SHRP 2 Capacity Project C04

Improving Our Understanding of How Highway Congestion and Pricing Affect Travel Demand

Chapter 3: Demand Model Specifications and Estimation Results

UNABRIDGED • NOT EDITED

SHRP 2
STRATEGIC HIGHWAY RESEARCH PROGRAM
Accelerating solutions for highway safety, renewal, reliability, and capacity

TRANSPORTATION RESEARCH BOARD
OF THE NATIONAL ACADEMIES

ACKNOWLEDGMENT
This work was sponsored by the Federal Highway Administration in cooperation with the American Association of State Highway and Transportation Officials. It was conducted in the second Strategic Highway Research Program, which is administered by the Transportation Research Board of the National Academies.

NOTICE
The project that is the subject of this document was a part of the second Strategic Highway Research Program, conducted by the Transportation Research Board with the approval of the Governing Board of the National Research Council.

The members of the technical committee selected to monitor this project and to review this document were chosen for their special competencies and with regard for appropriate balance. The document was reviewed by the technical committee and accepted for publication according to procedures established and overseen by the Transportation Research Board and approved by the Governing Board of the National Research Council.

The opinions and conclusions expressed or implied in this document are those of the researchers who performed the research. They are not necessarily those of the second Strategic Highway Research Program, the Transportation Research Board, the National Research Council, or the program sponsors.

The information contained in this document was taken directly from the submission of the authors. This document has not been edited by the Transportation Research Board.

Authors herein are responsible for the authenticity of their materials and for obtaining written permissions from publishers or persons who own the copyright to any previously published or copyrighted material used herein.

The Transportation Research Board of the National Academies, the National Research Council, and the sponsors of the second Strategic Highway Research Program do not endorse products or manufacturers. Trade or manufacturers’ names appear herein solely because they are considered essential to the object of the report.

THE NATIONAL ACADEMIES

Advisers to the Nation on Science, Engineering, and Medicine

The **National Academy of Sciences** is a private, nonprofit, self-perpetuating society of distinguished scholars engaged in scientific and engineering research, dedicated to the furtherance of science and technology and to their use for the general welfare. On the authority of the charter granted to it by Congress in 1863, the Academy has a mandate that requires it to advise the federal government on scientific and technical matters. Dr. Ralph J. Cicerone is president of the National Academy of Sciences.

The **National Academy of Engineering** was established in 1964, under the charter of the National Academy of Sciences, as a parallel organization of outstanding engineers. It is autonomous in its administration and in the selection of its members, sharing with the National Academy of Sciences the responsibility for advising the federal government. The National Academy of Engineering also sponsors engineering programs aimed at meeting national needs, encourages education and research, and recognizes the superior achievements of engineers. Dr. Charles M. Vest is president of the National Academy of Engineering.

The **Institute of Medicine** was established in 1970 by the National Academy of Sciences to secure the services of eminent members of appropriate professions in the examination of policy matters pertaining to the health of the public. The Institute acts under the responsibility given to the National Academy of Sciences by its congressional charter to be an adviser to the federal government and, upon its own initiative, to identify issues of medical care, research, and education. Dr. Harvey V. Fineberg is president of the Institute of Medicine.

The **National Research Council** was organized by the National Academy of Sciences in 1916 to associate the broad community of science and technology with the Academy's purposes of furthering knowledge and advising the federal government. Functioning in accordance with general policies determined by the Academy, the Council has become the principal operating agency of both the National Academy of Sciences and the National Academy of Engineering in providing services to the government, the public, and the scientific and engineering communities. The Council is administered jointly by both Academies and the Institute of Medicine. Dr. Ralph J. Cicerone and Dr. Charles M. Vest are chair and vice chair, respectively, of the National Research Council.

The **Transportation Research Board** is one of six major divisions of the National Research Council. The mission of the Transportation Research Board is to provide leadership in transportation innovation and progress through research and information exchange, conducted within a setting that is objective, interdisciplinary, and multimodal. The Board's varied activities annually engage about 7,000 engineers, scientists, and other transportation researchers and practitioners from the public and private sectors and academia, all of whom contribute their expertise in the public interest. The program is supported by state transportation departments, federal agencies including the component administrations of the U.S. Department of Transportation, and other organizations and individuals interested in the development of transportation. **www.TRB.org**

www.national-academies.org

Contents

CHAPTER 3
Demand Model Specifications and Estimation Results

Chapter 3 provides a detailed technical discussion of the main focus of the C04 research project, the specification and estimation of new advanced forms of travel demand models that aim to substantially improve how road pricing and congestion can be more fully and realistically modeled for transportation policy and planning.

The first subsection provides further and more in depth discussion of the conceptual and behavioral framework adopted for the 04 research and the wide range of possible responses to congestion and pricing considered. This rest of the Chapter, focused on model estimation results developed with New York and Seattle data, is organized in a two-dimensional fashion, with the major (2 digit level) sub-sections organized by 1) model types – route choice, time-of-day choice, mode choice, and other choice dimension and the minor (3 digit level) subsections organized by 2) model features – main utility specification, segmentation, the incorporation of reliability, and other important model properties. The corresponding components developed and tested with the different models estimated in the course of the C04 research, using the data described in Chapter 2, are then presented back-to-back focused on each of the principal model choices and features proposed for improvement.

Given the complexity of the modeling issues and the need to adequately document the methods developed and applied for the C04 research in to advanced modeling, Chapter 3 is necessarily quite thorough and technically detailed in nature.

The two reader's guide charts below, however, are provided to help the reader navigate the presentation, either in order to select and focus on particular topics of interest, or to review the more general findings found in 1) Summary Comparison and Synthesis and 2) Overview of Section, Approach, and Main Findings within each subsection. These subsections of the most general interest are framed for easy recognition.

1. Model Types: **Revealed Preference (RP) Framework**	**Models Testing & Comparison**				**Major Sub-Section**
	New York	Seattle		Summary Comparison and Synthesis	
	NYBPM	PSRC Model	Traffic Choices Study		
Route Type (RT) Choice	Y				**3.2.**
Time of Day (TOD) and Joint RT+TOD Choice		Y	Y	Y	**3.3.**
Mode and Occupancy (MODE) Choice	Y	Y		Y	**3.4.**
Joint TOD and MODE Choice	Y	Y		Y	**3.5.**

	2. Model Features or Aspect **Revealed Preference (RP) Framework**	**3.2** **Route Type (RT) Choice**	**3.3** **Time of Day (TOD) and Joint RT+TOD Choice**	**3.4** **Mode and Occupancy (MODE) Choice**	**3.5** **Joint TOD and MODE Choice**
1	Overview of Section, Approach, and Main Findings	3.2.1.	3.3.1.	3.4.1.	3.5.1.
2	Basic Specification, Segmentation, and Associated Value of Time (VOT)	3.2.2.	3.3.2.	3.4.2.	3.5.2.
3	Impact and Segmentation of Congestion Levels and Facility Type	3.2.3.	3.3.3.	3.4.3.	3.5.4.
4	Incorporation of Travel Time Reliability Measures and Value of Reliability (VOR) Estimation	3.2.4.	3.3.4.	3.4.4.	3.5.9.
5	Impact of Gender, Age, and Other Person Characteristics	3.2.5.	3.3.5.	3.4.8.	3.5.8.
6	Effect of Household and Person Income	3.2.6.	3.3.6.	3.4.6.	3.5.6.
7	Impact of Car Occupancy and Joint Travel	3.2.7.	3.3.7.	3.4.7.	3.5.7.
8	Impact of Household Car Availability	n/a	n/a	3.4.5.	3.5.5.
9	Tour/Trip Length, Location and Non-Linear LOS Effects	3.2.8.	3.3.8.	3.4.9.	3.5.3.
10	Impact of Urban Density and Land Use	n/a	n/a	3.4.10.	3.5.10.
11	Preferred Model Specifications with Deterministic Coefficients	3.2.9.	n/a	3.4.11.	3.5.11.
12	Incorporating Unobserved Heterogeneity	3.2.10.	n/a	3.4.12.	n/a

3.1 Structural Dimensions for Analysis of Congestion and Pricing Impacts on Demand

3.1.1 Possible Choice Dimensions

The behavioral framework adopted for the 04 research has been constructed to include a wide range of possible responses to congestion and pricing, organized as shown in Table 3.1 in an approximate hierarchical order from the short-term to long-term.

Table 3.1. Possible Responses to Congestion and Pricing

Choice Dimension	Time Scale for Modeling	Expected Impact
Network route choice	Short-term – trip episode	Stratified response by user group
Pre-route choice (toll vs. non-toll)	Short-term – trip episode	Stratified response by user group
Car occupancy	Short-term – tour/trip episode	Planned and casual carpool
Mode choice	Short-term – tour/trip episode	Shift to transit, especially to rail and for low/medium income groups
Time-of-day / schedule	Short-term – tour/trip episode	Peak spreading
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 / escorting
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 – 1-6 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 – 1-5 years	Choice by transit accessibility; flexible schedules
Job /usual workplace location and schedule	Long term – 1-5 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

Most of the existing models for pricing (both in research and practice) have been largely focused on the subset of trip-level short term responses, including route, pre-route, car occupancy, mode choice, and departure time choice [*Brownstone, e al, 2003; Brownstone & Small, 2005; Lam & Small, 2001; Mahmassani, et al, 2005; Mastako, 2003; Verhoef & Small,* *2004*]. Within this limited framework, there have been only few examples of a full integration across all these choices – in the existing activity-based (AB) models developed for Columbus, OH [*The MORPC Travel Demand Model: Validation and Final Report, 2005*] and Montreal, QC [*Travel Demand Model Development for Traffic and Revenue Studies in the Montreal Region, 2003*].

There are, however, many other important travel dimensions that have been less explored. Long-term impacts of congestion and pricing may include fundamental changes in travel behavior patterns that cannot be captured and understood at the single trip level. For example, in urban over-congested areas like New York, Chicago, and San Francisco, many employers offer workers the possibility to choose a compressed work schedule (4 days, 10 hours per day). This new choice dimension can have a very significant impact on the amount and of travel produced and its temporal distribution. This choice, however, is clearly not a trip-level decision comparable to choice between Managed and Free lanes (or between toll and non-toll road) for a particular trip. Choices such as this should be modeled within a proper behavioral framework, including an extended time scale, with a robust set of explanatory variables, and linkages to the other short-term and long-term choices [*Pendyala, 2005; Spear, 2005*].

In general, the **important multiple possible behavioral responses** that are beyond a traditional trip-level modeling of choices can be grouped into the following broad classes:

- Trip/tour **destination choice** that is equally important for both AB and 4-step models; it is normally assumed that impacts of congestion and pricing should be captured through the generalized cost or mode choice logsum [*Erhardt, et al, 2003; Dehghani & Olsen 1999*]; however, there can be more direct and specific impacts that are worth exploring.
- Short-term choices that relate to **daily activity patterns** which cannot be fully captured at the elemental trip level. They include explicit joint travel arrangements [*Vovsha, et al, 2003; Vovsha & Petersen, 2005*], tour formation [*NYMTC Transportation Model and Data Initiative: Final Report, 2004*], and daily pattern type [*The MORPC Travel Demand Model: Validation and Final Report, 2005*] (for example decision to stay at home on a given day). These choices can be applied only in an AB model framework (though there might be an additional use of this for 4-step models in order to investigate congestion and pricing impacts on trip generation). It is important to address these dimensions along with the conventional trip dimensions in view of the fact that many of the new pricing forms are not trip-based (for example daily area pricing schemes applied in London [*Litman, 2005*] and currently envisioned/modeled in New York and San Francisco).
- Medium term choices that relate to choice of **usual location and schedule for non-mandatory activities** (like shopping or entertainment). It might be beneficial for a deeper understanding and ability to forecast them, to put certain choices into a medium term framework in order to explore the impacts of congestion and pricing beyond a short-term single-trip consideration. This type of choices can be incorporated in an advanced AB model only.

- Medium / long term choices that relate to **person/household mobility attributes** like car ownership, transponder, transit path, parking arrangements, etc). There is a growing recognition of the importance of these choices in understanding and modeling impacts of congestion and pricing. There have been some initial attempts to formulate and estimate choice models related to the acquisition of transponders [*Yan, et al, 2002; Yan & Small, 2002*] simultaneously with pre-route, departure time, and/or car occupancy though the estimation was implemented at the single-trip level.
- **Long-term location choices** of residential place, workplace, and school, as well as land-use development impacts. A special methodology for analysis of congestion and pricing impacts on these choices has not yet been developed. The existing long-term models of this type operate with standard trip-level measures of accessibility [*Vovsha, et al, 2005*]; thus, the effect of a different and extended time scale is lost. We plan to explore data sets that include information on long-term choices (along with trip records, of course), in order to ascertain the differential impacts of congestion and pricing, over various time scales.

This classification of possible choice dimensions is incorporated in the formulation of a comprehensive conceptual model of travel behavior that served as the starting point in C04 for the specification of model systems that could be estimated with the selected data sets. Several of these choice dimensions represent relatively new choice models that have not been yet widely accepted and explored (only first attempts to formulate and estimate these models have been made and reported). These include integration of the binary pre-route choice (toll vs. non-toll) in the mode choice nested structure, payment type and associated vehicle equipment (cash, E-Z pass, transponder), as well as models of carpooling mechanisms (explicit modeling of joint travel).

3.1.2 Functional Forms for Highway Utility (Generalized Cost)

As described earlier in Section 1.4.1: Highway Utility Components, the highway travel utility function is a basic expression that combines various LOS (level-of-service) and cost attributes as perceived by the highway user. It is directly used in the highway trip route choice, for example between the Managed Lanes and General-Purpose Lanes on the same facility. It also constitutes an essential component in mode and time-of-day (TOD) choice utilities. The form of the highway utility function is also important for modeling other (upper-level) travel choices, since it serves as the basis for accessibility measures. Thus, it is essential to first explore the highway travel utility function and its components, before even considering a simplified framework of route choice in the highway network, since the complexity builds up when additional choice dimensions are considered.

In most travel demand models, including those developed for practical and research purposes, the highway utility function takes the following simple form:

$$U = a \times T + b \times C, \tag{3.1}$$

where:

T	=	travel time,
C	=	travel cost,
$a < 0$	=	coefficient for travel time,
$b < 0$	=	coefficient for travel cost,
a/b	=	Value of Time (VOT).

Coefficients for travel time and cost are normally take negative values, reflecting the fact that travel, in itself is an onerous function necessary only for visiting the activity location. Thus, the travel utility is frequently referred to as "disutility" of travel. It can be noted, however, that in some prior research, the negative character of travel utility has been questioned in some contexts. In particular, a positive travel utility was seen to be associated with long recreational trips on weekends [*Stefan at al, 2007*]. Also, an interesting effect was observed for commuting trips, where commuters seem to prefer a certain minimum time and are not interested in reducing it below a certain threshold [*Redmond & Mokhtarian, 2001*].

More importantly, it is clear that the standard representation of highway travel utility as a linear function of two variables with constant coefficients is an extremely simplified one. A great deal of the C04 research effort has been devoted to the elaboration of this basic form in the following ways:

- Investigation of the highway **user perception of travel time by congestion levels**. This means that a simple generic coefficient for travel time could be replaced with the coefficients differentiated by congestion levels.
- Inclusion and estimation of **additional components** of which travel time reliability has been currently identified as the most important one. Reliability is seen as an additional and non-duplicating term along with the average travel time and cost.
- Testing **more complicated functional forms** that are non-linear in time and cost, as well as account for **randomly distributed coefficients** or VOT (in addition to any explicit segmentation accounting for the observed user heterogeneity). With these enhancements, the VOT is no more assumed as a constant, but become a varying parameter depending on the absolute values of time and cost as well as reliability.

As a working model we have adopted the following general expression for the highway travel utility that will be explored component-by-component in the current research:

$$U = \sum_{k=1}^{5}\left[a_k \times \varphi_k(T_k)\right] + \sum_{m=1}^{3}\left[b_m \times \phi_m(C_m)\right] + \sum_{n=1}^{3} c_n R_n \;, \tag{3.2}$$

where:

$k = 1$ represents uncongested highway travel time component,
$k = 2$ represents congested highway travel time component (extra delay),
$k = 3$ represents parking search time,
$k = 4$ represents walk access / egress time for example from the parking lot to the trip destination,
$k = 5$ represents extra time associated with carpooling (picking-up / dropping/off passengers),
T_k = (average) travel time by component,
$m = 1$ represents highway toll value,
$m = 2$ represents parking cost,
$m = 3$ represents vehicle maintenance and operating cost,
C_m = travel cost value by component,
$n = 1$ represents disutility of time variation (1^{st} measure of reliability),
$n = 2$ represents schedule delay cost (2^{nd} measure of reliability),
$n = 3$ represents utility of (lost) activity participation (3^{rd} measure of reliability),
R_n = reliability measures by component.
a_k, b_m, c_n = coefficients to be estimated,
$\varphi_k(\ldots), \phi_m(\ldots)$ = functions for non-linear transformation of time and cost variables.

This formulation makes it more difficult to calculate VOT, although it is still possible. In the same way that Value of Reliability (VOR) can be calculated for the 1^{st} type of reliability measure (assuming that this reliability measure is in min). VOR essentially represents travelers' willingness to pay for reduction in travel time variability in the same way as VOT represents their willingness to pay for (average) travel time savings. More specifically, in the context of willingness to pay tolls for saving time in congestion conditions, VOT can be calculated by the following general formula:

$$VOT(T_2, C_1) = \frac{\partial U / \partial T_2}{\partial U / \partial C_1} = \frac{a_2 \varphi_2'(T_2)}{b_1 \phi_1'(C_1)} \tag{3.3}$$

A similar calculation can be implemented for VOR. With non-linear transformation functions, VOT and VOR are no longer simply constant values. They now vary and depend on the absolute values of time and cost variables at which the derivatives of the transformation functions are taken.

The innovative components of the C04 research that relate to perceived highway time, travel time reliability, and non-linear transformations are discussed in the subsequent sections. It should be noted that some components, specifically perceived travel time and some reliability measures might be correlated statistically (and also conceptually duplicative at least to some extent). Thus, it is highly improbable that the entire formula (Equation 3.2) would ever be applied, but it serves instead as a conceptual framework in which proposed model structures can be derived and statistically tested.

3.1.3 Dimensions for Model Segmentation

Another long-term gap in the understanding and the modeling of congestion and pricing is associated with inadequate segmentation of population and travel. It has been generally recognized by the both research and practitioner communities that the profession needs to advance beyond crude average VOT estimates (and other related behavioral parameters) obtained from aggregate analyses [*Hensher & Goodwin, 2005*].

There have been already a significant amount of research providing insights into behavioral mechanisms and statistical evidence on heterogeneity of highway users across different dimensions. Although income and trip purpose have been traditionally used in many models as the main factors that determine VOT, in reality VOT is a function of many other variables. In fact, in many cases, income and trip purpose might not even be the most important factors, especially when situational factors and time pressure come into play [*Spear, 2005; Vovsha, et al, 2005*].

A variety of traveler and trip type dimensions are understood to be important. We distinguish between the following main groups:

- **Socio-economic segments of population.** These characteristics are exogenous to all activity & travel choices that are modeled in the system. Thus, the corresponding dimensions can always be applied for any model, either for a full segmentation or as a variable in the utility function.
- **Segmentation of activities.** These characteristics are exogenous to travel choices, but endogenous to activity-related choices. Thus, in the applied model system, it is necessary that the corresponding activity choices are modeled prior to the given model; otherwise they cannot be used for the model segmentation.
- **Travel segmentation.** These characteristics are endogenous to the system of travel choices. In model estimation, they have to be carefully related to the model structure to ensure that all dimensions/variable used in each particular model have been already modeled prior in the model chain.

The socio-economic segmentation of population may best be addressed by:

- **Income, age, and gender.** A higher income is normally associated with higher VOT [Brownstone & Small, 2005; Dehghani et al, 2003]. Middle-age female status has also been associated with higher VOT. [*Mastako, 2003; Travel Demand Model Development for T&R Studies in the Montreal Region, 2003*].
- **Worker status.** Employed persons (even when traveling for non-work purposes), because of their tighter time constraints are expected to exhibit a higher VOT compared to non-workers.
- **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*].

The segmentation of activities may best be addressed by the following list:

- **Travel purpose.** Work trips, and, in particular, business-related trips, normally are associated with higher VOT (as compared to non-work purposes [Dehghani, et al, 2003; NYMTC Transportation Model and Data Initiative, 2004; Travel Demand Model Development for T&R Studies in the Montreal Region, 2003]. Another, frequently cited high-VOT trip purpose is a trip to the airport to catch an outbound flight [Spear, 2005]. A list of special trip purposes with high VOT might also include escorting passengers, visiting place of worship, medical appointment, and other fixed-schedule events (theater, sport event, etc). A deeper understanding of the underlying mechanisms for such behavior would be valuable, including a combination factors such as schedule inflexibility, low trip frequency, and situational time pressure.
- **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, including some examples of positive travel utility associated with long discretionary trips [Stefan et al, 2007]. It is yet to be determined if these differences can be explained by situational variables, or if there is an inherent “weekend” type of behavior that is different from the regular weekday behavior. In any case, whether directly or as a proxy for situational time pressure, it would be useful to test the differences statistically. A positive utility of travel has been found most notably in the choice of distant destinations for discretionary activities on weekends (perhaps with a sightseeing or excursion component). It should be explored, however, if this is actually correlated with tolerance to congestion delays and unwillingness to pay tolls.
- **Activity/schedule flexibility.** Fixed-schedule activities are normally associated with higher VOT for trips to activity because of the associated “penalty” of being late; this has manifested itself in many previous research works when VOT for the morning commute proved to be higher than for the evening commute; as it does for trips to airports reported, probably a similar mechanism (high penalty of being late) creates higher VOT estimates,.

We also expect that schedule flexibility will also be an important factor for non-work activities – for example trip to a theater might exhibit a high VOT while shopping might be more flexible.

The segmentation of travel can be best addressed with the following:

- **Trip frequency.** Regular trips, and their associated costs, may receive more – or less – formal consideration than those that occur infrequently. For example, a $1.50 for auto trip to work may be perceived as $3.00 per day (assuming a symmetric toll) and $60 per month, thus receiving special consideration. This perceptional mechanism is likely to be very different for infrequent and irregular trips, where the toll is perceived as a one-time payment. For intercity trips, travelers' recognition of the return trip is not obvious, since it may occur on a different day.
- **Time-of-day (TOD).** Prior research confirms that AM and PM peak periods are associated with higher VOT, as compared to off-peak periods, and that AM travelers (mostly commuters) are more sensitive to both travel time and reliability than PM commuters (who mostly are returning home) [*Brownstone et al, 2003*]. However, few have explored how these phenomena relate to schedule flexibility, or how time-of-day factors impact VOT for non-work trips.
- **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.** Interesting convey-shape function has been estimated for commuters' VOT by [*Steimetz & Brownstone, 2005*]; 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 a maximum; however, for longer commuters VOT goes down again since they presumably have self-chosen residential and work places based on the long-distance travel. Additionally, in the context of mode choice, strong distance-related positive biases have been found for rail modes in the presence of congestion (as a manifestation of reliability [*NYMTC Transportation Model and Data Initiative, 2004*]) and carpools (since carpools are associated with extra formation time).
- **Toll payment method**. This is an important additional dimension that has not been explored in detail. An analysis done by the Port Authority of New York & New Jersey has shown that the introduction of E-Z Pass at its tolled crossings attracted a significant new wave of users despite a relatively small discount [*Evaluation Study of PANYNJ Time of Day Pricing Initiative; 2005*]. In the same way that we speak about perceived time, we should also probably speak about perceived value of money in the context of pricing. Bulk discounts and other non-direct pricing forms should be modeled at the daily pattern level rather than trip level. We also have to understand congestion impact on the whole

daily patterns rather than by single trips, including analysis of daily time budgets and trade-offs made to overcome congestion (including work from home, compressed workweeks, compressed shopping, and moving activities to weekends, etc).

