is non-rival and non-excludable. This means consumption of the good by one individual does not reduce the amount of the good available for consumption by others and no one can be effectively excluded. A non-congested public highway can be considered a public good.

Recurrent delay – A type of highway delay that occurs regularly due to too much traffic and/or geometric constraints.

Single occupancy vehicle (SOV) – A vehicle containing only one occupant.

State Infrastructure Bank (SIB) – An ODOT-managed revolving loan fund available for transportation projects.

System-wide tolling – Implementing tolls on highways and major arterials to reduce congestion, minimize route diversion and increase transportation revenues.

Theory of the Second Best – In economics, a theory of what happens when one or more optimality conditions are not satisfied in an economic model. It implies the need to study the details of a situation prior to assuming theory based conclusions because improvements in market performance in one area may not mean an overall improvement. This is significant in congestion pricing schemes where theoretically optimal conditions are likely to be unachievable.

Time-of-day pricing – A tolling approach that varies by the time of day in order reduce congestion at peak hours; rates are higher at peak hours then at off-peak.

Tolling – Charging a price to use a road, bridge or tunnel.

Toll Revenue Bonds – A type of municipal bond where the principal and interest are secured by tolls paid by the users of the facility that is built with the proceeds of the bond issue.

Travel-demand forecasting – The analytical estimation of future travel volumes and patterns, typically performed with computer models. There are four basic components: (1) trip generation – predicting the number of trips that will be made; (2) trip distribution – determining where the trips will go; (3) Mode usage – how the trips will be divided among available modes of travel; and (4) Trip assignment – predicting which routes the trips will take, resulting in highway system and transit ridership forecasts.

Travel demand management – The application of techniques that affect when, how, where, and how much we travel done in a purposeful manner by government or other organizations. The techniques include education, policies, regulations or other combinations of incentives and disincentives.

Truck only toll (TOT) lanes – Limited access, normally barrier-separated toll lanes available only to trucks for a variably priced toll. All tolls are collected electronically.

Value of time – One of the most important benefits of road pricing, as well as other transportation projects, is travel time savings. What these savings are worth to motorists can vary by income, gender, age, trip purpose, mode used, length of trip, uncertainty of travel time and other factors. This in turn implies analytical difficulties in applying values to given situations.

Value pricing – Toll rates that vary in direct proportion to travel demand or congestion on alternative free routes.

Variable toll – A toll that changes by time of day, traffic volumes or other factor.