- **Situational context: time pressure vs. flexible time**. This 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 be willing to pay a lot for travel time savings if he/she is in a danger of being late to job interview or escorting a sick child. This factor is correlated with the degree of flexibility in the activity schedule (inflexible activities, trips to airport, fixed schedules, and appointments will be the activities most associated with time pressure), but does not duplicate it. For example, we might expect that even for a high income person traveling to airport, the VOT might not be that high if this person has a 4-hour buffer before the departure time. With AB models, we could use number of trips/activities implemented by the person in the course of a day, as well as the associated time window available for each trip/activity as an instrumental proxy for time pressure.

In model formulation, estimation, and application, it is crucial to follow a conceptual system design and obey rules of application of those variables that are exogenous to the current model. For example, if TOD model is placed after mode and occupancy choice, then mode and occupancy can be used as the TOD model segmentation. However, time of day in this case cannot be used for segmentation of the mode & occupancy choice models. If the order of models is reversed (TOD choice before mode & occupancy choice), then the segmentation restrictions would also be reversed. When different models are estimated it is essential to keep a conceptual model system (or at least a holistic framework as described below) in mind in order to make these models compatible and avoid endogeneity-exogeneity conflicts.

It should be understood that all these dimensions cannot be simultaneously included in operational models as explicit segments in Cartesian combination. With a 4-step model framework, this would immediately result in an unfeasibly large number of trip tables. The disaggregate basis of the AB model framework is more flexible, and theoretically can accommodate any number of segments. They are however, limited in practical terms by the sample size of the travel survey (normally several thousands of individuals) that quickly wears thin for multidimensional segments. However, there are other ways to constructively address segmentation in operational models that we can consider. They include flexible choice structures with parameterized probabilistic distribution for parameters of interests (for example, VOT), as well as aggregation of segments by VOT for assignment and other model components that are especially sensitive to dimensionality.

It should also be understood that VOT represents only one possible behavioral parameter, and that it is essentially a derived one. In most model specifications and corresponding estimation schemes, VOT is not directly estimated, but rather derived either as the ratio of the time coefficient to cost coefficient (in simple linear models as specified in Equation 3.1) or as the marginal rate of substitution between time and cost (in a general case as specified in Equation 3.3). Thus, very different behaviors can be associated with the same VOT. For example, both time and cost coefficients can be doubled which leaves the VOT unchanged; however, there would be very different estimated responses to congestion and pricing in these two models. Large coefficients will make the model more sensitive to any network improvement or change in costs, while smaller coefficients will make it less sensitive.

One of the most detailed VOT segmentation analyses of the type described in the previous sub-section was carried out for the Netherlands National Value of Time study [*Bradley & Gunn, 1991*], which used ten simultaneous segmentation variables. A similar approach was used for national studies in the U.K. and Sweden.

All else being equal, a more detailed segmentation typically tends to dampen the overall price sensitivity across the population, since a typical sigmoid response curve, like the logit model, has the steepest (most elastic) part in the middle, while the ends are quite flat, and market segmentation tends to move distinct groups "away from the middle".

3.1.4 Measures of Travel Time Reliability

In general, there are four possible methodological approaches to quantifying reliability suggested in either the 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 perceive each minute with a certain weight [*NCHRP Report 431, 1999; Axhausen et al, 2006; Levinson et al, 2004; MRC & PB, 2008*]. Perceived highway time is not a direct measure of reliability since only the average travel time is considered, although it is segmented by congestion levels. It can serve however, as a good instrumental proxy for reliability since the perceived weight of each minute spent in congestion is in part a consequence of associated unreliability.
- ***1st direct measure: Time variability (distribution***. This is considered as 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 that allow for forming the travel time distribution and calculation of derived measures, such as like buffer time [*Small, et al, 2005; Brownstone & Small, 2005; Bogers et al, 2008*]. One of the important technical details with respect to the generation of travel time distributions is that even if the link-level time variations are known, it is a non-trivial task to synthesize the OD-level time distribution (reliability "skims") because of the dependence of travel times across adjacent links due to a mutual traffic flow. The implementation challenge posed by this issue was specifically addressed in the course of this project.

- ***2nd direct measure: Schedule delay cost***. This approach has been adopted in many research works on individual behavior in academia [*Small, 1982; NCHRP Report 431, 1999*]. According to this concept, direct impact of travel time unreliability is measured through cost functions (penalties in 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 a practical model setting.
- ***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, the entire 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 a participation in the corresponding activity (or gain if travel time proved to be shorter) [*Supernak, 1992; Kitamura & Supernak, 1997; Tseng & Verhoef, 2008*]. Recently this approach was adopted in several research works on dynamic traffic assignment (DTA) formulation integrated with activity scheduling analysis [*Kim at al, 2006; Lam & Yin, 2001*]. Similar to the schedule delay concept, however, this approach suffers from the data requirements that are difficult to meet in practice. The added complexity of estimation / calibration of all temporal utility profiles for all possible activities and all person types is significant. This makes it unrealistic to adopt this approach as the main concept for the current project. This approach, however, can be considered in future research efforts.

We consider details of each approach in the subsequent sections.

3.1.5 Perceived Travel Time Weights by Congestion Levels

Variations in perceived utility of components of transit travel 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 and walk are weighted compared to in-vehicle travel time. It is not unusual to apply weights in the range of 1.5–4.0 reflecting that the travelers' perception of out-vehicle time is different and it is perceived as more onerous compared to in-vehicle time.

In contrast to transit modeling practice, virtually all travel models used for highway analysis include a single generic highway time term, i.e., the same coefficient is applied for each minute of highway time regardless of travel conditions. However, there is some compelling statistical evidence that highway users do perceive travel time differently by congestion levels. For example, driving in free-flow conditions is likely to be perceived less negatively than driving in heavily congested (stop-and-go) conditions. It is an intuitive and behaviorally appealing notion that highway users driving in congested conditions might perceive the longer travel time as an additional delay or penalty on the top of free-flow (or some expected reasonable) time.

With a segmentation of travel time coefficients by congestion levels, the time spent on links with congested conditions is expected to have a larger disutility. A larger disutility associated with congestion would have at least two behavioral interpretations:

- Negative psychological perception that is similar to the weight for walking to or waiting for transit service,
- Simplified operational proxy for reliability that should be explored in combination with the explicit reliability measures.

There are several research studies reporting statistical evidence of quite high perceptional weights that highway users put on travel time in congested conditions [*NCHRP Report 431, 1999; Axhausen et al, 2006; Levinson et al, 2004; MRC & PB, 2008; Wardman et al, 2008*]. Also, there have been multiple indications in recent analyses of travel surveys that a perception of the time saved by respondents in the Revealed Preference (RP) survey, is about twoce the actual measured time saved [*Small et al, 2005; Sullivan, 2000*]. In the RP framework, this might well be a manifestation that travelers operate with perceived travel times, where time spent traveling through congested segments is psychologically doubled.

In order to illustrate the magnitude of the possible weights, as well as possible approaches to differentiate travel time by congestion levels, two examples of estimated perceptions of travel time are discussed below. It should be noted that in both cases, the approaches are very simple to implement on the supply side. The network simulation can be performed, and the required LOS skims can be generated by static assignment methods, although DTA could offer additional benefits. This technique can be easily applied with both activity-based models (ABMs) and 4-step models.

In the first example [*NCHRP Report 431*, *1999*], travel time was broken into two parts:

- Time in uncongested conditions (LOS A-D),
- Time in congested conditions (LOS E-F that is close to the "stop-and-go" condition).

The choice framework presented in the SP survey context included only route choice only. Travel time and cost variables were not estimated, but stated in the SP questionnaires. The highway utility expression included total time, cost, and percentage of congested time. Using the previously introduced notation, the adopted utility specification can be written in the following way:

$$U = a \times (T_1 + T_2) + b \times C + c \times \frac{T_2}{T_1 + T_2} \quad (3.4)$$

This is different from the suggested formula (Equation 3.2), but could be transformed into an equivalent formula with certain assumptions (fixed total travel time). The estimation results confirmed a very high significance for the additional term of percentage of congested 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 3.2. By virtue of the specified utility function, the cost of shifting 1 min from uncongested to congested time is dependent on the total travel time. For an average time of 30 min, the VOT equivalent of the additional perceived burden associated with only congestion itself is about $15/hour, which is roughly equal to the average commuting VOT applied in most models.

Table 3.2. Cost of Shifting 1 Minute from Uncongested to Congested Time

Total travel time, min	Cost of shifting 1 min from uncongested to congested time, $	Equivalent in VOT $/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 [*NCHRP Report 431*, *1999*] study. However, the bottom-line results look similar in many respects. In this study, a mode choice model was estimated for 5 travel purposes and 2 time-of-day periods (AM and PM) based on the RP data from the large household travel survey (23,870 households representing a 5% sample). Travel time and cost variables were provided from static assignment equilibrium skims from the modeled network.

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 for [*NCHRP Report 431*, *1999*]):

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

The highway utility function had the following form:

$$U = a_1 \times T_1 + a_2 \times T_2 + b \times C + \sum_s \left(d_s \times h_s\right), \qquad (3.5)$$

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 3.3, as translated into VOT terms. They indicate 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 other segments, however, statistical tests did not show a significant difference between free-flow and congestion time components, thus two coefficients were pooled together.

Table 3.3. 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

The third example is taken from the research work of *Mark Wardman et al, 2008* where they provided new evidence on the variation in the valuation of motorists' travel time savings across a finer gradation traffic condition types, than had been previously attempted (6 different levels of congestion), by means of analyzing SP data collected from different tolled roads in the UK and US. The summary of the time relativities is presented in Table 3.4. The study further supports a finding that a reasonable value for the perceived time weight in congested conditions lies in the range 1.3 to 2.0.

Table 3.4. Highway Time Weight by Congestion Levels

Travel time conditions	UK	US
Free Flow	1.00	1.00
Busy	1.05	1.03
Light Congestion	1.11	1.06
Heavy Congestion	1.31	1.20
Stop Start	1.20	1.38
Gridlock	1.89	1.79

3.1.6 Mean-Variance, Buffer Time, and Other Time Variability Measures

Time variability can be measured by any compact measure associated with a travel time distribution, for example any combination of the mean, dispersion, or higher moments. Taking into account such considerations as behavioral realism and simplicity of the model estimation (specifically, the formulation of SP alternatives), as well as application, three main forms have been proposed and tested so far (see *ITS, 2008* for a good discussion):

- ***Standard Deviation***, that is a symmetric measure assuming that being early or late is equally undesirable (probably not a realistic assumption for many trips and underlying activities).
- The difference between the 80th, 90th, or 95th and the 50th percentile (median) of travel times is frequently referred to as ***buffer time***. This is an asymmetric and more behaviorally appealing measure since it specifically targets late arrivals and is less sensitive to early arrivals.
- Simplified asymmetric measures in terms of ***probability of certain delays***; delay thresholds such as 15 or 30 min are frequently used in the SP framework.

An illustrative example of the Standard Deviation approach is provided in [*NCHRP Report 431, 1999*] in the context of binary route choice. The following form of utility function was adopted:

$$U = a \times T + b \times C + c \times SD(T), \qquad (3.6)$$

where:

$SD(T)$ = standard deviation of travel time.

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 to each minute of standard deviation, 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 as summarized in Table 3.5 (for one of the several reported model specifications).

Table 3.5. 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, higher income	0.258	15.5
Work trips, lower income	0.215	12.9
Non-work trips, higher income	0.210	12.6
Non-work trips, lower income	0.167	10.0

A good example of the second time variability measure was presented in [*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 3.1). 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).

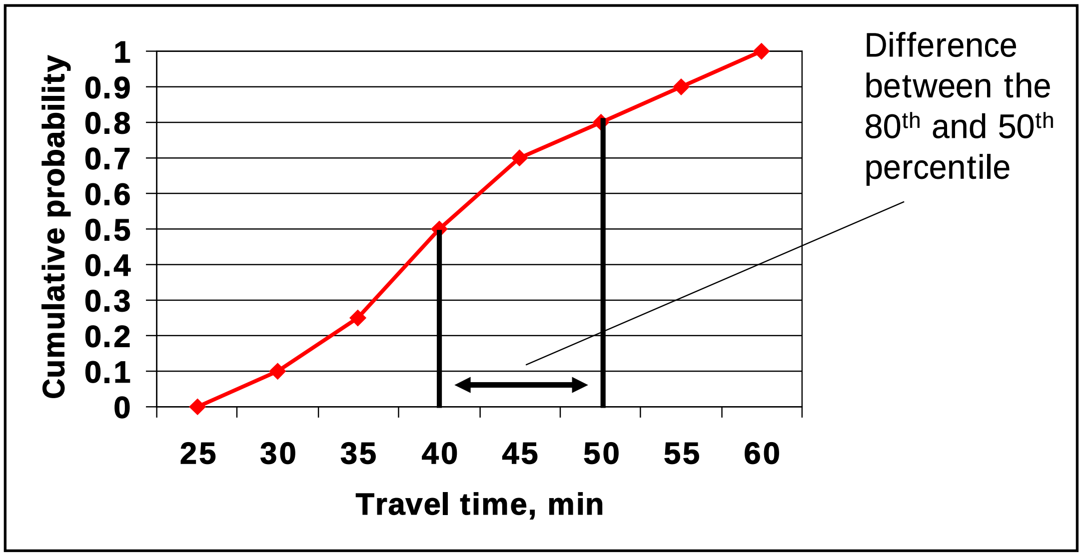


Figure 3.1. Travel time variability measure.

The choice context included binary route choice between the Managed (tolled) Lanes and General Purpose (free) lanes on the section of SR-91 in Orange County, CA. The survey included actual users of the facility and the model was estimated on the 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 that were aligned with the pricing experiment. Distribution of travel times was calculated based on the independently observed data. The measures were 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 based on their past experience. The utility function was specified by the following formula:

$$U = a \times T + b \times C + c \times R(T), \tag{3.7}$$

where:

$R(T)$ = difference between the 80th and 50th percentile.

Reliability, as defined above, proved to be valued by travelers as highly as the median travel time (VOT was roughly equal to VOR, i.e., $a \approx c$). This particular model form, with the condition of equal VOT and VOR, has a very interesting and intuitive interpretation (that itself could be used for a model formulation in a slightly simplified form where it is assumed from the outset that $a = c$). Indeed, if we assume that the willingness to pay for saving 1 min of average travel time (the 50th percentile) is equal to the willingness to pay for a 1 min of reduction of the difference in time between the 80th and 50th percentile, then we can combine both terms in the highway utility function since they have the same coefficient. This means that the underlying decision-making variable is the travel time value at the 80th percentile. This variable essentially combines both average travel time and time variation measure.

An example in Table 3.6 illustrates this possible approach. In the example, we assume that the highway user has to choose between two roads for commuting that are characterized by different time distributions. Road 1 is longer but more reliable – the travel time varies from 41 min to 50 min. Road 2 is shorter but travel time is less predictable and varies from 29 min to 52 min. We assume that the highway user is familiar with both roads and makes his/her choice based on a rational consideration of the known distributions. In practical terms, this can be interpreted as a recollection of at least 10 trips on each road in the past, sorted by travel times from the best to worst.

Table 3.6. Illustration of Reliability Impact on Route Choice

Percentile	Travel time, min		Preference
	Road 1	Road 2	
10	41	29	
20	42	30	
30	43	35	
40	44	39	
50	45	40	Road 2 by conventional approach
60	46	41	
70	47	45	
80	48	50	Road 1 by suggested approach
90	49	51	
100	50	52	

Although Road 2 has a better (lower) average travel time and would be preferred in most conventional modeling procedures, Road 1 has a better 80th percentile measure. In reality, the user would probably prefer Road 1 as the more reliable service. This choice framework with a single measure can be used as a simplified version of the approach. Rather than estimating two separate terms (average travel time and additional time associated with 80th-50th percentile, a single measure of 80th (or any other percentile large than 50th if it yields a better statistical fit) could be used. For example, in a similar context, a 90th percentile measure was used in [*Brownstone & Small, 2005*]. This framework is based on a plausible assumption that travelers under congestion conditions, characterized by travel time uncertainty, behave as rational risk-minimizers. They do not base their decisions on the 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 the 80th and 90th percentiles.

It is important to note that making this approach operational within the framework of regional travel models requires explicitly deriving these measures from simulation of travel time distributions, as well as adopting assumptions regarding the ways in which travelers acquire information about the uncertain situation they are about to experience. 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.

Other approaches for measuring variability of travel time can also be considered. They are similar to the approach described above in conceptual terms, but use a different technique in both the model estimation and the application stages. For example, in the travel model developed by for the [*Toll T&R Study in Montreal, 2002*], the probability of delays longer than 15 and 30 min was introduced in the SP questionnaires for trucks. The subsequent estimation of the choice model revealed a very high significance of this variable comparable with the total trip time (in line with the VOR estimation of *Small, et al, 2005*). Application of this model required special probability-of-delay skims that were calculated based on the observed statistics of delays as a function of the modeled Volume-over-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. A problem yet to be resolved, however, is that 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, and people are paying for changes in both variables, so omitting one will tend to attribute the total effect to the other. Consequently, an important use of SP data sets that include reliability is to use them in combination with RP data sets for which good objective estimates of travel time variability can be derived.

It should be mentioned that the direct use of travel time variability in the framework of behavioral modeling is not the most appealing approach, when compared to the other two (discussed below). The principal conceptual drawback of this approach is that it does not explicitly consider the nature of underlying activities and mechanisms that create the disutility. Needless to say, the largest part of the disutility associated with unreliable travel time is being late (or too early) at the activity location, and consequently, losing some part (or in some case all) of participation in the planned activity. The clear practical advantage of the time variability approach, however, is in its relative simplicity and exclusive reliance on the data supplied by the transportation networks.

3.1.7 Schedule Delay Cost Approach

This approach has been widely accepted by the research community since its inception [*Small, 1982*]. According to this approach, the impact of travel time (un)reliability is measured by 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 costs 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). It is logical to assume that 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 (being late is more onerous than being early). The details, however, depend on the activity type, person characteristics, and situational context.

The most frequently used forms include simple linear function (i.e., constant schedule delay cost per minute), non-linear convex function (assuming that large delays are associated with a growing cost per minute), and various piece-wise functions accounting for fixed cost associated with any delay along with a variable cost per minute – see Figure 3.2.

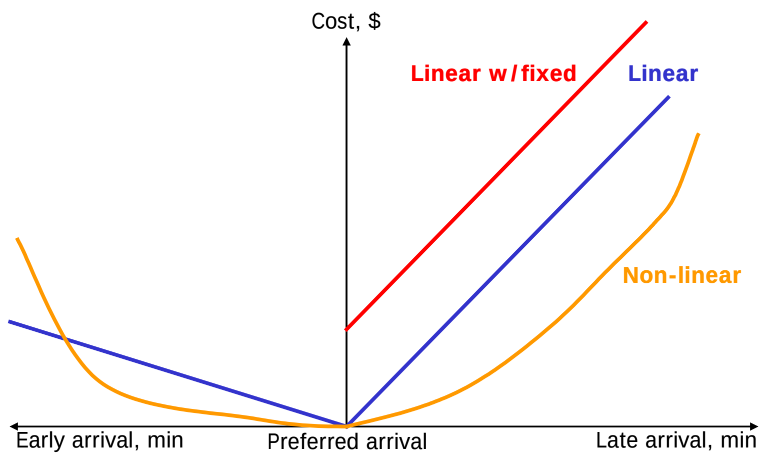


Figure 3.2. Schedule delay cost functions.

An example of a schedule delay model estimated in a highway route choice context with a specially designed SP survey is given in [*NCHRP Report 431*, *1999*]. The utility function was specified in the following way:

$$U = a \times T + b \times C + c \times SD(T) + \beta(\Delta t) + \gamma(\Delta t), \tag{3.8}$$

where:

Δt	=	difference between 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.

The estimation results with respect to the schedule delay cost are summarized in Table 3.7 (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 costs, it is unnecessary to include the additional cost of unreliability of travel time (standard deviation).

Table 3.7. Estimation Example for Schedule Delay Cost

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/arrival time, although 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.

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 perceived penalties associated with not being at the activity location on time. The schedule delay approach, however, has its own theoretical limitations as identified by the following:

- The approach is applied separately for each trip made by a person during the day and it is assumed 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. In general, this is 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 that the travel time variability approach ignores.
- 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 overweighting 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 the preferred arrival time is generally known to the traveler (or perceived subconsciously), it is generally not observed by the modeler in RP type of data. To explore this phenomenon and estimate models that address it, the SP framework proved to be very effective, since the preferred arrival time and schedule delays can be stated in the design of alternatives. In some research, simplified assumptions about the preferred arrival time were 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 could 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.

3.1.8 Loss of Activity Participation Utility: Temporal Utility Profiles for Activity Participation

The third approach is based on a concept of time-dependent utility profile by activity type [*Supernak, 1992; Kitamura & Supernak, 1997*]. Recently this approach was adopted in several research works on DTA formulation integrated with activity scheduling analysis [*Kim at al, 2006; Lam & Yin, 2001*]. The essence of this approach is that each individual has a certain temporal utility profile for each activity that is characterized by function U(t). The utility profile can either be estimated as a parametric or a non-parametric function of time, and time can be modeled in either continuous or discrete form. The utility profile represents an instant utility of participation in the activity at the given point of time (or during the discrete time unit that starts at the given point of 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):

$$U(\tau,\pi)=\int_{\tau}^{\pi}u(t)dt\,. \tag{3.9}$$

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

$$U(\tau,\pi)=\int_{\tau}^{\pi}u(\tau,t-\tau)dt\,. \tag{3.10}$$

A hypothetical, but typical temporal utility profiles specified in a discrete space with an hourly resolution are shown in Figure 3.3. 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). The shopping activity profile is much more uniform, with an additionally assumed convenience to undertake this activity after usual work hours. In both cases the utility is measured versus staying at home (i.e., not participating in any out-of-home activity that would require travel) as the reference (zero) utility. Thus, the utility profile can take both positive and negative values.

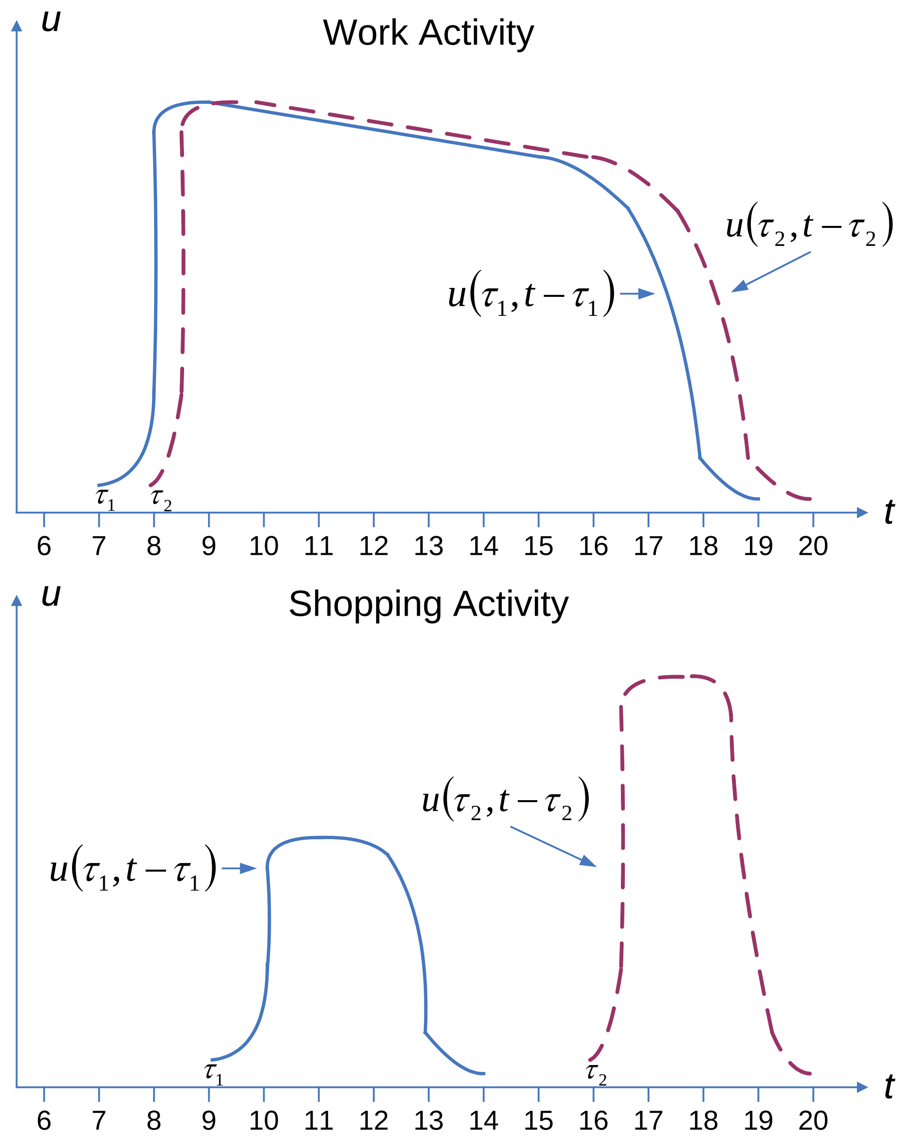


Figure 3.3. Examples of temporal profiles of activity participation utility.

The concept of utility profiles is instrumental 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 time profile of the second activity exceeds the time profile of 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 3.4.

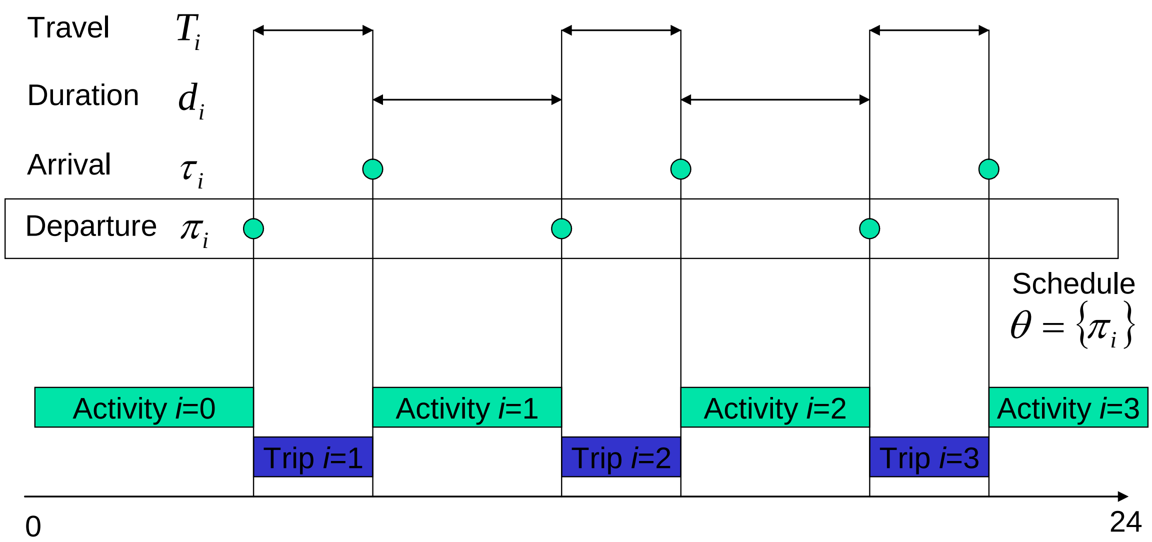


Figure 3.4. Consistent individual daily schedule.

The effect of unreliability of travel times can be directly measured by comparison of the planned and actual total daily utility of the schedule that includes all activity and travel episodes. For simplicity, but without essential loss of generality, we assume that the sequence of activity episodes and trip departure times are fixed. We will also assume that travel time delay never exceeds the planned duration of the subsequent activity; thus, activities cannot be cancelled as a result of unreliable travel time. Thus, 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:

$$L = \sum_i \left(U_i^P - U_i^A \right) . \qquad (3.11)$$

where:

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

where the planned and actual utilities can be written as follows:

$$U_i^P\left(\tau_i^P\right) = a \times T_i^P + b \times C_i^P + \int_{\tau_i^P}^{\pi_{i+1}} U_i(t)\,dt \, . \qquad (3.12)$$

$$U_i^A\left(\tau_i^A\right) = a \times T_i^A + b \times C_i^A + \int_{\tau_i^A}^{\pi_{i+1}} U_i(t)dt \qquad (3.13)$$

.

where:

$$T_i^P = \tau_i^P - \pi_i\,;\;\; T_i^A = \tau_i^A - \pi_i\,. \qquad (3.14)$$

By substituting expression (Equation 3.14) into formulas (Equation 3.12) and (Equation 3.13), and then, substituting formulas (Equation 3.12) and (Equation 3.13) into the basic expression (Equation 3.11) we obtain:

$$L = \sum_i \left[a \times \left(\tau_i^P - \tau_i^A\right) + b \times \left(C_i^P - C_i^A\right) + \int_{\tau_i^P}^{\tau_i^A} U_i(t)dt \right]. \qquad (3.15)$$

where the last term (integral) represents the loss of activity participation, while the first two terms represent extra travel time and cost.

A logical relationship between temporal activity profiles of utilities and schedule delay cost was explored by [Tseng & Verhoef, 2008] that led to an insightful general framework. It can be shown that these two approaches are not independent. The schedule delay cost functions can always be consistently 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. Interestingly, the opposite is true, i.e., temporal utility profiles could be fully restored from the schedule delay cost functions only under some specific assumptions.

3.1.9 Accounting for Unobserved Heterogeneity and Situational Variability

Increasingly, travel demand analysts are looking beyond average user responses to travel costs, travel times and other attributes, towards accounting for heterogeneity or differences in user response across the population. Capturing heterogeneity in user valuation of attributes, such as travel costs and travel times, is important in order to correctly predict overall (market) responses to measures such as pricing, as well as to provide policy makers with information about the impacts of policies on different segments of the population. For example, the money value of time for users may vary considerably across a population, and policies based on the assumption of a mean money value of time may not produce the anticipated impacts (Sillano and Ortuzar, 2005). As shown in the previous sections, a well-specified demand model will attempt to include as many of the observable factors that can be shown to affect travel time valuation in a systematic way. However, these factors may not always be known to the analyst, and in many cases various other sources can account for the varying valuations across the population; this is referred to as unobserved heterogeneity. Major advances in choice model formulation and estimation over the past decade have produced relatively robust methods to incorporate such unobserved heterogeneity, particularly in the form of random coefficients, i.e., model parameters that are assumed to follow a distribution across the user population. This section provides a general framework for accounting for unobserved heterogeneity in travel demand models, specifically discrete choice models. The next section discusses heterogeneity, both unobserved and observed, and how to account for them within a discrete choice modeling framework. Model specification and estimation issues are briefly discussed, followed by an example to illustrate the range of questions that can be addressed with a model that accounts for unobserved heterogeneity.

Accounting for Observed and Unobserved Heterogeneity

The response of users towards attributes, such as travel time savings and cost, of different alternatives varies in general over the population of users. For example, low income individuals are probably more concerned about and sensitive to toll prices, compared to a high-income individual. From a practical standpoint, a common method for capturing such heterogeneity, controlling for other factors such as trip purpose, is to segment the sample of users based on exogenous criteria, such as income level, trip length and time of day (peak vs. non-peak). Separate models are then estimated for each segment. Another practical approach is to interact attributes of the alternatives with exogenous criteria. Consider a user's choice between taking a toll or a non-toll route to work. Assume the only two attributes observed are travel cost, TC_j for route type j, and travel time TT_j. The importance that users place on these two attributes, reflected in the coefficients α_n and β_n, may vary over the population with the utility for each alternative written as:

$$U_{nj} = \alpha_n TT_j + \beta_n TC_j + \varepsilon_{nj}, \qquad (3.16)$$

where j is either toll or free, and α_n and β_n are parameters specific to individual n. One common method for accounting for heterogeneity in response is interacting the travel time or cost terms with exogenous criteria such as income. Assuming that the importance of travel cost is inversely related to the observed income of the users, I_n, with low-income individuals placing more importance on travel costs, the coefficient for travel cost can be expressed as:

$$\beta_n = \frac{\theta}{I_n}, \qquad (3.17)$$

where θ can be regarded as the mean value or importance placed on cost, across all users.

An alternative approach is to allow further differences by expressing the parameters that represent preference weights (α_n and β_n) as random parameters, as opposed to point estimates, such that the distribution for these preference weights can obtained and used in the derivation of value of travel time, which in turn will be distributed across the population. These distributions can also be a function of exogenous variables. Randomness in preference weights results from a variety of reasons, possibly just because people are inherently different. Assume that users' response to travel costs, reflected by the parameter α_n, varies across all users, but is linked to unobserved factors or is intrinsically random. Examples of these unobserved or latent factors may include differences in familiarity with the network, or differences in general stress levels. The resulting α_n can be expressed as:

$$\alpha_n = \rho + \mu_n \tag{3.18}$$

with ρ reflecting the mean response of users to travel time and μ_n is a randomly distributed term that captures deviations from this mean value. Substituting Equations 3.17 and 3.18 back into Equation 3.16 provides a utility expression that reflects both unobserved and observed heterogeneity in user responses to travel costs and travel times, shown below:

$$U_{nj} = (\rho + \mu_n)TT_j + \left(\frac{\theta}{I_n}\right)TC_j + \varepsilon_{nj} = \underbrace{\rho TT_j + \left(\frac{\theta}{I_n}\right)TC_j}_{\text{Observed or Systematic}} + \underbrace{\mu_n TT_j + \varepsilon_{nj}}_{\text{Unobserved or Random}}, \tag{3.19}$$

The above utility expression accounts for both *observed* and *unobserved heterogeneity*. The response of users towards travel costs varies systematically according to observed income, as expressed in Equation 3.17, while users' response to travel times varies randomly according to unobserved factors, as expressed in Equation 3.18. The analyst needs to specify a distribution for the random coefficient α_n. For example, the analyst may assume this distribution to be normal, with mean and variance to be estimated in order to make inferences and gain insight on the distribution of users' response to travel times, including related measures such as money value of time.

Given an estimated distribution of the value of time, the proportion of a population P that decide to pay a toll C_{toll} is given by the proportion with values of time saved *greater* than C_{toll}:

$$P_{C_{toll}} = \int_{C_{toll}}^{\infty} f(VOT) \tag{3.20}$$

The analyst selects the distribution f(.) of VOT, in order to find a satisfactory representation of the "true" empirical distribution. This is illustrated below in Figure 3.5, where the proportion of payers is the blue area, given that the toll is set to $20.

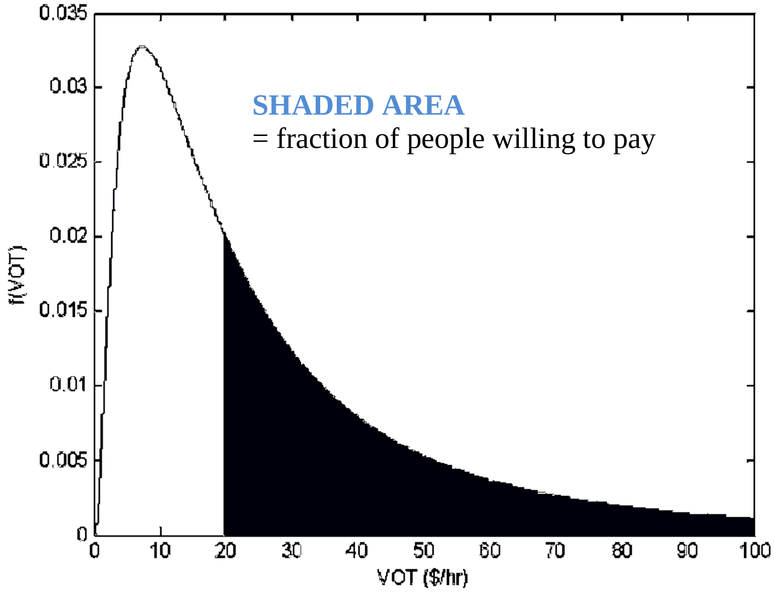


Figure 3.5. Proportion of payers with lognormal distribution for VOT for toll=$20.

The shaded area to the right is the measure of the number of people who have values of time savings exceeding the toll charged and would therefore pay it. In the case of the substantially skewed lognormal distribution, the mean is not the center of the distribution and for the case shown in Figure 3.5, there will be fewer people in the population actually ready to pay for the toll.

The next section discusses the estimation in relation to discrete choice models that can capture unobserved heterogeneity and the forms these models can take.

Discrete Choice Model Form and Estimation Issues

The model form these models take is dictated partly by assumptions on the error terms, which in turn are dictated by the need to account for unobserved heterogeneity. In Equation 3.19, since μ_n is not observed, the term $\mu_n TT_j$ becomes part of the unobserved component of the utility $\widetilde{\varepsilon_{nj}}$. Equation 3.19 can be expressed as:

$$U_{nj} = \rho TT_j + \left(\frac{\theta}{I_n}\right) TC_j + \widetilde{\varepsilon_{nj}}, \tag{3.21}$$

where

$$\widetilde{\varepsilon_{nj}} = \mu_n TT_j + \varepsilon_{nj} \tag{3.22}$$

The example above illustrates the concept of heterogeneity in terms of the value individuals place on the attributes of alternatives. Heterogeneity can be captured within a discrete choice framework by linking this variation to observed or unobserved characteristics. As an example of observed heterogeneity, individual response to cost, β_n, was linked to an individual's income level, such that low income individuals were more sensitive relative to high income individuals. If individual response is linked to unobserved variables or is purely random, then the analyst would need to account for unobserved ***heterogeneity***. In the example above, variation in response to travel time α_n was assumed to be random, as expressed in Equation 3.19, leading to total error for the utility expressed in Equation 3.22.

The type of heterogeneity present and accounted for dictates the type of choice model that is appropriate. If only observed heterogeneity is captured and accounted for, and the error term ε_{nj} is still distributed independently and identically Gumbel, a logit formulation can be used. If unobserved heterogeneity is accounted for, a logit formulation cannot be used since the total error term $\widetilde{\varepsilon_{nj}}$ is no longer distributed independently and identically. If the heterogeneity in tastes is linked to unobserved variables and is random, a logit model form would be a misspecification. As an approximation, the logit model may capture average tastes fairly well, but it cannot provide information on the distribution or heterogeneity of tastes around the average. This distribution is very important in many situations, such as forecasting the market share for tolled routes that appeal to a minority of people rather than to the average tastes. To incorporate random taste variation appropriately and fully, probit and/or mixed logit model forms may be used instead.

The mixed logit and probit models are particularly well suited for incorporating unobserved heterogeneity. Continuing the previous example, assuming the coefficient for travel time varies randomly over individuals, the utility is expressed in Equation 3.18 where α_n is assumed to be distributed with a density $f(\alpha)$ with parameters θ, which can consist of a mean b and a covariance W.

The goal of estimation is to determine values for b and W. Several different distributions can be assumed, both continuous and discrete. The analyst observes the travel times TT_j but not the individual specific parameters α_n or the errors $\widetilde{\varepsilon_{nj}}$. If α_n were known, then the choice probability for an alternative, conditional on knowing α_n, would be:

$$Pr_{ni}(\alpha_n) = \frac{\exp\left(\alpha_n TT_i + \left(\frac{\theta}{I_n}\right) TC_i\right)}{\sum_j \exp\left(\alpha_n TT_j + \left(\frac{\theta}{I_n}\right) TC_j\right)} \tag{3.23}$$

However, since the analyst often does not know α_n, he cannot condition on α. The unconditional choice probability is therefore the integral of $Pr_{ni}(\alpha_n)$ over all possible values of α_n:

$$Pr_{ni} = \int \left(\frac{\exp\,(\alpha_n TT_i + \left(\frac{\theta}{I_n}\right) TC_i)}{\sum_j \exp\,(\alpha_n TT_j + \left(\frac{\theta}{I_n}\right) TC_j)} \right) \cdot f(\alpha) \cdot d\alpha \tag{3.24}$$

The parameters in the choice probability in Equation 3.24 are estimated using simulated maximum likelihood estimation. This is accomplished by taking several draws from the distribution of α and averaging the choice probability Pr_{ni} across all these draws. The probability express in Equation 3.23 are approximated through simulation for given parameter values. This average simulated probability is expressed as:

$$\widetilde{Pr_{ni}} = \frac{1}{R}\sum_{r=1}^{R} Pr_{ni}(\alpha_n^r) \tag{3.25}$$

$$Pr_{ni}(\alpha_n^r) = \frac{\exp\left(\alpha_n^r TT_i + \left(\frac{\theta}{I_n}\right)TC_i\right)}{\sum_j \exp\left(\alpha_n^r TT_j + \left(\frac{\theta}{I_n}\right)TC_j\right)} \tag{3.26}$$

where R is the number of draws. The simulated probabilities (Equations. 3.25 and 3.26) are inserted into the log-likelihood function to give a simulated log-likelihood function:

$$SLL = \sum_{n=1}^{N}\sum_{j=1}^{J} d_{nj} ln(Pr_{ni})$$

where d_{nj}=1 if person n chose j and zero otherwise. The maximum simulated likelihood estimator is the value of the parameters that maximizes the SLL.

Distributions for Travel Time Coefficient

Several distributions may be assumed for the travel time coefficient β^{time}, though commonly for value of time studies, this is assumed to be a truncated normal or truncated lognormal distribution. The normal distribution has been shown to cause some problems when applied to coefficients of undesirable attributes, such as travel time and cost, due to the possibility of positive coefficient values for these attributes (Hensher and Greene 2000; Cirillo and Axhausen 2006). To circumvent this, the normal is usually truncated to ensure that coefficients are negative for undesirable attributes, and positive for desirable attributes. The lognormal distribution has the nice property of being bounded below by zero. It is useful for coefficients of attributes that are liked (or disliked) by all users. The sign is reversed for undesirable attributes, such as a travel time variable, such that the coefficient is necessarily negative. In studies of willingness to pay, the log-normal distribution has been shown to produce large and unreasonable variances and means (Hensher and Greene 2000; Hess et al. 2005). Evidence of this can be seen in the estimation results below for an “unbounded” log-normal distribution. To circumvent this, the log-normal distribution may need to be truncated to ensure reasonable means and variances.

The researcher specifies a distribution for the coefficients and estimates the parameters of that distribution. In most applications, $f(\alpha)$ is specified to be normal or lognormal:

$\alpha \sim N(b, W)$ or

$[\ln(\alpha)] \sim N(b, W)$

with parameters b and W that are estimated.

The lognormal distribution is useful when the coefficient is known to have the same sign for every decision maker, such as a travel time coefficient that is known to be negative for everyone. Triangular and uniform distributions have also been used (Hensher and Greene 2003). With the uniform density, β is distributed uniformly between $b - s$ and $b + s$, where the mean b and spread s are estimated. The triangular distribution has positive density that starts at $b - s$, rises linearly to b, and then drops linearly to $b + s$, taking the form of a triangle. The mean b and spread s are estimated, as with the uniform, but the density is peaked instead of flat. These densities have the advantage of being bounded on both sides, thereby avoiding the problem that can arise with normals and lognormals having unreasonably large coefficients for some share of decision makers.

One way around the unbounded nature of the normal and lognormal distributions is to truncate these distributions, specifying either a lower or upper bound, or both. In studies of willingness to pay, the Log-normal distribution has been shown to produce large and unreasonable variances and means (Hensher and Greene 2000; Hess et al. 2005). Evidence of this can be seen in the estimated models for an "unbounded" log-normal distribution, presented in Section 4.2.9. To circumvent this, the log-normal distribution may need to be truncated to ensure reasonable means and variances. Another alternative is to use an S*b*-Johnson distribution, which requires specifying an upper and lower bound. The *Sb* distribution is useful for a variety of purposes. *Sb*-Johnson densities can be shaped like log-normals but with an upper bound and with thinner tails below the bound. *Sb* densities are more flexible than log-normals: they can be shaped like a plateau with a fairly flat area between drop-offs on each side and can even be bi-modal (Train and Sonnier 2004). When a lower bound other than zero is specified, the distribution is useful for an attribute that some people like and others dislike but for which there is a limit for how much the person values having or avoiding the attribute. In general, the analyst should specify a distribution that results in plausible behavior and provides good fit to the data.

3.2 Route Type Choice – Revealed Preference Framework (New York Model)

3.2.1 Overview of Section, Approach, and Main Findings

Auto route choice in the highway network represents the simplest and most basic platform for understanding and modeling behavior of highway users and their underlying generalized cost functions. Route choice is essentially a trip-level decision with no significant tour-level effects or constraints. In this choice context, we assume that trip origin, destination, departure time, and auto occupancy are fixed and are taken from the corresponding decisions were modeled earlier in the model system hierarchy. Thus, the choice set consists of different highway network routes that may differ by time, cost, distance, reliability, or other measures, while the effects of person and household variables are included via interactions with route variables, or as segmentation variables. This specification allows us to focus on the basic form of the highway utility (generalized cost) function that, in later sections, is incorporated as part of the (more complicated) mode and time-of-day utility expressions.

Despite the attractiveness of the route choice framework as a platform for analysis of the highway utility function, there is limited supporting evidence in the literature on estimated route choice models. This is primarily due to the lack of available datasets with actual auto route itineraries reported or recorded. The common practice in most travel surveys is to collect only trip origins and destinations. Even if the actual route can be restored from some indicators on major facilities used, there is a non-trivial issue to identify reasonable alternative routes to form a choice set. These problems were resolved to some extent with the two RP datasets available and extended for the current research.

The first route choice dataset was based on the Household Travel Survey in the 28 county New York region, collected in 1997 and 1998. In the survey, each auto trip has an attribute of toll value paid. In the New York region most tolls are clearly associated with major facilities like bridges and tunnels around Manhattan or the New Jersey Turnpike, and specific facilities are clearly the best tolled options for certain subsets of origin and destination zone pairs. There are a significant number of auto trip records in the survey with origins and destinations for which both a tolled route and a free route are feasible and reasonably competitive in terms of generalized cost. Thus, it proved to be possible to from a binary route type choice model (tolled vs. free) and to support it by the corresponding set of skims for the reported time-of-day period, including time, cost, distance, and reliability measures (generated by the method described above in Section 2.2), along with the possibility of segmentation by congestion levels and facility type. The synthetic congested travel time estimates used for this model are, of course, subject to the limitations of Static Traffic Assignment procedures, although the simulations were implemented for each hour of the day separately.

The second dataset was created from the Seattle Traffic Choices Study from 2006 (see Section 2.4) where the GPS time and location data streams from travel on actual routes were available. The chosen route types were identified and the best alternative routes were constructed to support the same binary route type choice model, (a tolled freeway route vs. a non-freeway route with a lower toll cost). Travel time distributions were calculated based on the actual average time variability across the GPS traces for each network link-pair (further aggregated to origin-destination pair) over all weekdays in the 12-month survey period. The route type choice framework with the Seattle data was extended to incorporate time-of-day (departure time dimension)

As is the case with practically all RP datasets, only the first two types of reliability measures described earlier (perceived highway time and travel time distribution) were available. Analysis of the other two reliability measures (schedule delays and temporal utility profiles) could not be supported by the available data in the survey, and no reasonable way of generating these measures synthetically was found within the research project framework.

The estimation results for these models are analyzed in this sub-section and compared to other relevant studies reported in the literature. We start with the most basic linear specification. In each subsequent sub-section, we analyze one particular aspect one at a time pivoting off the base specification. In the penultimate subsection, we combine the best features in one recommended specification of the highway generalized cost function that is the main constructive outcome of the current stage of research. This form of the generalized cost function linearly combines mean travel time, cost, and travel time reliability with a consideration of non-linear effects of distance, income, and car occupancy on these three main terms. This form is used as a seed construction that is further analyzed as part of extended choice models that include mode and time-of-day dimensions (Sections 3.3–3.5).

In the final subsection, this specification is additionally analyzed with respect to unobserved heterogeneity where some of the coefficients were estimated as random rather than as deterministic values.

3.2.2 Basic Specification, Segmentation, and Associated VOT

The New York model is specified as a binary logit choice between tolled and non-tolled routes for the observed auto trips for which both options are feasible. Overall, the Household Travel survey supplied 3,663 trip observations for which both route types where feasible. Of those, 958 trips used tolled routes and 2,705 used non-tolled routes.

The basic utility specification included only travel time and cost variables in a linear fashion with the coefficients generic for both alternatives. The utility expressions for this model can be written in the following general way:

$$U(i) = \Delta(i) + a \times T(i) + b \times C(i) \tag{3.27}$$

where:

$i = 1,2$ represent the toll and free route alternatives correspondingly,

$\Delta(i)$ = route type specific biases where $\Delta(1) = 0$ as the reference case,

$T(i)$ = average congested travel time for each route,

$C(i)$ = travel cost (toll) for each route,

a,b = generic time and cost coefficients.

The model was fully segmented by two major trip purposes – work-related (2,314 observations, 670 used toll routes) and non-work (1,349 observations, 288 used toll routes). Any attempt of further segmentation by trip purpose or time of day did not yield additional meaningful or statistically significant results. Two versions of the model were explored – with and without toll bias (alternative-specific constant). The results are summarized in Table 3.8. An interesting feature of the estimated model for both purposes is that there is strong statistical evidence of a negative toll bias that improved the goodness of fit significantly, as well as ensured that both time and cost coefficients would have logical negative sign and reasonable ratio between them (VOT).

Table 3.8. Route Type Choice, New York, RP, Basic Specification

Variable	Work-related		Non-work	
	Coefficient	T-Stat	Coefficient	T-Stat
Toll route bias	-1.095	-15.39	-1.492	-15.33
Travel time, min	-0.04205	-6.66	-0.02337	-3.17
Travel cost (toll), $	-0.08241	-2.12	-0.07391	-1.35
VOT, $/hour	30.6		19.0	
Likelihood with constants only	-1603.943		-935.056	
Final likelihood	-1369.3363		-693.8515	

Presence of a strong negative toll bias (that is equivalent to more than 25 min of travel time in this case) is normally explained by the toll-averse behavior or general negative reaction to any idea of tolling regardless of the travel time savings that the toll route might bring. However, this is most frequently observed in SP studies undertaken in regions where toll roads do not exist yet. In our case, we are dealing with the RP data in the New York region where tolls have been applied for a very long period of time and have become a part of the routine travel behavior. It is also interesting that these significant toll biases coexist with comparatively high VOT for both work and non-work purposes. As will be discussed in subsequent sections, this toll bias proved to be very persistent through different model formulations including route choice and mode choice.

A possible behavioral interpretation of this seemingly contradictory result is that the actual willingness to pay for travel time improvements is not a constant value but rather a non-linear function of the relative level of service provided by the toll route compared to free route. If toll route does not provide significant time savings the general toll-averse behavior manifest itself strongly. The more significant the time savings are the closer willingness to pay become to the reported VOT. The important policy implication from this finding is that pricing should provide tangible travel time improvements to be favorably accepted by the highway users. If that is the case, some users will be willing to pay high tolls. However, if pricing does not improve travel time to a noticeable extent, it will probably result in a very negative reaction.

A second possible behavioral interpretation of anti-toll "biases" is the extra time and delay required to stop and pay a toll at the facility. The New York data set is from 1996, before the time when electronic transponders were the main form of payment for most urban tolled facilities. However, such bias is still found in studies using more recent RP and SP data sets reflecting electronic toll payment, so delay required for payment does not appear to be the major cause for bias. A more likely cause is the fact that any toll payment is required at all. As recent research by behavioral economists has indicated [*Ariely, 2009* in "Predictably Irrational"], even a good or service that is offered at a very nominal price is perceived as qualitatively different from a good or service that is offered for free.

3.2.3 Impact of Congestion Levels and Facility Type

Multiple statistical trials were implemented with travel time segmented by one or several attributes in order to capture possible differential perception of travel time by highway users depending on the driving conditions. Using perceived travel time has long become a routine practice in transit modeling. It is quite common to weight transit wait and walk time 2-3 times higher than transit in-vehicle time. It is less common in highway modeling, although recent publications strongly indicate significant weights (up to 2 – 2.5) associated with driving in congested conditions relative to free-flow conditions [*Wardman, 2008, NCHRP 431*]. In addition, it is commonly recognized that, all else being equal, drivers might prefer simpler routes with the maximum use of freeway facilities to routes that use the street network with a significant number of traffic lights. In this regard, for the New York Binary Route Type Choice model, the following approaches to splitting travel time into components were tested statistically:

- Time on highways and freeways vs. time on arterial and local roads,
- Time under reasonable conditions where link Volume over Capacity (V/C) ratio is under 0.9 (would roughly correspond to level of service A-D) vs. time under congested conditions where V/C is equal to or greater than 0.9 (would roughly correspond to level of service E-F),
- Free flow time vs. travel time due to additional delay.

The utility expressions for this model can be written in the following general way:

$$U(i) = \Delta(i) + \left[\sum_k a_k \times T_k(i)\right] + b \times C(i) \qquad (3.28)$$

where:

k = components of travel time,

$T_k(i)$ = values of travel time components for each route type,

a_k = coefficients differentiated by travel time components.

For the New York model, for work trips, neither of the multiple trials brought a reasonable and statistically significant result that could be adopted. For non-work trips, some of the estimation runs showed a logical effect expressed in a large negative coefficient for congestion delay versus free flow time as well as large negative coefficient for travel time spent on local roads vs. highways – see Table 3.9.

Table 3.9. Route Type Choice, New York, RP, Travel Time Segmentation

Variable	Non-work (1st form)		Non-work (2nd form)	
	Coefficient	T-Stat	Coefficient	T-Stat
Toll route bias	-1.504	-15.09	-1.457	-14.20
Travel time on highways/freeways, min	-0.01981	-2.06		
Travel time on arterial/local roads, min	-0.02344	-3.17		
Free-flow time, min			-0.01518	-1.40
Delay, min			-0.03760	-2.42
Travel cost (toll), $	-0.06737	-1.22	-0.07615	-1.31
VOT/highways, $/hour	17.6			
VOT/locals, $/hour	20.9			
Perceived weight, locals	1.18			
VOT/free-flow, $/hour			12.0	
VOT/delay, $/hour			29.6	
Perceived weight, delays			2.48	
Likelihood with constants only	-935.056		-935.056	
Final likelihood	-693.686		-693.3081	

We consider these results as a manifestation of perceived highway time that is a valid general phenomenon confirmed in other studies. The fact that it did not come out statistically significant for work trips is difficult to explain from the behavioral standpoint. It is probably an indication that for this level of details, the synthetic skimming procedures implemented with Static Traffic Assignment are too crude.

Segmentation of highway time into differently perceived components can be used as a partial proxy for travel time reliability. The main advantage of this method is simplicity in both model estimation and application, since it does not require any direct measure of travel time variability (like standard deviation or buffer time) to be generated. It can be equally applied in 4-step and Activity-Based models with both STA and DTA. This method can be put into practice immediately as a temporary solution, until more advanced methods that operate with direct measures of reliability have become available. However, for the current research, this result is rather peripheral since the main focus of the project is on advanced modeling approaches. A related research question to what extend perceived highway time and direct reliability measures could complement each other in the same model will be addressed in the subsequent sub-sections.

Additional tests that can also be roughly classified as travel time segmentation were performed with alternative-specific coefficients on time, i.e., assuming that travel time on tolled and free routes can be perceived differently. The utility expressions for this modification can be written in the following way:

$$U(i) = \Delta(i) + a(i) \times T(i) + b \times C(i) \tag{3.29}$$

The results of this test are summarized in Table 3.10. The results are reported for work-related purpose only since the same test for non-work purposes failed to produce a reasonable model with statistically significant and different coefficients for toll and free routes.

Table 3.10. Route Type Choice, New York, RP, Alternative-Specific Time Coefficient

Variable	Work (1st form)		Work (2nd form)	
	Coefficient	T-Stat	Coefficient	T-Stat
Toll route bias	-0.8247	-8.38		
Travel time on tolled route, min	-0.05998	-7.49	-0.07703	-9.43
Travel time on free route, min	-0.05223	-7.46	-0.05696	-7.81
Travel cost (toll), $	-0.06508	-1.66	-0.07615	-3.92
VOT/toll, $/hour	55.3		30.1	
VOT/free, $/hour	48.2		22.3	
Perceived weight, toll	1.15		1.35	
Likelihood with constants only	-1603.943		-1603.943	
Final likelihood	-1361.462		-1396.495	

In both model forms (with and without toll bias) there is a statistically significant difference in travel time coefficients between toll and free routes. Travel time on a toll route is weighted more compared to travel time on the free route. This might be a manifestation of the higher expectations with regard to travel time and its reliability if “money is paid”. Logically, this segmentation reduces the absolute value of the negative toll route bias, and even produces a reasonable model without toll bias. While this model feature was not adopted in the final model because it clashed with some other important features discussed below, it in itself is an interesting observation that could be explored in future research.

3.2.4 Incorporation of Travel Time Reliability Measures and VOR Estimation

For the New York model, various travel time Reliability measures were statistically tested including travel time standard deviation for the entire trip, standard deviation per unit of distance, difference between 80th or 90th percentile of travel time distribution and the median, etc. The utility expressions with the addition of reliability term can be written in the following general way:

$$U(i) = \Delta(i) + a \times T(i) + b \times C(i) + c \times R(i) \tag{3.30}$$

where:

$R(i)$	=	reliability measure,
c	=	coefficient for reliability measure.

The results proved to be interesting and somewhat different from the multiple studies implemented so far (mostly with SP data). The most successful model forms in terms of statistical significance and behavioral interpretation are presented in Table 3.11.

Table 3.11. Route Type Choice, New York, RP, Reliability Measures

	Work		**Non-Work**		
	1st form	**2nd form**	**1st form**	**2nd form**	**3rd form**
Variable	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**
Toll route bias	-1.043 (-14.32)	-1.087 (-15.25)	-1.493 (-15.30)	-1.490 (-15.30)	-1.457 (-14.19)
Travel time, min	-0.04382 (-6.88)	-0.04116 (-6.15)	-0.02319 (-3.10)	-0.02290 (-3.08)	
Free-flow time, min					-0.01513 (-1.39)
Delay, min					-0.03661 (-2.34)
Travel cost (toll), $	-0.05399 (-1.36)	-0.08035 (-2.07)	-0.06953 (-1.25)	-0.06428 (-1.17)	-0.03523 (-2.34)
STD time, min			-0.01129 (-0.14)		
STD time/toll route, min	-0.08012 (-3.11)				
STD time per unit distance, min/mile		-0.7260 (-1.46)		-0.5178 (-0.56)	-0.4306 (-0.47)
VOT, $/hour	48.7	30.7	20.0	21.4	
VOT/free-flow, $/hour					25.8
VOT/delay, $/hour					62.3
VOR/toll, $/hour	89.0		9.7		
VOR/10 miles, $/hour		54.2		48.3	73.3
Reliability ratio			0.49		
Reliability ratio/toll	1.83				
Reliability ratio/10 miles		1.76		2.26	
Reliability ratio/free-flow/10 miles					2.85
Reliability ratio/delay/10 miles					1.18
Likelihood with constants only	-1603.943	-1603.943	-935.056	-935.056	-935.056
Final likelihood	-1363.999	-1368.089	-693.842	-693.687	-693.192

In most cases, model estimation with such measures of reliability as standard deviation (STD) of travel time and difference between the 80/90th percentile and median failed to produce reasonable and statistically significant results. The major reason for this general problem was a high level of correlation between average travel time, STD and any travel time distribution percentile between 50 and 100. This of course in part is a consequence of the way that the travel time distribution skims were produced, including inherent limitations of the Static Traffic Assignment method. However, this is also a manifestation of the well known problem with most RP studies that they include only a narrow range of variation in time and cost variables, resulting in high correlations and a limited range of trade-offs. This frequently results in unreasonable estimated of time and cost coefficients, even without considering reliability. From this point of view, SP is preferable because the level of variation is predetermined by the survey design. This, of course, does not solve the fundamental issue with SP data that the choices are hypothetical and may not always reflect behavior in real situations.

For both segments (work and non work) the best and most stable results were achieved with a standard deviation of time per distance unit. This measure has a significant practical advantage of generally having a low correlation with travel time. It proved to be quite significant statistically and resulted in reasonable ranges for all related model coefficients. However, using a measure like STD of time per distance unit is associated with some problems (or at least inconvenience) when such measures as Value of Reliability (VOR) and Reliability Ratio (RR - that is VOR divided by VOT) are computed. In particular, in order to make VOR and RR comparable to the other model forms, the estimated coefficient for STD per mile has to be divided by a certain assumed average distance (we used 10 miles in Table 3.11). If the distance changes, all else being equal, then VOR and RR change inversely proportionally to the distance. The behavioral interpretation of this form with "floating" VOT and RR is that reliability is perceived relatively to the travel time and distance rather than as strictly additive to them. In other, words, STD of 10 min is associated with very negative perception for a short route with average travel time of 10 min while it is quite tolerable if average travel time is 60 min. An additive linear formulation of travel time, cost, and STD, would not incorporate this effect properly. Note that the standard deviation of travel time divided by distance also reflects the variability in the inverse of travel speed (time/distance). A behavioral interpretation of this measure is that people perceive variation in speed more strongly than variation in journey time itself.

More specifically, in the first form for work-related purposes, a standard deviation (STD) of travel time was tested as measure of reliability. The only modification that brought reasonable results with statistical significance was a form where STD was included for the toll route alternative only. This form may have some behavioral explanation in that travel time reliability is only important if "money is paid" while those who choose free routes are tolerant to travel time variability. This, however, was rejected as the base vehicle for the final formulation since it is generally recognized that reliability is important for route choice without tolling as well. Also, with this form, somewhat unreasonably high values for VOT and VOR were obtained.

In the second form for work-related purposes, STD of travel time per unit distance was used as the measure of reliability. This form yielded reasonable results in general with a significant RR of 1.76 calculated at distance of 10 miles. VOT proved to be quite stable and similar to the previously estimated value of $30/hour with the base form without reliability (Equation 3.27). This form was selected for use in for the final synthesis.

The first form for non-work purpose was the only formulation with (non-scaled) STD where all coefficients obtained the right sign. However, statistical significance of the STD coefficient proved to be quite low and it was unstable when additional terms were added. Thus, this structure could not be used as the main source for further analysis. It also had a relatively low RR (0.49) although this value is in the reasonable range for non-work travel.

The second form for non-work purpose mimics the second (most successful) form for work-related purposes. It is based on the STD of time per distance unit. All three coefficients obtained the right negative sign and reasonable values, although the coefficient for reliability proved to be not extremely significant. VOT was quite stable and similar to the previously estimated value of $20/hour with the base form without reliability. VOR is very high (48$/hour) at the assumed 10-mile distance and the resultant RR is equal to 2.26, which is at the high end of estimates reported so far, although not unusual [*Zheng Hensher & Rose*, *2010*]. This formulation was adopted as the source for the final synthesis in parallel with the model for work-related purposes.

The third form for non-work purpose represents an attempt to hybridize a structure where travel time is segmented by free-flow and delay components (Equation 3.28) with a direct reliability measure (Equation 3.30). The utility function for this modification can be written in the following way:

$$U(i) = \Delta(i) + \left[\sum_k a_k \times T_k(i)\right] + b \times C(i) + c \times R(i) \tag{3.31}$$

The rationale behind this formulation is that travel time segmentation can capture some additional behavioral aspects like psychological aversion to low-speed driving in congested conditions even if the travel time is predictable and unreliability is not an issue. This form was the only one where all four coefficients (free-flow time, congestion delay, travel cost, and STD per mile) obtained logical negative signs and reasonable magnitudes of values. Logically, each minute of congestion delay proved to be more than as twice as onerous compared to free-flow time and on top of it, STD per mile proved to be almost as significant as in the second model form described above. This model formulation has some behavioral appeal and potential that is worth exploring in future when better (non-synthetic) data on travel time distributions has become available. In the current project, it was not used in the final synthesis since it proved to be too "fragile" statistically after additional terms had been added.

For the rest of the statistical tests reported below, we adopted STD per mile as the main reliability measure. It was routinely included in all model formulations.

3.2.5 Impact of Gender, Age, and Other Person Characteristics

Several different attempts were made to capture affects associated with person (driver) characteristics such as gender, age, worker status (for non-work trips), etc. These model structures included person specific toll bias as well as segmentation of time, cost, and/or reliability coefficients by person type. The corresponding utility expressions can be formalized in the following way:

$$U_q(i) = \Delta_q(i) + a_q \times T(i) + b_q \times C(i) + c_q \times R(i) \tag{3.32}$$

where:

q	=	driver person type,
Δ_q, a_q, b_q, c_q	=	model coefficients estimated separately by person type.

For the New York Model, only gender proved to be statistically significant but quite contrary to the most of other reported sources. Females proved to have a large negative toll bias compared to males (i.e., stronger toll-averse behavior) as shown in Table 3.12. Despite the statistical significance, we decided that the contradictory gender effect cannot be adopted from this particular model. This effect will be revisited in a more general framework of mode and time-of-day choice in subsequent sections. Age or worker status did not improve the model fit and produced either illogical or statistically insignificant results.

We believe that there is room for further research with respect to person characteristics. For example, type of daily activity pattern may have a significant impact on VOT and VOR. In general one could speculate that people with busier daily patterns and larger number of trips should have a higher VOT and VOR due to the time pressure. This effect and the corresponding behavioral interpretations might be similar to the discussion on trip-length effects below. This is a very attractive avenue that should be considered for future research and borrow from microeconomic theory.

Despite the statistical significance, we decided that the contradictory gender effect cannot be adopted from this particular model. This effect will be revisited in a more general framework of mode and time-of-day choice in subsequent sections. Age or worker status did not improve the model fit and produced either illogical or statistically insignificant results.

We believe that there is room for further research with respect to person characteristics. For example, type of daily activity pattern may have a significant impact on VOT and VOR. In general one could speculate that people with busier daily patterns and larger number of trips should have a higher VOT and VOR due to the time pressure. This effect and the corresponding behavioral interpretations might be similar to the discussion on trip-length effects below. This is a very attractive avenue that should be considered for future research and borrow from microeconomic theory.

Table 3.12. Route Type Choice, New York, RP, Gender Impact

Variable	Work		Non-Work	
	Coefficient	T-Stat	Coefficient	T-Stat
General toll route bias	-0.9688	-12.18	-1.261	-11.12
Additional toll route bias for females, min	-0.3220	-3.20	-0.5101	-3.70
Travel time, min	-0.04052	-6.39	-0.02273	-3.05
Travel cost (toll), $	-0.08565	-2.20	-0.07751	-0.46
STD time per unit distance, min/mile	-0.7199	-1.45	-0.5322	-0.58
VOT, $/hour	28.4		17.6	
VOR/10 miles, $/hour	50.4		41.2	
Reliability Ratio/10 miles	1.78		2.34	
Likelihood with constants only	-1603.943		-935.056	
Final likelihood	-1362.859		-686.682	

3.2.6 Effect of Income

There is no argument that under the most general circumstances, household and/or person income should positively affect VOT. This is also almost by default extended to VOR although one might speculate that, for example, low-income workers in general have fixed schedules while high-income workers have more flexible schedules. Hence, low-income commuters might be more sensitive to travel time reliability than to average travel time. There have been multiple publications on the impact of income on VOT with different methods of analysis employed and different conclusions regarding the functional form. A comprehensive meta-analysis and review of VOT as function of GDP per capita was implemented by [*Abrantes & Wardman, 2009*]. They found that elasticity of VOT with respect to GDP per capita is 0.9 although they admitted that this elasticity is significantly higher than what had normally been found in most of the previous studies. The elasticity is higher for work-related trips and lower for non-work trips across most of the reviewed studies.

As part of the current project, the Resource System Group summarized 22 independent studies conducted in different geographies where VOT was estimated for commuters to work with similar methods (i.e., estimation of mode and/or choice models) – see Figure 3.6. They found that overall VOTs average 56% of hourly wage rate but vary between 25% and 95% of actual income.

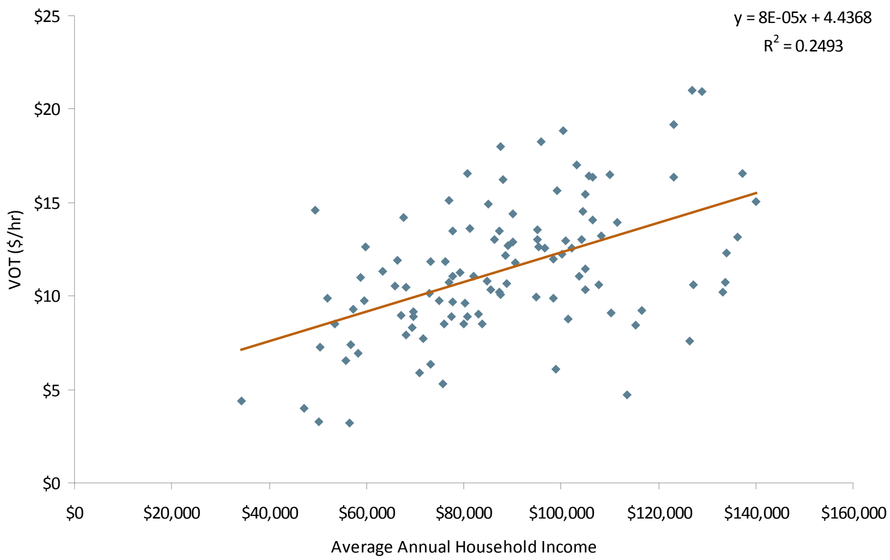


Figure 3.6. Income effect on VOT – meta-analysis of RSG.

For the New York model, for both purposes there is a logical impact of income that proved to be the most statistically significant if captured through income-specific toll bias. The statistical trials included income-group-specific toll bias, segmentation of time, cost, and/or reliability coefficients by income group, and scaling of cost coefficient by a power function of income.

Additional attempts were made to calculate disposable (shifted) income by subtracting certain fixed amount (between $5K and $25K) from the gross household income. This, however, did not improve the results and gross household income was eventually adopted as the main variable. (Further research could be done to derive a function to approximate disposable income as a function of gross income, household size and composition, auto ownership, and housing type, using, for example, data from national expenditure surveys.)

The adopted function with cost scaling by income has the following general form:

$$U(i) = \Delta(i) + a \times T(i) + b \times \left[C(i)/I^{\mu}\right] + c \times R(i) \qquad (3.33)$$

where:

I	=	Household income,
$0 \le \mu \le 1$	=	Scaling parameter for income.

The adopted functional form (Equation 3.33) is in line with other independent research where VOT elasticity with respect to income was generally considered constant and in the region between 0.5 and 1 [*Wardman et al, 2009; Fosgerau & Karlstrom, 2007*]. Indeed, VOT can be derived from (Equation 3.33) in the following way:

$$VOT = \frac{a}{b} \times I^{\mu} \tag{3.34}$$

From (Equation 3.34), VOT elasticity with respect to income can be calculated as follows:

$$\frac{\partial VOT/VOT}{\partial I/I} = \frac{\left(\frac{a}{b} \times \mu \times I^{\mu-1}\right)\partial I \bigg/ \left(\frac{a}{b} \times I^{\mu}\right)}{\partial I/I} = \mu \tag{3.35}$$

There are valid behavioral reasons why the household income effect on VOT is more direct for work-related trips (scaling parameter is equal to 0.6) and less direct for non-work trips (scaling parameter is equal to 0.5). Work-related trips are implemented by workers whose personal earnings directly contribute to the household income. Non-work trips are implemented by both workers and non-workers. The personal VOT for non-workers might be less correlated with the household income.

Table 3.13. Route Type Choice, New York, RP, Income Impact

Variable	Work		Non-Work
	1st form	2nd form	1st form
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
General toll route bias	-1.074 (-12.61)	-1.081 (-15.55)	-1.476 (-15.43)
Low-income (less than $50K) bias	-0.1789 (-1.56)		
High-income (more than $100K) bias	0.1345 (1.18)		
Travel time, min	0.04051 (-6.37)	-0.04085 (-6.74)	-0.02426 (-3.40)
Travel cost (toll), $	-0.07760 (-1.99)		
Travel cost (toll) divided by income to the power of 0.6, $/($)$^{0.6}$		-0.6291 (-2.53)	-0.5283 (-1.60)
STD time per unit distance, min/mile	-0.7313 (-1.47)	-0.7525 (-1.50)	-0.5166 (-0.56)
VOT, $/hour	31.3		
VOT/$12.5K, $/hour		11.2	7.9
VOT/$37.5K, $/hour		21.6	15.3
VOT/$62.5K, $/hour		29.4	20.8
VOT/$87.5K, $/hour		36.0	25.4
VOT/$125K, $/hour		44.5	31.5
VOT/$175K, $/hour		54.5	38.5
VOR/10 miles/62.5K, $/hour	56.5	54.1	44.3
Reliability ratio	1.81		
Reliability ratio/10 miles/62.5K		1.84	2.13
Likelihood with constants only	-1603.943	-1603.943	-935.056
Final likelihood	-1365.228	-1366.880	-693.398

3.2.7 Impact of Car Occupancy

For the New York Model, several alternative specifications were tried including occupancy-specific cost coefficient, occupancy-specific toll bias, and cost variable scaling by occupancy. For some segments, like non-work trips, occupancy-specific cost coefficient exhibited a statistically significant difference with a negative cost coefficient for SOV large than for HOV by almost factor of 3. This might be a consequence of high average occupancy of HOV for discretionary trips as well as consequence of a special character of carpools formed for discretionary purposes (frequently special events, shows, etc).

$$U(i) = \Delta(i) + a \times T(i) + b \times \left[C(i) / \left(I^{\mu} \times O^{\nu}\right)\right] + c \times R(i) \tag{3.36}$$

where:

O	=	Car occupancy,
$0 \le \nu \le 1$	=	Scaling parameter for car occupancy.

Table 3.14. Route Type Choice, New York, RP, Occupancy Impact

Variable	Work		Non-Work	
	Coefficient	T-Stat	Coefficient	T-Stat
Toll route bias	-1.081	-15.54	-1.477	-15.37
Travel time, min	0.04083	-6.73	-0.02418	-3.35
Travel cost (toll) divided by income to the power 0.6 and occupancy to the power 0.8, $/[($)^{0.6}(O^{0.8}]$	-0.6215			
Travel cost (toll) divided by income to the power 0.5 and occupancy to the power 0.7, $/[($)^{0.5}(O^{0.7}]$			-0.5256	-3.40
STD time per unit distance, min/mile	-0.7527	-1.50	-0.5166	-0.57
VOT/SOV/$12.5K, $/hour	11.3		9.3	
VOT/SOV/$37.5K, $/hour	21.9		16.2	
VOT/SOV/$62.5K, $/hour	29.7		20.9	
VOT/SOV/$87.5K, $/hour	36.4		24.7	
VOT/SOV/$125K, $/hour	45.1		29.5	
VOT/SOV/$175K, $/hour	55.1		34.9	
VOT/HOV2/$12.5K, $/hour	19.7		16.2	
VOT/HOV2/$37.5K, $/hour	38.1		28.1	
VOT/HOV2/$62.5K, $/hour	51.8		36.3	
VOT/HOV2/$87.5K, $/hour	63.3		43.0	
VOT/HOV2/$125K, $/hour	78.5		51.3	
VOT/HOV2/$175K, $/hour	96.0		60.8	
VOR/SOV/10 miles/62.5K, $/hour	54.8		43.9	
VOR/HOV2/10 miles/62.5K, $/hour	95.4		76.5	
Reliability ratio/10 miles/62.5K	1.84		2.11	
Likelihood with constants only	-1603.943		-935.056	
Final likelihood	-1362.960		-692.749	

Although, with the New York dataset and binary route type choice framework, the difference between the scaling factors for occupancy between work-related travel (0.8) and non-work travel (0.7) proved to be not extremely significant we found it is logical to expect that cost sharing for work carpools should be somewhat lower than for non-work carpools. This can be explained by a significantly large share of intra-household carpools and travel parties with children for non-work trips. This model feature can be refined in further research by explicitly considering different types of carpools and travel party compositions for both work and non-work purposes. In order to explain the cost sharing assumptions associated with each value of scaling parameter we summarize them in Table 3.15 across the entire possible range of the parameter between 0 and 1 with some qualitative explanation of the expected impact of carpool type. From this illustration, it is clear that negative values or values greater than 1 would result in illogical VOT effects.

Table 3.15. Illustration of Cost-Sharing Assumptions for Carpools

Type of carpool	Scaling parameter	Share of cost perceived by driver			VOT multiplier compared to SOV		
		HOV-2	HOV-3	HOV-4	HOV-2	HOV-3	HOV-4
Inter-household with adults only	1.0	0.50	0.33	0.25	2.00	3.00	4.00
	0.9	0.54	0.37	0.29	1.87	2.69	3.48
	0.8	0.57	0.42	0.33	1.74	2.41	3.03
	0.7	0.62	0.46	0.38	1.62	2.16	2.64
↓	0.6	0.66	0.52	0.44	1.52	1.93	2.30
	0.5	0.71	0.58	0.50	1.41	1.73	2.00
Intra-household with children	0.4	0.76	0.64	0.57	1.32	1.55	1.74
	0.3	0.81	0.72	0.66	1.23	1.39	1.52
	0.2	0.87	0.80	0.76	1.15	1.25	1.32
	0.1	0.93	0.90	0.87	1.07	1.12	1.15
	0.0	1.00	1.00	1.00	1.00	1.00	1.00

If the scaling parameter takes value of 1.0 it is assumed that the cost is fully shared between the members of the travel party. This is a frequent assumption in travel demand models. However, this is realistic only for inter-household carpools of adults (which constitute majority of work-trip carpools but a small share of non-work carpools). On the opposite side of the range is value of scaling parameter of 0.0 that correspond to an assumption that driver bears the entire cost like if it was SOV. This is realistic for traveling with children from the same household. Somewhere between these two extremes lies the real cost sharing magnitude where presence of household members and children in the travel party should in general reduce the cost-sharing probability. With the adopted specification of the utility function (Equation 3.39), the derived VOT will be inversely proportional to cost sharing (in terms of share of cost perceived by the driver). Of course, other factors besides strictly rational considerations of cost-sharing enter into travel behavior, so the findings cannot be interpreted completely in those terms. Nevertheless, the empirical findings indicate that people behave as if the cost is shared between car occupants for the most part, but not entirely.

If the scaling parameter takes value of 1.0 it is assumed that the cost is fully shared between the members of the travel party. This is a frequent assumption in travel demand models. However, this is realistic only for inter-household carpools of adults (which constitute majority

of work-trip carpools but a small share of non-work carpools). On the opposite side of the range is value of scaling parameter of 0.0 that correspond to an assumption that driver bears the entire cost like if it was SOV. This is realistic for traveling with children from the same household. Somewhere between these two extremes lies the real cost sharing magnitude where presence of household members and children in the travel party should in general reduce the cost-sharing probability. With the adopted specification of the utility function (Equation 3.36), the derived VOT will be inversely proportional to cost sharing (in terms of share of cost perceived by the driver). Of course, other factors besides strictly rational considerations of cost-sharing enter into travel behavior, so the findings cannot be interpreted completely in those terms. Nevertheless, the empirical findings indicate that people behave as if the cost is shared between car occupants for the most part, but not entirely.

3.2.8 Non-Linear LOS and Trip Length Effects

Impact of trip length on VOT (and possibly VOR) has been analyzed in several interesting past studies from both theoretical and empirical perspectives. There is no full consensus regarding the direction of impact. Positive, negative, and non-monotonic effects all have been considered and found at least with some datasets and forms of analysis. However, probably in the majority of previous studies, the authors arrived at the conclusion that VOT should grow monotonically with trip length.

In [*Ben-Akiva, et al, 1987*] the authors proposed several behavioral mechanisms that could cause a VOT change with trip length:

- Risk aversion. Travelers dislike variation in travel time that presumably increases with trip length. According to this VOT should grow because of the growing time coefficient. This factor, however, is valid only for models without direct reliability measures.
- Disutility of unfamiliarity with distant locations. With this mechanism, VOT should grow equally due to the effects of a growing time coefficient and a declining cost coefficient.
- Relative rather than absolute perception of time and cost changes. Due to this effect, for longer trips, marginal disutility of both time and cost should decline. The impact on VOT would depend on the relative magnitude of declining in sensitivity to time vs. sensitivity to cost.
- Time and money budget constraints. Long-distance travel consumes more of the travelers' time and money budgets. This should result in both time and cost coefficients to grow with trip length. However, the time budget is more rigid since money can be accumulated and transferred between periods but time cannot. This should cause the time coefficient to increase at a higher rate than cost coefficient, which would result in overall VOT growth with trip length.
- Correlation between long-distance commuting and cheaper housing. As the result of this correlation, long-distance commuters will have more disposable income and prefer more expansive and faster modes that would be expressed in generally higher VOT.

It should be noted that these effects are ambiguous in terms of the direction of impact on VOT and specific impacts on either time or cost marginal disutility. This leaves open the form of generalized cost function that would best suit the regional conditions.

In [*Daly & Carrasco, 2009*] the authors reported empirical findings that the increase of VOT with trip length appears to be caused by a declining marginal disutility of cost, not an increasing marginal disutility of time. They in general favor a logarithmic transformation of cost variable that in combination with linear inclusion of time variable would ensure the VOT growth with trip length. In addition to [*Ben-Akiva, et al, 1987*] they offered some alternative explanations for the increase of VOT with trip length:

- Structure of the transportation system where faster and more expensive modes are applied for longer distances; hence the proportion of travelers with high VOT can be found for long trips (on these modes) compared to short trips.
- Differential perception of tolls and parking cost vs. car operating cost. Tolls and parking cost are perceived directly (out-of-pocket) while car operating cost is perceived poorly. The proportion of poorly perceived cost is higher for longer trips. This might explain a declining marginal disutility of cost with trip length.
- Effect of trip frequency inversely proportional to the trip length (for non-work travel). This makes long non-work trips rarer and the willingness to pay higher.
- Multi-destination nature of long trips. For example, longer commuting might be associated with more opportunities to chain trips. This added utility can manifest itself through an increase in VOT if not accounted explicitly.
- Correlation between trip length and car occupancy. Car occupancy, in general, increases with trip length for both work-related and non-work trips. Carpools in general exhibit a higher VOT compared to single-occupancy vehicles. If car occupancy is not controlled for explicitly trip length can pick up this effect.

In a similar vein, [*Daly, 2010*] advocates "cost damping" in travel models through either distance effects or transformation of the cost variable. It is shown that the basic logic of a microeconomic model with constrained time and cost budgets does not directly dictate the form of the trip length effect on VOT. Different forms are possible although some other logical tests can reject certain forms. For example, if a power transformation of the cost variable is used the parameter should be between 0 and 1 where the value of 0 implies using a natural log of cost. However, it was shown that a simple log transformation does not pass the so-called "kilometrage" test that is essentially a test on model performance in a destination choice context. If cost is logged in the destination choice utility, then, say, doubling the cost of all trips (for example, as the result distance-based tolling) would not affect the destination choice (and average trip length) at all. This is generally considered as illogical model response. Thus, some more elaborate forms of utility functions should be explored.

The same meta-analysis of 22 independent studies conducted by the Resource System Group that was cited before in the context of income effect was used to analyze the impact of commuting trip length. It can be seen from Figure 3.7 that despite a wide variation of the results there is a certain monotonic effect for VOT to somewhat grow with average trip length.

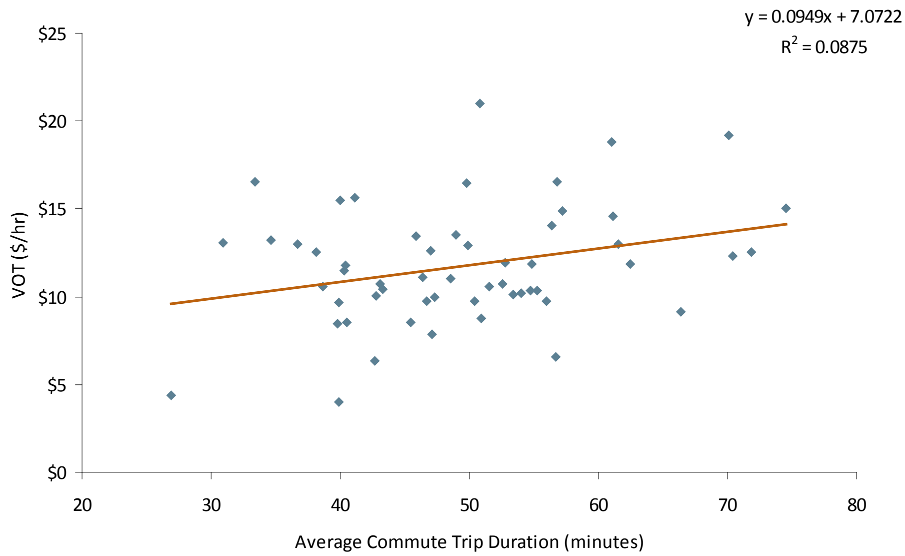


Figure 3.7. Trip Length effect on VOT – meta-analysis of RSG.

In a different study [*Steimetz & Brownstone, 2005*], the authors mentioned that interacting median time savings with distance offers an additional dimension of observable heterogeneity in VOT, which gives rise to the ‘‘inverted U’’ shape illustrated in Figure 3.8. Figure 3.8 plots median VOT for work-trip travelers against distance, where income group and employment status vary; a similar pattern is exhibited for non-work trips (not shown in the figure). The quadratic form is appealing since the downward-sloping portion of the function accounts for the possible self-selection of low-VOT commuters who are willing to spend more time on the road and thus travel greater distances. Counteracting this effect is the increasing scarcity of leisure time as travel time cuts into it, or possibly that VOT is lower for shorter trips since people might appreciate some transition time between home and work; both of these notions help to explain the upward-sloping portion of the function.

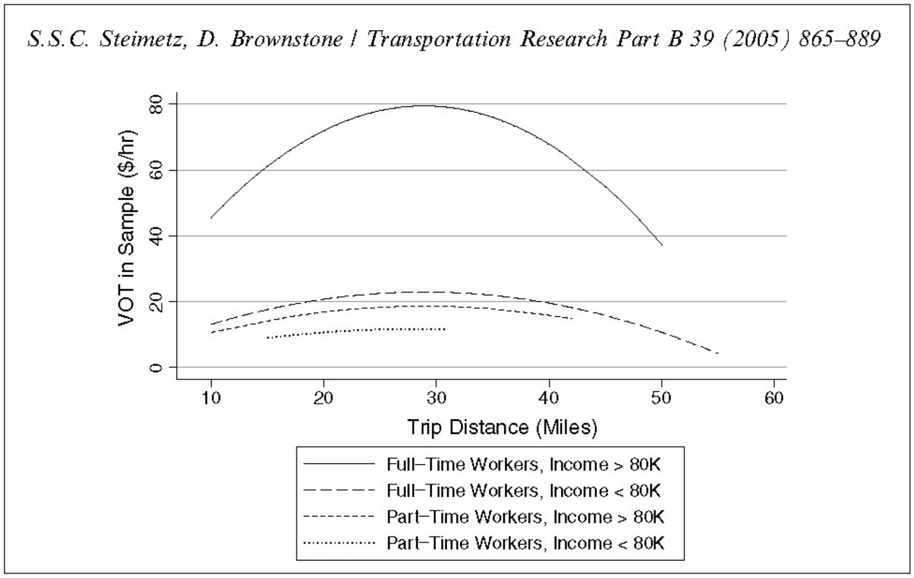


Figure 3.8. Trip length effect on VOT – Steimetz & Brownstone.

We have implemented a large number of various tests where either time or cost coefficient was interacted with distance. In some of these tests, travel time was broken into free-flow and delay components and each of them was tested separately with respect to interaction with distance. The interaction was implemented by using different forms of distance functions multiplied by time or cost. An analytically convenient way is to specify a distance function as $1 + d \times \phi(D)$ where the coefficient d can be estimated together with the time or cost coefficient. We decided to avoid simple discrete segmentation of time or cost coefficient by distance ranges because it would involve an arbitrary setting of breakdown points.

We also preferred using a distance-based function rather than non-linear transformation of time or cost variables although the difference is subtle because travel time and distance are strongly correlated in the dataset.

The adopted forms of utility function can be written in the following general way:

$$U(i) = \Delta(i) + a \times T(i) \times \left\{ 1 + \sum_n d_n \phi_n [D(i)] \right\} + b \times \left[C(i) / \left(I^{\mu} \times O^{\nu} \right) \right] + c \times R(i) \qquad (3.\ 37)$$

where:

$D(i)$	=	Travel (highway) distance,
n	=	Distance function terms,
$\phi_n(...)$	=	Distance function forms (log, linear, squared, cubed, etc),
d_n	=	Estimated coefficients for distance function terms.

In the model estimation the utility form (Equation 3.37) is linearized with respect to coefficients. Thus the products of coefficients $a \times d_n$ are estimated and reported rather than coefficients d_n themselves. However, when needed for specific analysis of trip-length effects, coefficients d_n are calculated by dividing the product $a \times d_n$ by estimated value of a.

Estimation results for the most interesting and reasonable model specification forms are presented in Table 3.16. For each travel purpose, we present two forms that differ only by the distance function. The first form includes a linear and squared distance terms. The third form includes also a cubed distance term that allows for more elaborate curvature for the entire distance multiplier on VOT.

Table 3.16. Route Type Choice, New York, RP, Trip Length Impact

Variable	Work		Non-Work	
	1st form	2nd form	1st form	2nd form
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Toll route bias	-1.143 (-14.84)	-1.134 (-14.58)	-1.665 (-15.06)	-1.662 (-14.64)
Travel time, min	0.04426 (-2.34)	-0.03128 (-1.28)	-0.08734 (-3.59)	-0.08482 (-2.50)
Travel time multiplied by distance, min×mile	-0.0008608 (-1.74)	-0.001593 (-1.58)	0.0005295 (0.90)	0.0004074 (0.32)
Travel time multiplied by squared distance, min×mile^2	0.00001130 (2.86)	0.00002410 (1.55)	0.000002251 (0.54)	0.000004147 (0.23)
Travel time multiplied by cubed distance, min×mile^3		-0.0000000684 (-0.87)		-0.0000000090 (-0.11)
Travel cost (toll) divided by income to the power 0.6 and occupancy to the power 0.8, \$/[(\$)$^{0.6}$(O$^{0.8}$]	-0.7411 (-2.85)	-0.7309 (-2.81)		
Travel cost (toll) divided by income to the power 0.5 and occupancy to the power 0.7, \$/[(\$)$^{0.5}$(O$^{0.7}$]			-0.5228 (-1.21)	-0.5200 (-1.50)
STD time per unit distance, min/mile	-0.6674 (-1.33)	-0.6517 (-1.29)	-0.3089 (-0.33)	-0.3110 (-0.34)
VOT/SOV/10 miles /$12.5K, $/hour	12.4	10.3	27.3	26.7
VOT/SOV/10 miles /$37.5K, $/hour	23.9	20.0	52.9	51.6
VOT/SOV/10 miles /$62.5K, $/hour	32.4	27.1	71.8	70.1
VOT/SOV/10 miles /$87.5K, $/hour	39.7	33.2	87.9	85.8
VOT/SOV/10 miles /$125K, $/hour	49.2	41.1	108.9	106.3
VOT/SOV/10 miles /$175K, $/hour	60.2	50.3	133.2.5	130.1
VOR/10 miles/62.5K, $/hour	40.8	40.4	26.7	27.1
Reliability ratio/SOV/10 miles/62.5K	1.26	1.49	0.37	0.39
Likelihood with constants only	-1603.943	-1603.943	-935.056	-935.056
Final likelihood	-1347.400	-1347.068	-674.827	-674.821

Models estimated for work-related purpose have reasonable values for all coefficients, and thus resulted in VOT, VOR, and reliability ratio with a generally high statistical significance. These models hold promise as seed structures for further research. Models for non-work purposes are more problematic. They are characterized by unreasonably high VOT that cannot be adopted. However, we keep these models for a specific analysis of distance effects presented below.

The entire additional multiplier on the travel time that collects all distance terms is of special interest since it directly expresses the impact of distance on VOT. It is shown for work-related purposes in Figure 3.9 and non-work purposes in Figure 3.10. This multiplier is bound to be equal to 1 at zero distance by specification (Equation 3.37).

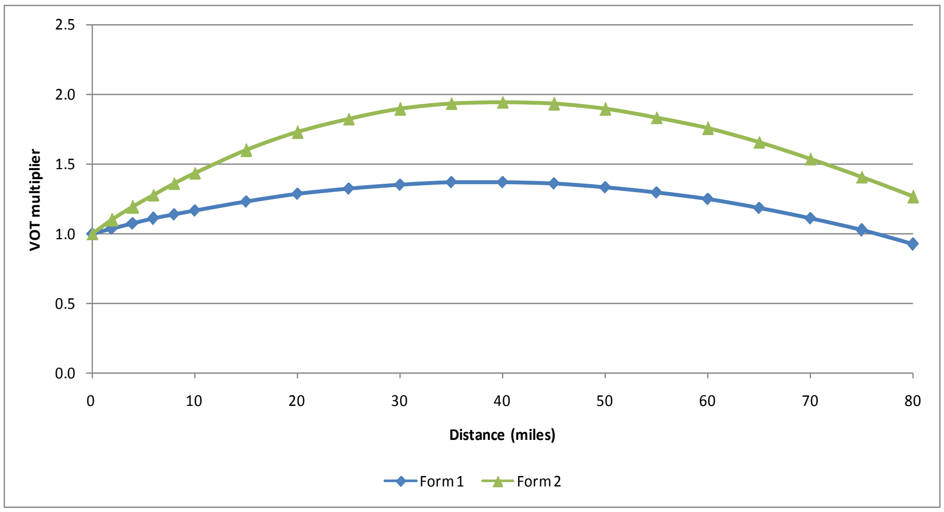


Figure 3.9. Trip length effect on VOT – work-related trips.

The shape of the distance-effect curves in Figure 3.9 is similar to the shape reported by [*Steimetz & Brownstone, 2005*]. Depending on the highest order of polynomial function used in the model specification (squared or cubed) the inverted "U" effect can be less or more prominent with a very small impact on the overall model fit. In addition to the explanation given by [*Steimetz & Brownstone, 2005*] that was cited above we offer an alternative explanation of the non-monotonic effect for commuters. We believe that the lower VOT for long-distance commuters is a manifestation of restructuring the daily activity-travel pattern. In particular, long-distance commuters tend to simplify their patterns and not to have many additional out-of-home activities on the day of regular commute since the work activity and commuting would take the lion share of the daily schedule. To compensate for this, they tend to have compressed work weeks or telecommute more frequently that gives them an opportunity to combine non-work activities in one particular day of the week (most frequently, Friday) when they do not commute to work. Contrary to that, short-distance commuters tend to have multiple additional out-of-home activities that add pressure to the daily schedule. In a certain sense, there are also lifestyle and residential self-choices embedded here, i.e., long-distance commuters are willing to sacrifice out-of-home non-work activities for better living conditions (and presumably more intensive in-home activities).

An additional factor that may result in higher tolerance to long travel times for commuters is the possibility to use the commuting time productively (especially if convenient transit modes like commuter rail are used). Using cell phones and laptops or reading a newspaper/book reduces the burden of travel time. This is somewhat less relevant for auto trips, although cell phone usage in auto travel is becoming quite common as well.

At this stage of analysis we prefer the more conservative Form 1 that is characterized by a smaller impact of trip distance on VOT compared to Form 2. This is more in line with the previous research. Also, in the absence of a consensus in the literature regarding the shape of the curve, it is reasonable to avoid extreme cases and model formulations that might be oversensitive to distance.

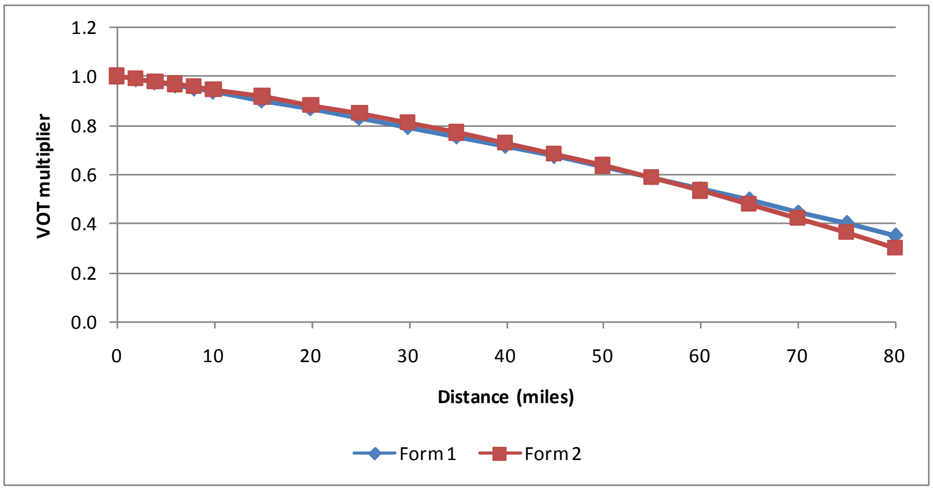


Figure 3.10. Trip length effect on VOT – non-work trips.

The shape of distance-effect curve proved to be different from most of the previously conducted studies. We found that VOT for non-work trips declines with distance. The effect proved to be quite stable with respect to the functional from specification. Addition of the cubed term for the second form did not change the shape significantly within the observed range of distances. Possible explanation for the effect of declining VOT with distance for non-work trips is that longer non-work trips on a regular weekday are most frequently implemented by non-workers and workers with an adjusted daily activity pattern (day-off or shortened workday). While there is still a frequently used stereotype in behavioral analysis to consider work as the highest-priority decision in individual scheduling, work is fact can be one of the most flexible activities. In particular, many workers adjust their schedules to accommodate one-time joint family activities like major shopping (furniture, car, appliances) or discretionary activity (theater, show, family event). For a full-time worker who worked 8 hours, it is problematic to implement a 30-mile trip for shopping or recreation on the same day. Longer travel time for non-work activities is also correlated with longer durations. Indeed, it is unusual to travel 30 miles and spend only 15 min on the activity itself. As the result, we might observe a self-selection bias for long non-work trips that are largely a "privilege" of persons with daily patterns that are less busy.

Although these effects for the New York model were confirmed with statistical significance, they have to be considered with caution. First of all, by virtue of the dataset construction there is a limited geographic range for the trips in the sample. Only origin-destination pairs with both valid toll route and free route were included. In particular, this rule discarded a bulk of short non-work trips that would otherwise dominate the sample. Another important point is that the functional forms found the most statistically significant in the current study with respect to distance effect are very different from the conclusion at which the other studies arrived.

For these reasons, we do not recommend including these trip distance effects immediately as the main functional form in operational models. We feel that more research efforts are needed to formulate this model feature with certainty. Also, since the distance effect for each particular trip are closely intertwined with the entire-day schedule of the individual, it is necessary to consider more variables that relate to the other trips and activities on the same day in order to explain the associated time pressure and VOT fluctuations. In this sense, some borrowing of ideas from the microeconomic approaches might be an interesting avenue. There is no doubt that VOT (and probably VOR as well) are rather entire-day characteristics than elemental-trip-level attributes. It is very appealing to consider daily activity-travel scheduling as a microeconomic utility optimization model with a clear time budget constraint (24 hours per day!). However, the corresponding techniques of quantitative analysis are yet to be developed since the standard microeconomic approach operates with continuous dividable quantities of goods rather than discrete trips and activity episodes.

3.2.9 Preferred Model Specifications with Deterministic Coefficients

After numerous statistical trials and comparison of the several most promising specifications for the New York binary-route-type choice model that combine the best features discussed above, we recommend to adopt (Equation 3.37) for work-related purposes and (Equation 3.36) for non-work purposes. These specifications can be written now in the following more specific forms that will be further investigated in more general frameworks of mode choice and time-of-day choice:

$$\begin{aligned} U(i) = \; & \Delta(i) + a_1 \times T(i) + a_2 \times T(i) \times D(i) + a_3 \times T(i) \times D(i)^2 + \\ & b \times \left[C(i) / \left(I^{0.6} \times O^{0.8} \right) \right] + c \times R(i) \end{aligned} \tag{3.38}$$

$$U(i) = \Delta(i) + a \times T(i) + b \times \left[C(i) / \left(I^{0.5} \times O^{0.7} \right) \right] + c \times R(i) \tag{3.39}$$

There are several specific features of the dataset itself and the ways that the variables were used that have to be kept in mind when the coefficient values reported in Table 3.8 through Table 3.16 are compared to the other studies and regions.

First of all, comparatively high values for VOT and VOR were systematically obtained through the entire range of different model formulations. These values are in generally higher than obtained in majority of other studies. This phenomenon, however, can be explained by the fact that the dataset consisted of highway users only and majority of trips were to and from the New York City, where the actual mode choice shares are 80% for transit modes and only 20% for auto modes on a regular weekday. Within the subsample, a significant share of users actually paid tolls at the level of $5-$8 that is unusually high compared to most of the other metropolitan areas in the U.S. One can speculate the psychological tolerance to tolls in New York should be the highest since high tolls have been applied there for more than 50 years. Thus, the segment of New York drivers (especially on toll facilities) on a regular weekday is probably comprised of the highway users with the highest situational willingness to pay. These values of VOT and VOR cannot be directly transferred to the other regions without adjustment.

Secondly, with respect to the very high Reliability Ratio compared to the usual range of 0.5-1.0 found and recommended in many other studies [*Eliasson, 2004; Li et al, 2010; CUTR, 2009*], the following factors should be taken into account. In the defined framework of binary route choice between toll and free routes for trips to and from the New York City there is indeed a significant difference in congestion levels and associated travel time variability between the alternatives. In particular, the free bridges (and roads leading to them) around Manhattan are more congested than tolled bridges and tunnels. The proposed measure of reliability as STD of travel time per mile helps avoid correlation between average travel time and reliability. However, there might be another systematic correlation between travel cost (toll) and reliability that is difficult to avoid in an RP setting.

It should also be mentioned again that the synthetic procedure applied to generate travel time and reliability skims was based on hourly STA that is a rather crude network simulation tool. It is difficult to say whether STA would tend to mask the actual travel time variability or rather exaggerate it compared to reality. Some local experts in our group expressed an opinion that for both regions – New York and Seattle – the resultant distributions of travel time for selected origin-destination pairs looked too narrow to their experience, especially if non-recurrent cases of extreme congestion are taken into account (for example, because of traffic accidents). We, however, have to be careful accepting this word without actual statistical data on travel times and speeds. There is a possibility today with the new sources of information to build a regional database of actual origin-destination travel times and speeds that would serve as a better basis for model estimation as well as could help calibrate traffic assignments more close to the reality. This is an important general avenue in travel modeling profession that is fully reflected in some other SHRP 2 projects but could not be incorporated in the current project. If we, however, assume that there is some systematic bias in the travel reliability measure itself, i.e., the STD used for model estimation is smaller than the actual STD this might cause the coefficient for this variable (as well as the Reliability ratio) to be somewhat high as a result.

Additionally, it is unknown at this stage to what extent the toll was reimbursed by the employer or included as a direct expense by self-employed people and business owners. This factor can also result in higher VOT and VOR. That is why questions on reimbursement are included in the recent travel surveys in the U.S. but this information was not collected in the New York survey used for the current study.

Finally, consideration of VOT and VOR in presence of a strong negative toll bias is different compared to models that do not have a toll bias. Without a toll bias, willingness to pay for travel time improvements directly relates to VOT. With a toll bias, willingness to pay for travel time improvements (in the sense of a probability to choose the toll alternative that is faster but more expensive that the free one) is suppressed to an extent. In the model application, the negative toll bias and high VOT are intertwined and work together to ensure a reasonable behavioral response. Their combined effect is essential and it is impossible to transfer only one of the parameters to a different regional model without the other.

Best Combinations

	With Toll Bias										Without Toll Bias									
	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat
Toll Route Type																				
Constant	-0.934	-8.84	-0.813	-7.10	-0.706	-5.27	-1.123	-12.54	-1.052	-9.37										
Income Groups																				
Less than 50K	-0.294	-1.96			-0.333	-2.21			-0.278	-1.85										
50K to 100K	0.000	0.00			0.000				0.000											
More than 100K	0.107	0.70			0.116	0.76			0.131	0.86										
Level-of-Service Variables																				
Cost per Occupant (cents)	-0.0009	-1.87	-0.0009	-1.86	-0.0007	-1.57	-0.0005	-1.00	-0.0004	-0.75			-0.0018	-3.78			-0.0039	-8.90		
Income Groups																				
Less than 50K											-0.005	-6.66			-0.0034	-4.53			-0.0053	-6.82
50K to 100K											-0.003	-4.88			-0.0007	-1.25			-0.0029	-5.03
More than 100K											-0.002	-3.03			0.0003	0.32			-0.0025	-3.17
Congested Time (min)	-0.041	-5.28									-0.012	-1.58								
Alternative Specific																				
Toll Route			-0.057	-5.89	-0.056	-5.78							-0.074	-7.67	-0.074	-7.46				
Free Route			-0.051	-6.02	-0.050	-5.82							-0.056	-6.48	-0.055	-6.21				
By Components																				
Free Flow Time (minutes)							-0.064	-6.40	-0.062	-6.19							-0.006	-0.62	-0.003	-0.30
Delay (minutes)							-0.006	-0.48	-0.004	-0.29							-0.034	-2.50	-0.031	-2.27
Std. Deviation- Congested Time per mile (min/mile)	-0.735	-1.32	-0.717	-1.32	-0.732	-1.34	-0.847	-1.44	-0.851	-1.45	-1.258	-2.26	-0.917	-1.75	-0.966	-1.81	-1.152	-2.12	-1.185	-2.16
Final likelihood	-1014.061		-1014.254		-1010.2469		-1012.0343		-1008.6019		-1090.0189		-1039.4192		-1029.2061		-1096.3543		-1088.5978	
Likelihood with no Coefficients	-1174.1913		-1174.1913		-1174.1913		-1174.1913		-1174.1913		-1174.1913		-1174.1913		-1174.1913		-1174.1913		-1174.1913	
Value of Time ($/hr)	28.3		39.3	35.3	45.9	40.7	79.0	8.0	101.6	6.4	2.5		25.3	19.2	61.0	45.6	0.9	5.2	0.6	6.5

Best Combinations

	With Toll Bias						Without Toll Bias	
	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat	Coeff	T-Stat
Toll Route Type								
Constant	-1.386	-10.50	-1.395	-10.47	-1.365	-10.13		
Income Groups								
Less than 50K	0.000							
50K to 100K	0.000							
More than 100K	0.526	2.35	0.524	2.34	0.521	2.33		
Level-of-Service Variables								
Cost per Occupant (cents)	-0.002	*(fixed)*	-0.002	*(fixed)*	-0.002	*(fixed)*	-0.001	-1.10
Income Groups								
Less than 50K								
50K to 100K								
More than 100K								
Congested Time (min)	-0.035	-4.16						
Alternative Specific								
Toll Route							-0.063	-4.78
Free Route							-0.038	-3.26
By Facility Type								
Highways			-0.031	-2.65				
Local Roads			-0.035	-4.10				
By Components								
Free Flow Time (minutes)					-0.027	-2.03		
Delay (minutes)					-0.046	-2.62		
Std. Deviation- Congested Time per mile (min/mile)	-1.681	-1.27	-1.607	-1.21	-1.593	-1.21	-1.737	-1.51

Final likelihood	-464.166		-464.039		-463.8939		-489.3867	
Likelihood with no Coefficient:	-612.7421		-612.7421		-612.7421		-612.7421	
Value of Time ($/hr)	10.5		9.2	10.4	8.2	13.9	46.8	27.9

As an additional note we would like to mention that we deliberately decided to avoid model segmentation by time-of-day periods, although some previous studies have indicated possibly higher VOT in peak periods compared to off-peak periods, and that is also a common practice in applied travel modeling. The common logic behind this segmentation is that it would account for differences in congestion levels as well as underlying schedule delay penalties (one can speculate that VOT and VOR should be higher in the AM period when commuters go to work).

- The first reason for our decision is that we believe that an explicit inclusion of reliability should make a better distinction between less congested and more congested conditions.
- Secondly, this binary route choice model is applied in combination with a tour time-of-day choice model that operates with the entire-day schedule (time of day choice model results are reported in later sections).
- Thirdly, the stereotype of a worker who has to be exactly on a fixed time schedule to and from work every day is becoming less relevant with the growing share of workers with flexible schedules. According to the latest household surveys in such major metropolitan areas as Chicago and San-Francisco, less than a quarter of workers have a fixed schedule while more than three quarters have at least some flexibility.

3.2.10 Incorporating Unobserved Heterogeneity

Incorporating unobserved heterogeneity in the route type decision is accomplished by a random coefficients specification where the travel time coefficient is assumed to have a distribution $f(\beta^{TT})$ with a mean b and a variance s^2. Assume the choice between a toll and a free route is only a function of travel time, travel cost and reliability of this travel, measured through the standard. The utility for each alternative (toll and free) is expressed as:

$$U_{Toll} = \alpha_i + \beta_i^{cost} \cdot COST_{Toll} + \beta_i^{time} \cdot TIME_{Toll} + \beta_i^{reli} \cdot STDDEV_{Toll} + \varepsilon_i \tag{3.40}$$

$$U_{Free} = 0 + \beta_i^{cost} \cdot COST_{Free} + \beta_i^{time} \cdot TIME_{Free} + \beta_i^{reli} \cdot STDDEV_{Free} + \varepsilon_i \tag{3.41}$$

where

$\beta^{time} \sim \text{Normal}(b\square, s^2)$ or $ln(\beta^{time}) \sim \text{Normal}(b, s^2)$

The exogenous variables entering (Equation 3.40) and (Equation 3.41) are defined as follows:

COST =Cost of Travel per Occupant (cents)
TIME = Travel Time (minutes)
STDDEV = Standard Deviation of Travel Time per Mile (minutes).

Unobserved heterogeneity is captured by assuming individual response to travel time follows a particular distribution, either normal or log-normal. The normal and log-normal distributions are truncated to prevent behaviorally unrealistic responses, such as negative values of time. A mixed logit model of user's choice between a tolled or free route is estimated using the data from the NYMTC Best Practice Model. The coefficients of travel time and travel cost naturally take a negative sign. The coefficient of travel time β_n^{time} is given an independent lognormal distribution. The mean and standard deviation of the log of the coefficient β_n^{time} are estimated, and the mean and standard deviation of the coefficient itself are calculated numerically. Furthermore, the distribution is truncated in the upper part of the tail past 1.25 standard deviations from the mean. Since the lognormal distribution is defined over the positive range and travel time is expected to have a negative coefficient for all users, the negative of travel time enters the model.

The estimation results are shown in Table 3.17. Estimation Results for RP Route Type Choice. The results illustrate some important insights that can be gained by accounting for unobserved or random heterogeneity in travel time response.

- First, for both mixed logit models, there was an improvement in the log-likelihood function value. Although this improvement was small, this may be partly due to the truncation of the distribution. Looking at the estimation results for non-truncated distributions in Appendix 1 we can see that there is a significant improvement in the log-likelihood function given unbounded distributions.
- Second, notice that the estimated variance of the random coefficient β_n^{time} is highly significant. This indicates that, with respect to travel time, the coefficient varies across the population.
- Third, by capturing the distribution of individuals' value of time, the proportion of the population with a specific value of time can be determined.

In contrast with assuming that all individuals have the same value of time represented by the average, Figure 3.11 shows that individuals vary greatly in their value of time. Additionally, depending on the assumed distribution, the value of time varies over the population differently. Assuming a lognormal distribution gives a steeper initial cumulative distribution relative to the normal distribution. Assuming a normal distribution suggests that most individuals are near the mean value of time, whereas a lognormal distribution suggests that most individuals have lower values of time relative to the overall mean value of time.

Consider further the lognormal coefficient for travel time. The ratio of a user's travel time coefficient and the travel cost coefficient is a measure of the money value of time or the amount a traveler is willing to pay to reduce the travel time by an additional minute. The mean value of time is $28.92 per hour of travel with a standard deviation of $15.42 per hour. This variation is quite large. The cumulative probability distribution function for the lognormal distribution of value of time is shown in Figure 3.11.

Table 3.17. Estimation Results for RP Route Type Choice

Model Description	Logit		Mixed Logit		Mixed Logit	
Assumed Distribution	---		Normal [-1.25,1.25]		Lognormal [upper=1.25]	
Number of Observations	1694		1694		1694	
Likelihood with Zero Coefficients	-1174.1913		-1174.1913		-1174.1913	
Likelihood at Convergence	-1017.4036		-1013.2293		-1015.6495	
Parameter	Coefficient	T-Statistic	Coefficient	T-Statistic	Coefficient	T-Statistic
Contant for Toll Route	-1.0155	-11.794	-1.2387	-10.481	-1.0512	-14.041
Highway Cost (Dist*16+Tolls, cents) by Occupancy	-0.0010	-2.058	-0.0016	-2.308	-0.0010	-2.350
Congested Time (minutes)	-0.0430	-5.569	-0.0861	-5.849	-0.0484	---
Scale Factor (Reliability/Travel Time)	---	---	---	---	---	---
Standard Deviation - Congested Time per Mile	-0.7344	-0.650	-0.4878	-0.848	-0.7333	-1.312
Error Term Parameters						
Variance Beta-Congested Time	---	---	0.0552	0.516	0.0007	---
Values of Time ($/hr)						
Mean Based on Congested Time	26.50		33.29		28.92	
Standard Deviation Based on Congested Time	---		59.02		15.42	

MEAN (β_i^{time}) = Orange; VARIANCE (β_i^{time}) = Purple

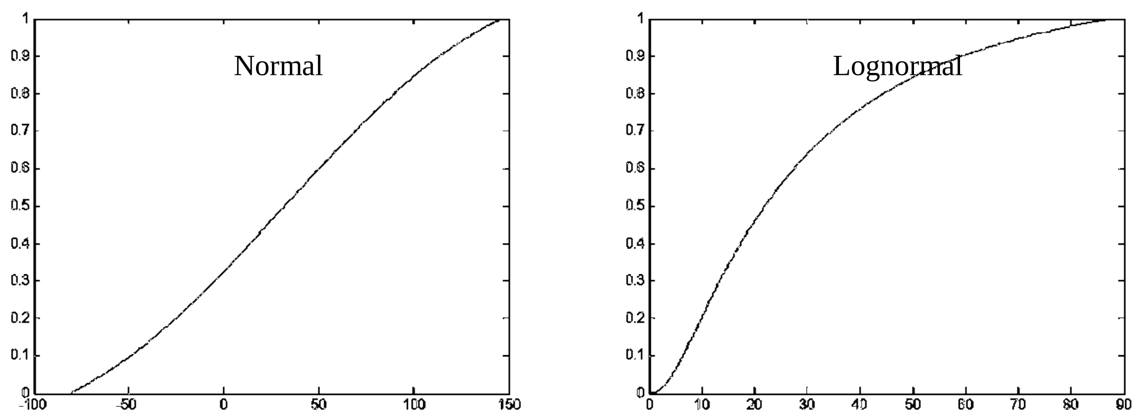


Figure 3.11. Cumulative distribution functions for VOT for different distributions.

The cumulative distribution function shows that the majority of users in the population have a value of time less than $40 per hour. However, a meaningful proportion of users have a value of time above $60 per hour, which is quite significant. As this case study illustrates, by capturing unobserved heterogeneity, the extent to which travelers differ in their preferences for route type attributes. The variances of the travel time coefficients enter significantly, indicating their importance. The next section discusses the assumptions made on the distribution of the travel time coefficient.

3.3 Time of Day Choice (TOD) and Joint TOD and Route Type Choice – Revealed Preference Framework (Seattle)

3.3.1 Overview of Section, Approach, and Main Findings

In this section we explore another primary dimension—time-of-day choice—in the most basic trip framework. Two datasets with different model specifications were used. The first one is based on the Household Travel Survey in Seattle, 2000. This set was used to estimate a trip time-of-day (departure time) model.

The second dataset was created from the Seattle Traffic Choices Study from 2006 where the GPS time and location data streams from travel on actual routes were available. The chosen route types were identified and the best alternative routes were constructed to support the same *binary route type choice* model, (a tolled freeway route vs. a non-freeway route with a lower toll cost) as was estimated for New York and discussed above (see Section 3.2). Travel time distributions were calculated based on the actual average time variability across the GPS traces for each network link-pair (further aggregated to origin-destination pair) over all weekdays in the 12-month survey period. The route type choice framework with the Seattle data was extended to incorporate time-of-day (departure time dimension)

The combined route type and TOD choice model estimated for Seattle is not equivalent to the pure route type choice model estimated for New York. However, some comparisons across the coefficients that describe the route dimension are possible. As is the case with practically all RP datasets, only the first two types of reliability measures described earlier (perceived highway time and travel time distribution) were available. Again, we start with the most basic linear specification. In each subsequent sub-section we analyze one particular aspect one at a time pivoting off the base specification.

The following main findings regarding time of day choice are summarized:

- The coefficients for the main model variables of average time and cost proved to be in the reasonable range relative to previous studies. Extra delay variables (for time longer 1.2 of free-flow time) proved to have an additional impact on time-of-day as a result of avoiding driving in congestion conditions.
- A direct measure of travel time reliability like standard deviation of travel time or standard deviation of travel time per unit distance proved to be statistically significant and performed better than more elaborate measures such as buffer time (difference between 90th and 50th percentile).
- Time-of-day choice is subject to many person and household variables. In particular, such variables like full-time vs. part-time work status and income proved to have a significant effect on work schedules. Part-time workers and low-income workers have shorter activity durations compared to full-time high-income workers. The longer work activity (tour) duration corresponds to earlier departures from home and later arrivals back home for higher incomes. Interestingly, after controlling for worker status and income, age and

gender proved to have only minor impacts on work schedules. More than 80% of part-time workers are female which can explain why the gender variable might be significant if work status is not included as a variable.

- Carpools for non-work purposes tend to have a later schedule compared to drive-alone non-work trips. The majority of the non-work carpools (about 75%) correspond to joint travel by household members where the schedule consolidation (especially if workers are involved) required this trip to be pushed to a later (after work) hour.

These effects are further explored in a more general framework of joint mode & TOD choice with cross-comparison between the New York and Seattle regions in Section 3.5.

The following main findings regarding route type choice can be summarized with a special emphasis on generic impacts that proved to be common for both New York and Seattle:

- When compared to the basic specification of the New York route-type choice model, in general, the travel time coefficients across travel purpose and regions proved to be in the reasonable range (from -0.02 to -0.07) with the tendency for work purpose to have a greater coefficient compared to non-work purpose. However, the VOTs obtained for New York (19-30$/h) are significantly higher than VOTs for Seattle (7-12$/h).
- In the previously discussed results for New York, travel time segmentation between arterial & local roads vs. highways & freeways resulted in a statistically significant difference in coefficients. Arterial & local roads were characterized by a significantly higher (negative) coefficient than for highways & freeways. The Seattle model formulation adds an additional important facet to this analysis. The advantage of driving highways & freeways manifest itself only if a substantial portion of the overall trip can be driven on highway & freeways. If the freeway component is very small it loses its advantage, since the access to and egress from the freeway become as onerous as driving through intersections and stopping on traffic lights.
- A direct measure of travel time reliability such as standard deviation of travel time or standard deviation of travel time per unit distance proved to be statistically significant and performed better than more elaborate measures like buffer time (difference between 90^{th} and 50^{th} percentile). However, the coefficients for standard deviation and standard deviation per unit distance obtained with the New York data were significantly larger than those obtained with the Seattle data. The corresponding Reliability Ratio for New York exceeded 1.0 in many cases, while it stands significantly below 1.0 for Seattle.
- These results contribute to the general observation from the multitude of previous studies that simple models are in general not easily transferable, and depending on the regional conditions, model specification and the manner in which reliability measures were generated, the Reliability Ratio can be range between 0.5 and 2.0. For this reason, in the final synthesis and recommendations we do not follow either New York model or Seattle model directly but rather consider them as somewhat extreme examples.

3.3.2 Basic Specification, Segmentation, and Associated VOT

Seattle RP Model

The first set of models estimated using the Seattle 2006 Household Survey (RP) data were simple models of time of day (TOD) choice for auto trips. The trip records from the household survey were augmented with travel time skim data provided by Puget Sound Regional Council (PSRC), prepared using their EMME network software for a 2006 base year traffic forecast. The basic model specification is as follows:

- The choice was modeled as one of 17 different time periods – 15 one-hour periods from 5 AM to 8 PM, plus two longer periods with relatively little traffic congestion, one from 8 PM to 11 PM ("evening"), and then one from 11 PM to 5 AM ("night").
- There were no auto tolls or pricing in the Seattle region in 2006, only a couple of toll bridges with fixed tolls not varying by time of day. Thus, there was no significant variation in auto cost across times of day (except possibly for some variation in downtown parking price at different arrival times, which we did not have in our data set).
- With no time of day auto pricing, we cannot estimate a cost coefficient in the TOD model. The basic model specification includes only an auto travel time coefficient, plus alternative-specific constants (ASCs) for each of the available time periods except for one.

Typically, it is very difficult to estimate travel time coefficients from RP-based time of day choice models. The main reason for that is that people tend to travel most often in periods when there is the most congestion, as the congestion is caused by the fact that people are constrained by schedules to travel in the peak period. Ideally, we would know each traveler's *desired* departure and arrival times, and measure the deviation from those times as a function of traffic congestion and travel times. However, such a question on desired schedule is rarely asked in RP surveys, and may be difficult to answer in any case for a given travel day, as schedules may vary from day to day. Also, people may give their habitual choices as their "desired" choices, even if in reality they have already adjusted their schedules to accommodate congestion. If people have fixed work start and end times, those can be used as a proxy for the desired times for work trips. However, the percentage of workers with inflexible start and end times is getting smaller over time, and the work schedule may not be a constraint for a specific person's specific travel day.

Without data on desired schedules, we can estimate a negative coefficient of auto travel time on TOD choice only if there is sufficient geographic variability in the data to distinguish different peaking patterns for O-D pairs with different congestion levels. For O-D's with very high peak hour congestion levels and travel times (relative to off-peak times), one would expect to find more people avoiding the peak hours—either traveling in the shoulders or avoiding the peak altogether.

Table 3.18 shows the estimated auto travel time coefficients for 8 different exploratory models for work-related trips, for each combination of:

- Direction: Home to work trips separately from work to home trips.
- Choice definition: Whether the chosen alternative is based on the hour in which the trip departs from the origin or else the hour at which it arrives at the destination
- Number of skim periods used: PSRC provided us with two different sets of travel time skims; one for 5 broad time periods (AM peak, midday, PM peak, evening and night) and another set for 17 different detailed time periods—the same ones used to define the alternatives in the model.

Table 3.18. Trip TOD Choice, Seattle, RP, Basic Specification Tests

Trip direction:	**Home to work**	**Home to work**	**Work to home**	**Work to home**
Choice is specified as:	Time departed from home	Time arrived at work	Time departed from work	Time arrived at home
Model – with 5 broad skim periods	TODA2	TODA4	TODA2R	TODA4R
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Total travel time (/min)	-0.0314 (-6.5)	-0.0027 (-0.6)	0.0145 (3.8)	-0.0108 (-3.0)
Model – with 17 detailed skim periods	TODA1	TODA3	TODA1R	TODA3R
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Total travel time (/min)	-0.0084 (-2.4)	0.0122 (3.4)	0.0143 (4.6)	-0.0042 (-1.4)

The models in the table are based on approximately 5,000 trip observations for each direction. The table does not show the ASC's for the different time periods, as those were not the focus of these tests.

The table shows some interesting differences in the estimated coefficients. The biggest difference is that the travel time coefficients when the choice is specified using the time on the home end of the trip (in either direction) are of the expected negative sign, while when the choice is based on the work end of the trip, the sign is usually positive. The implication of this finding is that if people choose work trip schedules to avoid longer travel times, then, according to the data, this is better reflected in the time they leave and arrive back home than it is in the time they arrive at and leave work. (Note that in past practice, the midpoint of the trip—halfway between home and work—has been used instead of the time at either trip end. That practice simply results in estimates somewhere between the ones shown above, less significant and closer to 0, so does not seem to be a good solution.)

The second main difference in the table is between the use of 5 broader skim periods or 17 detailed skim periods to reflect temporal variations in travel time. The use of fewer, broader periods for skims gives more negative and more significant estimates, so the two “best” estimates in the table are for the home and of the trip using 5 broad skim periods (coefficients of approximately -0.03/minute from home to work and -0.01/minute from work to home). As we have not carried out this type of test on other data sets (because two different sets of skims are rarely available), we cannot say whether or not this finding can be generalized. It may be due to the fact that the time of day variation coming from the skims is based on static equilibrium assignment applied to the output of a model (rather than detailed data on actual traffic counts at many different locations for different hours of the day). As a result, it may simply increase the general correlation between the peak times of day and travel time, without adding very much geographic, O-D-specific accuracy in the skims. Perhaps skims produced from dynamic traffic assignment (DTA), and validated to detailed traffic counts, would prove more beneficial for TOD modeling. In any case, this finding may be rather specific to model estimation. In model *application*, there may be a benefit in using more detailed skim periods to model peak spreading, even if it is not beneficial for estimation of coefficients.

Seattle Traffic Choices Model

The Seattle Traffic Choices data set, introduced in Section 2.4.1, provides a unique opportunity to investigate the effect of time-of-day pricing on auto trip departure time and route type choice. The toll table and map in Figure 2-4 show that the per-mile tolls on the freeways were twice as high as on the other major roads, and tolls also varied by time of day and day of week, with the highest tolls in weekday peak periods. Using this data, it would be possible to analyze either route type choice or time of day choice in isolation from the other (and we did estimate such models for exploratory purposes). However, the tolls were clearly presented to people as varying by both TOD and route type, so a joint route type/TOD model is most appropriate, and is what we focus on in this report.

Though the Traffic Choices Data provides some unique information, it also presented quite a few challenges in preparing the data for analysis. This was mainly due to the unfamiliar form of the data—GPS trace data for a limited number of vehicles (roughly 450 vehicles from 250 households), but over a quite extended period of time (approximately one year). This project was the first time that the data has been used for disaggregate, trip-level modeling, and provided a useful learning experience in dealing with the complexities of this type of data. Although we will not go into great detail in this report about the steps followed in preparing the data for estimation, we will summarize the major tasks involved in the sections that follow. (Some further details of the GPS data preparation can be found in selected project memos that are included in the appendices.)

First, the trips in the GPS data were analyzed to determine the chosen alternative. This was done by examining the tolled links traversed in each trip record, including the time that the link was entered and the link type (freeway or non-freeway). In total, over 6,400 different tolled links in the network were used, covering virtually every highway and arterial in the Seattle area.

Using the toll table and the distance traveled on each link type, we calculated the toll that the respondent should have paid for the trip and compared it to the toll reported in the data, to screen out cases with possible errors in the data. For each trip, the chosen alternative was thus designated as a combination of one of two route types (*freeway* links included or else *no freeway* links included), and one of 17 time of day periods—the same 17 periods used in the Seattle RP analysis described above.

Note that we excluded any trips that did not use any of the toll links at all. By design, the tolled network was so comprehensive that it would have been difficult for someone to make an auto trip of more than a mile or two without using any of the tolled links, and the tolled links were not an attractive option for very short trips. We also limited the sample to trips made on weekdays, as we are not modeling the shift of trips between weekdays and weekends. Also, because we based our analysis of reliability measures on observed travel times for many different GPS trips (see Section 3.3.4, I), we excluded trips that went outside of the greater Seattle area, as well as trips made between 11 PM and 5 AM.

Although GPS-based data has a great amount of detail on time and location, it is also missing some information that is typically present in travel survey data. For one thing, we only have trips made by auto in the data, and do not know anything about other trips made by the same people using transit or other modes. In addition, the data only identifies the vehicle and not the occupants, so we have no data on vehicle occupancy, or even on who the driver is for each trip. As a result, disaggregate mode choice modeling is not possible with such data.

The GPS data also provide no information on the destination purpose of each trip. However, through analysis of the multi-day GPS data, it was possible to impute the likely home and workplace locations (if any) of the main driver of each vehicle. Using that data, we restricted our analysis to home-based trips—trips where one of the trip ends was at the home location, and divided the resulting sample into home-based work (HBW) trips to the usual workplace, and all other home-based (HBO) trips.

As is typically the case with RP data—even experimental RP data—we only observe travel via the alternatives that the respondents choose, and not via the alternatives that they reject. For example, we may have a GPS trace for a respondent using a non-freeway path for a given OD at a given time of day, but do not know what the travel time would have been had the selected a path using freeway links. With this data set, there are two possible ways of approaching this issue.

First, we can use the standard method of using travel time skims from network representations. PSRC kindly provided us with separate O-D travel time skim matrices of shortest path travel times for both route types (routes including freeway links and routes with no freeway links). Also provided were corresponding skim matrices of the distances along the freeway links and tolled non-freeway links for both path types.

Alternatively, we could use the observed travel times from all of the GPS trips, averaged across all respondents by combination of O-D pair, route type and time of day period. Although we did use a similar approach to derive measures of travel time variability (Section 4.3.3), we found that the measures of average or median travel time generated by this approach were similar to the network assignment-based travel time measures, but with much more noise due to small sample sizes in many of the cells. For that reason, we relied on the skim-based travel time and distance estimates as the main supply data for our analysis.

The results for the most basic model specification are shown in Table 3.19. The models include only travel time and toll cost coefficients, along with TOD period-specific constants that are not reported in the table. We did not include a toll bias constant, because both route types were tolled, albeit at different levels. The results show that both travel time and toll have significant estimates of the expected negative sign for both HBW and HBO trips. The imputed value of time (VOT) is somewhat higher for non-work trips than for work trips, but both are in a typical range. Note that our method of imputing trip purpose from the GPS location data may not always be accurate, and this may influence the differences in coefficients between the purposes.

We also investigated nesting structure in the joint route type/TOD models. For HBW trips, no nesting coefficient significantly different from 1.0 could be estimated, so the model was constrained to be MNL (non-nested). For HBO trips, initial estimates showed that route type choice should be nested under TOD choice, with a logsum parameter somewhere in the range of 0.15 to 0.30. For the models reported in this chapter, the logsum coefficient for HBO trips was constrained to 0.25.

Table 3.19. Trip Route Type and TOD Choice, Seattle, Traffic Choices, Basic Specification

Variable	**HBW**	**HBO**
	routodw01a	**routodn01a**
	Coefficient (T-Stat)	**Coefficient (T-Stat)**
Travel time, min	-0.0697 (-6.0)	-0.0347 (-13.1)
Toll cost, $	-0.58 (-8.5)	-0.17 (-2.8)
Imputed VOT, $/hr	7.2	12.2
Observations	1,350	7,828
Rho-squared	0.253	0.072
Final log-likelihood	-2611.2	-21495.7

Comparison and Synthesis: Seattle and New York

When compared to the basic specification of the New York route-type choice model, in general, the travel time coefficients across travel purpose and regions proved to be in the reasonable range (from -0.02 to -0.07) with the tendency for work purpose to have a greater coefficient compared to non-work purpose. For New York, this also resulted in an expected higher VOT for work trips compared to non-work trips that is also the most common result with many other models. However, for Seattle a different result was obtained with the work VOT being lower than non-work VOT. Also, in general, the VOT obtained for New York (19-30$/h) are significantly higher than VOT for Seattle (7-12$/h). The overall difference between the regions can be easily explained by the difference in average income (and income segmentation is not applied yet). The reversed ratio between the work and non-work VOT in Seattle is difficult to substantiate and it may be a consequence of a relatively small subset of non-work trips with tolled routes in the Seattle Traffic Choices Study.

3.3.3 Impact of Congestion Levels and Facility Type

Seattle RP Model

For the Seattle RP TOD models, we repeated the exploratory analysis reported above in Table 3.18, but this time, using two different travel time measures: (a) the total auto travel time on all links, and (b) the "extra" auto travel time spent on links with travel times greater than 20% above free flow time. The latter set of skims was generated as follows:

- Run a set of highway skims using the full speed-flow curves – this produces the total travel time.
- Run a second set of highway skims using the same O-D flows as the first set, but now truncating the travel time on all links to a maximum of 1.2 times the free flow link time.
- Subtract the second set of skims from the first set – this produces skims of the "extra" time spent in congested conditions.

The results shown in Table 3.20 are for the same 8 basic specifications as shown in Table 3.18, but now including two different auto travel time variables instead of just the total time. The two time coefficients are additive, so one would expect the total travel time coefficient to remain negative, and the "extra" travel time variable to have an additional negative effect that is additive to the first. The table shows that there are no cases where both variables are negative and significant. In cases where the extra time is negative and significant (particularly the cases with 17 skim periods), the total travel time coefficient becomes positive. In general, the two variables tend to be highly correlated with one another, so that when the coefficient for one goes up, the coefficient for the other goes down. To reduce the correlation, we also tested specifications (estimates not shown here), where the extra travel time was divided by trip distance, but that yielded positive coefficients on the extra time variable. Overall, this approach for segmentation of travel time does not appear to be a promising direction, particularly given that it requires the production of a completely separate set of highway travel time skims, which can consume both time and computer resources.

Table 3.20. Trip TOD Choice, Seattle, RP, Segmentation of Time by Congestion Level

Trip direction:	Home to work	Home to work	Work to home	Work to home
Choice is specified as:	Time departed from home	Time arrived at work	Time departed from work	Time arrived at home
Model – with 5 broad skim periods	TODC2	TODC4	TODC2R	TODC4R
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Total travel time (/min)	-0.0283 (-4.5)	0.0068 (1.0)	0.0497 (3.0)	-0.0239 (-1.5)
Extra time on links above 1.2 times link free flow time (/min)	-0.0039 (-0.6)	-0.0156 (-2.2)	-0.0368 (-2.2)	0.0137 (0.8)
Model – with 17 detailed time periods	TODC1	TODC3	TODC1R	TODC3R
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Total travel time (/min)	0.0124 (1.3)	0.0095 (0.9)	0.0441 (6.1)	0.0212 (2.8)
Extra time on links above 1.2 times link free flow time (/min)	-0.0251 (-0.6)	-0.0156 (-2.2)	-0.0393 (-4.6)	-0.0342 (-3.7)

Although the “extra time” variable did not have a significantly different coefficient when used as a period-specific variable, further tests show that this variable does have a significant value if it is used as a TOD “shift variable”. Shift variables are used to describe which observations tend to leave home and/or arrive back at home significantly earlier or later than other observations, and they are applied for specific person, household or trip characteristics, similar to mode preference variables in mode choice models. The exact specification of shift variables is provided elsewhere in this report.

Table 3.21 shows qualitative results for several time of day shift variables estimated for base TOD models ***tonlyw*** and ***tonlyn*** (more detailed estimation results are provided in the appendices.) If a shift coefficient is applied for the extra travel time in the peak hours with the most congestion (8-9 AM and 5-6 PM, in this case), it does show significant effects. For the HB Work model, the higher the peak hour congestion in the AM peak, the earlier that people tend to leave home. The PM peak effect is just the opposite, with people tending to arrive back at home somewhat later. For HB Other trips, however, people tend to move the entire trip later in the day when there is significant peak hour congestion, applying to both the AM and PM peaks. It is interesting that this particular congestion variable is also used in the TOD models in the Sacramento SACSIM choice model system, where it showed similar time shift effects. It is likely, however, that this variable represents a rather crude measure of reliability, which might be better addressed through some of the other approaches described in this report.

Note: The results for the remaining shift variables in Table 3.21 are discussed in later subsections.

Table 3.21. Trip TOD Choice, Seattle, RP, Qualitative Results for Time Shift Variables (t-stats in paren.)

Model	tonlyw	tonlyw	tonlyn	tonlyn
Purpose	HB Work	HB Work	HB Other	HB Other
Relevant time modeled	Leave from home	Arrive back home	Leave from home	Arrive back home
"Extra time" on congested links above during peak hours (8-9 AM and 5-6 PM)	Earlier (-4.5)	Later (1.5)	Later (2.5)	Later (3.9)
Shared ride auto trip	insig. (-0.2)	Later (2.0)	Later (16.1)	Later (9.9)
Household income ($/year)	Earlier (-5.2)	Later (4.9)	insig. (-0.6)	Earlier (-3.3)
Female	insig. (0.3)	insig (-0.7)	Earlier (-5.2)	Earlier (-8.7)
Age (years over 18)	Earlier (-1.7)	Earlier (-9.3)	Earlier (-8.3)	Earlier (-10.9)
Part time worker	Later (1.7)	Earlier (-2.3)	Earlier (-8.3)	Earlier (-16.3)
Shopping trip			Later (5.2)	Earlier (-3.3)
Meal/restaurant trip			Later (3.1)	Later (7.9)
Social visit/recreation trip			Later (7.1)	Later (9.3)

Seattle Traffic Choices Model

The Traffic Choices models also provide some evidence on the effect of facility type on choice. The models in Table 3.22 are an extension of those presented above in Table 3.19, but this time adding two variables for the freeway route type alternatives. One variable is a simple constant, while the second is the fraction of the distance on the freeway path that is on freeway links. The addition of these two variables improves the log-likelihood of both the HBW and HBO models significantly, and the effects are similar in both models. When plotted in Figure 3.12, we can see that if a freeway path type has very little distance along the freeway, then there is a strong preference against using it. This may be due to the (risk of) delay getting on and off the freeway, in exchange for little benefit of using it. The higher the percentage of the path that is on the freeway, the higher the benefit, with a higher overall preference for using the freeway path for HBO trips relative to HBW trips (when normalized to minutes of travel time).

Note that the toll cost coefficients are now stronger than in the simple models of Table 3.19. This is particularly so for HBO trips, to the extent that the imputed VOT is now quite low at $3.7/hour, and lower than for HBW trips. This result highlights one of the complications of modeling tolls when the pricing is purely distance-based—any other variables based on distance are now strongly correlated with the toll variable, and the estimated coefficients become less stable.

Table 3.22. Trip Route Type and TOD Choice, Seattle, Traffic Choices, Effect of Facility Type

Variable	HB Work routodw01c Coefficient (T-Stat)	HB Other routodn01c Coefficient (T-Stat)
Travel time, min	-0.0640 (-5.1)	-0.0234 (-6.9)
Toll cost, $	-0.61 (-9.0)	-0.38 (-5.4)
Freeway route type constant	-3.98 (-5.8)	-1.01 (-7.2)
Fraction of freeway route type distance on freeway links	5.59 (5.8)	2.41 (8.2)
Imputed VOT, $/hr	6.3	3.7
Observations	1,350	7,828
Rho-squared	0.275	0.074
Final log-likelihood	-2532.5	-21460.9

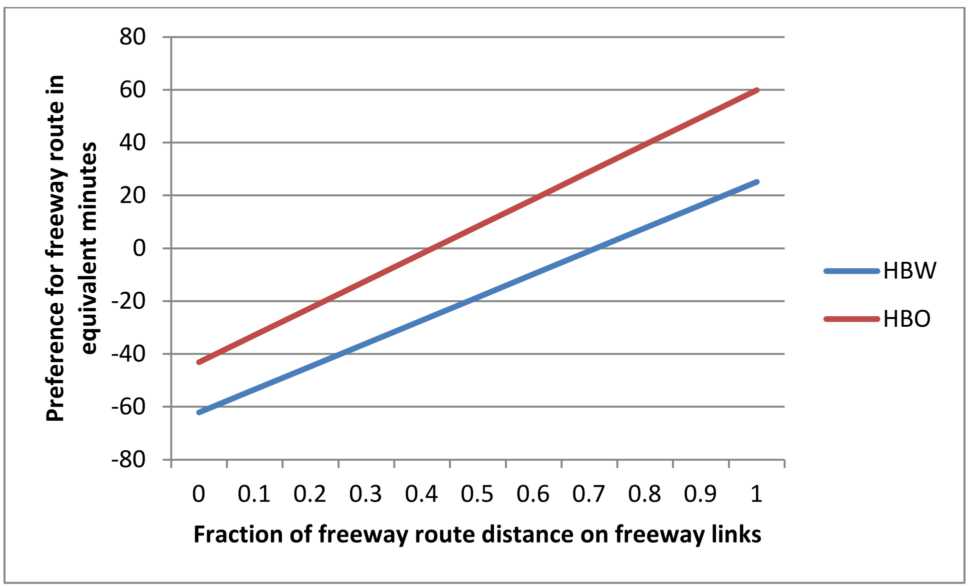


Figure 3.12. Facility type results for traffic choices data.

Comparison and Synthesis: Seattle and New York

The New York route type choice model used a different specification from the Seattle model for the facility type analysis. Thus, a direct comparison of the facility type impacts between the two is difficult. However, the analysis in both regions supported somewhat complementary results. In the previously discussed results for New York, travel time segmentation between arterial & local roads vs. highways & freeways resulted in a statistically significant difference in coefficients (at least for the non-work travel purpose). Arterial & local roads were characterized by a significantly higher (negative) coefficient compared to highways & freeways. This implies a general user preference for highways & freeways compared to arterials & local roads. This is in line with the common consideration that intersections and traffic lights are perceived negatively by drivers in addition to travel time itself. It might also be tempting to interpret the higher (negative) travel time coefficient for arterials & local roads as a proxy for travel time reliability (as is the case with travel time segmentation by congestion levels). However, this is questionable since the freeway congestion levels are as significant as for arterials & local roads.

The Seattle model formulation adds an additional important facet to this analysis. The advantage of driving highways & freeways manifest itself only if a substantial portion of the trip can be driven on highway & freeways. If the freeway component is very small it loses its advantage since the access to and egress from the freeway become as onerous as driving through intersections and stopping on traffic lights. This finding is behaviorally appealing. In general, we believe that further research should be encouraged with respect to segmentation by facility type and construction of route utility function that includes variables like facility type, intersection type, and presence of traffic lights in addition to travel time and cost.

With the New York route type choice model discussed above, a significant differentiation of time by congestion levels was found. It was technically implemented by dividing the total auto time into free-flow time and congestion delay. It is only slightly different from the Seattle RP formulation where the time breakdown point was 1.2 of the free-flow time rather than 1.0 of free-flow time. In the Seattle RP formulation this segmentation did not work directly in the trip departure time choice context, but the delay variable proved to be statistically significant as a shift variable. This means that highway users not only tend to avoid routes with a higher congestion levels, but also tend to adjust their schedule to avoid driving in the congestion periods. However, as was mentioned before, these effects may just be proxies for direct impacts of reliability measures.

3.3.4 Incorporation of Travel Time Reliability Measures and VOR Estimation

Seattle RP Model

For the analysis of the Seattle Household survey RP data, PSRC does not routinely generate estimates of day-to-day travel time variability. PSRC did provide us, however, with sufficient traffic count data and EMME network files in order to apply the method of synthesizing skims of day-to-day variability in travel times, as described in Section 2.2.2, Method for the Generation of Travel Time Distributions and applied with the New York RP data in Section 3.2. We generated 20 different matrices for each of 17 different skim periods (the same 17 periods described above), and then calculated distribution statistics such as median, standard deviation, and 90th percentile travel times for each O-D pair and time period. One estimation test that we did to gain some confidence in the results was to estimate simple models using the median travel times from this method in place of the standard travel time skims previously provided by PSRC, and the results (not shown here) gave quite similar estimates for the travel time coefficient.

Table 3.23 shows the results of estimating models with just a median travel time coefficient, as well as the results of adding four different reliability variables—the standard deviation, the standard deviation per mile, the "buffer time" (90^{th} percentile time minus the median time), and the "buffer time" per mile. For the HB Work purpose, the results are not promising. The coefficient for each of these measures is significant with the incorrect sign, and, to offset the effect, the median travel time coefficient becomes much more negative than in the basic model. This is due to high correlation between the median and the other distribution effects. The correlation is somewhat lower when the reliability variable is divided by distance, as indicated by the somewhat smaller change in the median travel time coefficient and somewhat larger improvement in log-likelihood.

For the HB Other models in Table 3.23, the results are more promising, at least when using the standard deviation variable. When standard deviation is used by itself, the coefficient is negative and significant. Due to correlation, however, the median travel time variable has become insignificant and quite small, so that the "reliability ratio"—the ratio of the standard deviation coefficient to the median coefficient is nearly 10, an unrealistically high result. When the standard deviation is divided by distance, however, the coefficient becomes less significant, but stays negative with a reasonable ratio to the median travel time variable. (The reliability ratio would be 1.0 at a distance of approximately 8 miles, above 1.0 for trips shorter than 8 miles, and below 1.0 for trips longer than 8 miles.)

The buffer time (90^{th} percentile minus median time) and buffer time per mile variables have the incorrect sign for both purpose segments.

We also tested specifications (results not shown here) where instead of dividing by distance, we divided the standard deviation and 90^{th} percentile time by the mean time or the median time. These models gave results very similar to the models where the measures were divided by distance.

This initial application of this method of generating synthetic reliability measures for use with the Seattle RP data has indicated that the estimation results are very sensitive to correlations between the variables, making it very difficult to obtain conclusive results. In later sections, we add mode choice effects into the choice models as a further test.

Table 3.23. Trip TOD Choice, Seattle, RP, Inclusion of Reliability Variables

Trip type:	**HB Work**	**HB Work**	**HB Work**	**HB Work**	**HB Work**
Choice is specified as:	**Time at home end**	**Time at home end**	**Time at home end**	**Time at home end**	**Time at home end**
Model – with 5 broad skim periods	**tonlyw**	**tonlywb**	**tonlywc**	**Tonlywd**	**Tonlywe**
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Median travel time (min)	-0.0158 (-5.4)	-0.0252 (-5.6)	-0.0208 (-6.4)	-0.0279 (-4.2)	-0.0243 (-7.2)
Std. deviation of travel time (min)		0.0844 (2.8)			
Std. dev.travel time / distance (min/mile)			1.37 (3.6)		
Buffer (90^{th} % - median) time (min)				0.0133 (2.1)	
Buffer (90^{th} % - median) / distance (min/mile)					0.317 (5.2)
Observations	9876	9876	9876	9876	9876
Final log-likelihood	-21230.8	-21227.0	-21224.3	-21228.7	-21217.3
Trip type:	**HB Other**	**HB Other**	**HB Other**	**HB Other**	**HB Other**
Choice is specified as:	**Time at home end**	**Time at home end**	**Time at home end**	**Time at home end**	**Time at home end**
Model – with 5 broad skim periods	**tonlyn**	**tonlynb**	**tonlync**	**Tonlynd**	**tonlyne**
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Median travel time (min)	-0.0195 (-4.5)	-0.0090 (-1.4)	-0.0185 (-3.8)	-0.0243 (-3.6)	-0.0244 (-5.0)
Std. deviation of travel time (min)		-0.0906 (-2.2)			
Std. dev.travel time / distance (min/mile)			-0.154 (-0.5)		
Buffer (90^{th} % - median) time (min)				0.0074 (1.0)	
Buffer (90^{th} % - median) / distance (min/mile)					0.136 (2.4)
Observations	18958	18958	18958	18958	18958
Final log-likelihood	-47963.3	-47960.8	-47963.2	-47962.9	-47960.5

[Originally Table B5.]

Seattle Traffic Choices Model

One of the most attractive features of using the Traffic Choices data for this project is that it can provide directly observed measurements of day-to-day variability in travel times for specific O-D pairs. In practice, deriving such measurements proves quite complicated, and a fruitful area for continuing research and refinement. In this project, we used the following approach:

- First, the trips in the GPS trace data were summarized in terms of the number of times each non-adjacent pair of tolled links was traversed. These link pairs were treated as pseudo-OD pairs for purposes of summarizing data on travel time variability. Adjacent link pairs were excluded as being unrealistically short trips that would not reflect the travel time characteristics of actual trip O-D paths.
- Next, the O-D (link) pairs with at least 500 observations were analyzed to obtain the median, mean, standard deviation, 80th percentile, and 90th percentile travel times, separately for each time period of the day. (Note that for TOD modeling we need to have at least 10 observations or so for each time period of the day to provide a reasonable profile of changes in reliability across the day, so we need to select on OD pairs with many total observations. In future research, it may be possible to combine some periods or otherwise allow the use of more link pairs to make the most efficient and optimal use of the GPS data.)
- Next, the distributions for the link-to-link pseudo O-D pairs were aggregated up to TAZ-TAZ level OD pairs, so that the distribution for a TAZ-TAZ pair is the weighted average of the distributions of all associated link-link pairs. With this approach, only commonly traversed TAZ pairs have enough data to provide adequate estimates of travel time variability, so only trips between those TAZ pairs can be used in estimating the effect of reliability. (It seems worthy of further research into the most efficient and accurate means of performing such aggregation.)
- Finally, the distributional information from the above steps was attached to the trip records for model estimation. Because we already have assignment-based estimates of expected travel times for O-D pairs, it was best to ensure that the reliability estimates would be somewhat consistent with those measures. To do that, we used the information on the standard deviation and "buffer time" (90th percentile minus median travel time) relative to the median travel time, and applied those ratios to the assignment-based measures of travel time. In other words:

  Std. Dev. (model) = Std. Dev.(observed) / Median(observed) × Assignment-based time

  Buffer time (model) = Buffer time(observed) / Median(observed) × Assignment-based time

The results of adding the standard deviation variable to the model specification are shown in Table 3.24. For both purposes, the reliability variable was tested in two ways, first as the standard deviation in units of minutes, and then as the standard deviation per mile of distance. For HBW, the results are quite promising. Adding the reliability variable in either form gives a significant improvement in likelihood, without strongly effecting the base time or toll coefficients. For the first specification, the standard deviation of travel time has a coefficient of -0.042/minute, relative to -0.058 for travel time, giving an imputed reliability ratio (RR) of 0.72. This is in the range of values that have been obtained from other studies (but very few of them based on observed measures of day-to-day travel time variability). The second specification, with standard deviation divided by distance, gives an even better improvement in likelihood than the first. At a distance of 4 miles or so, the RR is about the same as in the linear specification, but it goes down steadily at longer distances. At 10 miles, the RR would be about 0.26. This result is similar to that obtained for HBW trips in the New York route type choice models.

Table 3.24. Trip Route Type an d TOD Choice, Seattle, Traffic Choices, Effects of Reliability

Variable	HB Work routodw01d Coefficient (T-Stat)	HB Work routodw01e Coefficient (T-Stat)	HB Other routodn01d Coefficient (T-Stat)	HB Other routodn01e Coefficient (T-Stat)
Travel time, min	-0.0581 (-4.7)	-0.0612 (-5.0)	-0.0345 (-8.0)	-0.0268 (-7.7)
Toll cost, $	-0.60 (-8.7)	-0.64 (-9.4)	-0.38 (-5.5)	-0.38 (-5.5)
Freeway route type constant	-4.22 (-6.0)	-4.26 (-6.1)	-1.00 (-7.1)	-0.953 (-6.7)
Fraction of freeway route type distance on freeway links	5.82 (5.8)	6.00 (6.0)	2.38 (8.1)	2.33 (7.9)
Std. deviation of travel time, min	-0.0420 (-5.4)		0.0354 (4.6)	
Std. deviation of travel time divided by total distance, min/mile		-0.161 (-5.4)		0.097 (3.8)
Imputed VOT, $/hr	5.8	5.7	5.5	4.2
Imputed VOR, $/hr (*at 5 miles)	4.2	3.0*	incorrect sign	incorrect sign
RR = VOR / VOT (*at 5 miles)	0.72	0.53*	incorrect sign	incorrect sign
Observations	1,350	1,350	7,828	7,828
Rho-squared	0.280	0.281	0.074	0.074
Final log-likelihood	-2516.6	-2513.4	-21451.4	-21453.8

For HBO trips, the results for reliability are much less successful. Increasing standard deviation in travel time has a positive coefficient in both specifications. Also, the main travel time coefficient becomes much more negative than in the previous model in Table 3.22, suggesting a high correlation between the mean travel time variable and the standard deviation (but somewhat less correlation when the standard deviation is divided by distance).

For both HBO trips and HBW trips, we also tested the buffer time (90^{th} percentile minus median) travel time variable, both by itself and divided by distance (results not shown here). The estimate for the buffer time variable was significant with the incorrect (positive) sign in all cases, and indicated high correlation with the main travel time variable.

Overall, the analyses reported in this chapter have indicated that the Traffic Choices data can support detailed disaggregate model estimation and yield significant and reasonable results. However, this is a fundamentally different type of data than any of the other datasets analyzed for this project, and a type which we (nor anyone else) have had any previous experience for this type of modeling. There are several alternative approaches for data preparation and interpretation that could be tested as part of further research. However, results from a single data set will never be very definitive, so concurrent analysis of other GPS-based data on variability in travel choices is also recommended.

Comparison and Synthesis: Seattle and New York

Overall, the Seattle results with the Traffic Choices Study confirm the main findings described above for the New York model in a sense that standard deviation of time and standard deviation of time per unit distance performed better than other (more elaborate) measures of travel time reliability like a buffer time (difference between the 90th percentile and median). Standard deviation of travel time per unit distance has a significant practical advantage over a simple un-scaled standard deviation since the latter is frequently correlated with the mean travel time. This is not a conceptual advantage per se but a significant practical constraint that is difficult to resolve in the RP setting (can be overcome in the SP setting though by controlling the input LOS data).

The coefficients for standard deviation and standard deviation per unit distance obtained with the New York data were significantly bigger in magnitude than those obtained with the Seattle data. The corresponding Reliability Ratio for New York excided 1.0 in many cases while it stands significantly below 1.0 for Seattle. These results contribute to the general observation from the multitude of previous studies that simple models are in general not easily transferable and depending on the regional conditions, model specification, and the way how the reliability measures were generated, the Reliability Ratio can be between 0.5 and 2.0 or even exceed these limits for some particular cases [*Li et al, 2010; CUTR, 2009*]. For this reason, in the final synthesis and recommendations we do not follow either New York model or Seattle model directly but rather consider them as somewhat extreme examples. New York is characterized by extremely high congestion levels and notoriously unpredictable travel times. Coupling this with a relatively short average travel distance for auto trips (majority of long-distance commuters in New York use transit), a Reliability Ratio greater than 1.0 is behaviorally justified. Seattle has generally lower congestion levels across the region, hence the entire unreliability scale is set differently vs. the average travel time.

3.3.5 Impact of Gender, Age, and Other Person Characteristics

Seattle RP Model

Although we did not estimate VOT or variations in willingness to pay for the Seattle RP data (due to the lack of tolls or pricing in the region), we did estimate time of day shift effects, presented in Table 4.21.

- Females tend to make non-work trips earlier in the day than males, both for leaving home and arriving back at home. This may be related to roles within the household. There is no significant difference for females in the HB Work model, however.
- Age shows strongly significant effects, with older adults tending to perform activities earlier in the day than younger adults, both for HB Work and HB Other. This may be due to lower participation in out-of-home activities in the evenings.
- Part-time workers also show different TOD preferences relative to others, with somewhat shorter work activities (leaving home later, arriving back earlier) and earlier non-work activities in general. The latter effect is presumably because part-time workers can perform some activities during the daytime which full-time workers perform in the evenings after work.

We also included shift variables for certain trip purposes within the HB Other model, all relative to the "base" purpose of personal business/errands. Those on shopping trips tend to leave somewhat later and arrive back home later, indicating shorter activity duration compared to other non-work purposes. Restaurant and social/recreation trips show later times both leaving home and arriving back at home. Compared to other types of trips, these are more likely to be done in the evening hours.

Note that the specification of shift variables and TOD constants used in these models is somewhat simpler than typically used in full activity-based model systems with scheduling models. In particular, we did not make hours spent at work unavailable for non-work activities, as is typically done by specifying remaining available "time windows" for additional activities and travel. As the focus of this project is not on detailed scheduling models, we did not introduce that level of complexity. However, it is important to always include at least some representation of important TOD preference and shift effects in models to predict the TOD effects of changes in pricing and congestion, lest the omission of these effects cause spurious results for the VOT-related variables.

Seattle Traffic Choices Model

As mentioned previously, the Traffic Choices GPS data does not indicate which person or persons are in the vehicle for any given trip, so it was not possible to include person characteristics in the model.

Comparison and Synthesis: Seattle and New York

Due to the data limitation of the Seattle Traffic Choice Study, it was impossible to directly compare the results to New York in the route type choice context. However, it should be noted that even with the New York data where a rich set of person and household variables was available, only some gender effects proved to be statistically significant in a form of additional toll-averse bias. Gender, age, worker status, and other person characteristics manifest itself strongly in time-of-day choice. The cross-comparisons between New York and Seattle with respect to time-of-day choice will be discussed later in Section 3.5 with a full specification of joint mode & TOD choice model.

3.3.6 Effect of Income

Seattle RP Model

For the Seattle RP TOD models, there were no cost variables, so we did not expect a major effect of income. We did, however, include TOD shift variables related to household income, as shown above in Table 3.21. The effects for HB Work are quite significant, with those people with higher incomes tending to leave home earlier and arrive back home later compared to those with lower incomes. One reason for this may be longer work hours related to higher incomes. Another reason may be greater work schedule flexibility for higher income workers, allowing them to schedule their work hours to avoid the peak congestion periods. For the HB Other model, the income effects are weaker than for work trips, with higher income households tending to arrive home somewhat earlier.

Seattle Traffic Choices Model

Although some data on household income for the Traffic Choices sample was provided, we were not able to successfully match it to the specific vehicles in the data set. With further information, it would be possible to do so and include income variation on the toll coefficient. With only 250 households in the sample, however, such an analysis may be very sensitive to individual outliers.

Comparison and Synthesis: Seattle and New York

Again, the limitations of the Seattle Traffic Choice dataset prevents direct comparisons with the New York analysis. With the New York model, as discussed above, we substantiated a general functional form of highway generalized cost where the cost variable was scaled down by Income powered by 0.6. This formulation will be further tested in the extended choice frameworks of mode and TOD choice. Income has also a strong direct impact on TOD choice. The cross-comparisons between New York and Seattle with respect to time-of-day choice will be discussed later in Section 3.5, with a full specification of joint mode & TOD choice model.

3.3.7 Impact of Car Occupancy

Seattle RP Model

For the Seattle RP TOD models, there were no cost variables, so we did not expect a major effect of occupancy and cost sharing on behavior. We did, however, include TOD shift variables related to shared ride auto trips, as shown above in Table B3A. The effects for HB Work are not very significant, with carpoolers tending to arrive back home from work slightly later than those who drive alone. For the HB Other model, the effects are significant, with shared ride trips tending to be made later in the day than drive alone trips—presumably because that is when more people are free from work and school and can travel to joint activities.

Seattle Traffic Choices Model

As mentioned previously, the Traffic Choices GPS data does not indicate vehicle occupancy for any given trip, so it is not possible to analyze the effect of occupancy in the models.

Comparison and Synthesis: Seattle and New York

Again, the limitations of the Seattle Traffic Choice dataset prevented from direct comparisons with the New York analysis. With the New York model, as discussed above, we substantiated a general functional form of highway generalized cost where the cost variable was scaled down by Car Occupancy powered by 0.6. This formulation will be further tested in extended choice frameworks of mode and TOD choice. Car Occupancy (and joint household travel) has also a direct impact on TOD choice. The cross-comparisons between New York and Seattle with respect to time-of-day choice will be discussed later in Section 3.5, with a full specification of joint mode & TOD choice model.

3.3.8 Non-Linear LOS and Trip-Length Effects

Seattle RP Model

As reported earlier for the New York RP data, a test was done to specify the travel time coefficient as a quadratic function of distance rather than a single coefficient. The results are shown in Table 3.25 alongside simpler models. For the HB Work models, the results do indicate the same parabolic function, with the travel time coefficient first increasing and then decreasing with distance. However, the base travel time coefficient becomes positive, meaning that the total effect of travel time will be positive at short distances. For the HB Other model, the distance effects on the travel time coefficient are very small and insignificant, and the log-likelihood improves very little compared to the basic model. For a more successful analysis of trip length effects on the Seattle RP data, see section 4.4.7 on mode choice model results and 4.5.7 on combined mode and TOD model results.

Seattle Traffic Choices Model

We attempted analyses of trip length variation on VOT with the Traffic Choices data, but were not able to obtain reasonable results, perhaps due to restrictions on trip distance and sample size related to the selection of O-D pairs with sufficient trips to measure travel time variability.

Table 3.25. Trip TOD Choice, Seattle, RP, Variation of Time Coefficient with Distance

Variable	HB Work Tonlyw Coefficient (T-Stat)	HB Work Tonlywf Coefficient (T-Stat)	HB Other tonlyn Coefficient (T-Stat)	HB Other tonlynf Coefficient (T-Stat)
Auto in-vehicle time, min	-0.0158 (-5.4)	0.0136 (1.5)	-0.0195 (-4.5)	-0.0176 (-2.0)
Auto in-vehicle * O-D distance (min-mile)		-0.0012 (-2.5)		-0.00017 (-0.4)
Auto in-vehicle * O-D distance squared (min-mile-mile)		8.60 e-6 (1.3)		2.80 e-6 (0.8)
Observations	9876	9876	18958	18958
Final log-likelihood	-21230.8	-21220.9	-47963.3	-47962.5

Comparison and Synthesis: Seattle and New York

The previously discussed analysis with the New York data substantiated a seed functional form for an interactive term between auto time and distance for work trips. This form results in a parabolic function for VOT, where the maximum VOT is associated with commuting distance of about 30 miles, while for shorter and longer trips VOT is reduced. An attempt to replicate this effect with the Seattle data resulted in somewhat inconclusive functional forms, with the key coefficients being statistically insignificant. Part of the problem was that the Seattle data did not provide as long range set of travel distances as New York. Although the average commuting distance in the New York metropolitan region is relatively short (7.5 miles) the household survey of 11,000 households provided a significant number of observations of commuting distance beyond 30 miles. Thus, this particular model component needed further exploration and cross-regional comparisons in the mode and TOD choice frameworks, as discussed in Sections 3.4 and 3.5 below.

3.4 Mode and Car Occupancy Choice – Revealed Preference Framework

3.4.1 Overview of Section, Approach, and Main Findings

The models of mode & car occupancy choice represent the next tier of statistical analysis where the highway travel utility (generalized cost) is considered in the multi-modal context. All aspects described above for route choice are also relevant for mode choice as well, since the highway modes and route types represent alternatives in mode choice. However, because the choice framework is substantially extended to include transit modes, there are many more potential impacts, factors, and variables that come into play. Also, the mode choice framework naturally includes a much wider set of travelers, including transit users who may have very different perception of travel time, cost, and reliability. Additionally, the mode choice models estimated for New York used in this section are tour-based, which means that two-directional LOS variables are considered (for the corresponding outbound and inbound time-of-day periods). A tour framework is essential for analyzing mode preferences, since many mode constraints and relative advantages of different modes cannot be seen at the level of a single-trip..

A central research question at this stage is. whether the main findings regarding the functional form of highway travel utility from the route choice analysis described above. would hold in the more general framework of tour mode choice. In the subsections that follow, we apply the same approach as for the previously discussed route choice. Each major factor and associated impacts are analyzed on a one-at-a-time basis, by progressively incorporating all of them leading up to the final model structure. Each factor is statistically tested with the New York data and Seattle data, while trying to keep the model structures as close and compatible as possible. Each subsection concludes with a synthesis of main findings that proved to be common for both regions.

The following main findings regarding mode choice can be summarized with a special emphasis on the generic impacts that proved to be common for both New York and Seattle, as well as were similar to the route choice and mode choice frameworks:

- Both mode choice models have a rich set of explanatory variables, including LOS variables, as well as various person and household variables. The overall scale of time and cost coefficients (specifically for auto time that is in the focus of the current study) is reasonable. It should be taken into account that the LOS variables in a tour model should be approximately doubled when compared to a trip mode choice model. Thus, the corresponding coefficients for time and cost need to be halved for a trip mode choice model when compared directly to a tour mode choice model. This is the case for auto in-vehicle time, for example for work-relate travel, it is -0.014 for the New York tour mode model and -0.029 for the Seattle trip mode model. For work tours in New York and work trips in Seattle, the base model specifications showed a relatively low VOT for auto users of \$6/h-\$7/h. This value is not recommended for use in other models. However, we decided not to enforce a more reasonable VOT at this stage, but rather continue testing of more elaborate forms for generalized cost. For non-work travel, the VOT values are more reasonable although there was quite a significant difference between New York ($6/h) and Seattle ($11/h). This can be explained by the model specification differences.

- Segmentation of travel time by congestion levels brought very different results. With the New York data a statistically significant effect was confirmed and actually manifested itself in the mode choice framework much more strongly than in the route type choice framework. The congestion delay component of travel time proved to be weighted as 1.8-3.5 versus the free-flow time. A similar test with the Seattle data did not bring reasonable results. We may conclude that travel time segmentation by congestion levels works better in extremely congested areas, but is questionable for less congested regions.
- With respect to direct reliability measures, the most promising model estimated with the New York data is the model for non-work tours where a standard deviation of travel time per unit distance was used. The corresponding reliability ratio is about 1.5 at a 10-mile distance. The most promising models estimated with the Seattle data included a formulation with buffer time per unit distance for work and non-work trips, although a formulation with standard deviation of travel time per unit distance for non-work trips had the right sign for all LOS variables.
- The main common effects that relate to the impact of car ownership on mode choice can be summarized as follows. There is a common tendency for carpooling to be negatively correlated with car sufficiency. Bigger households (in terms of number of workers and in terms of overall size) with fewer cars are the most frequent carpoolers. For a sub-choice between transit modes, zero-car households are logically characterized by a strong propensity to use walk to transit rather than drive to transit access. The probability of walk to transit is highly affected by absence of cars in the household, or low car sufficiency. Households from these categories constitue the majority of transit users, many of them being transit captives since they either do not have cars at all, or have fewer cars than workers; hence, at least some of them become transit captives.
- Several different approaches to account for income were explored with both models, including scaling the cost variable by income (powered by a scaling parameter that should be between 0 and 1) and segmentation of the cost variable coefficient by income group. Although segmentation by income group resulted in many cases in better likelihood values, we believe that the income scaling version is more behaviorally appealing. With the New York model, a scaling parameter value of 0.8 was established for work tours and 0.6 for non-work tours, which is in line with the previously discussed findings for route type choice (0.6 and 0.5 respectively). The fact that the VOT elasticity with respect to income proved to be somewhat higher in the mode choice framework compared to route type choice framework can be explained. The mode choice framework includes transit users who in general have a lower VOT and income. The corresponding version of the Seattle model, with the coefficients values corresponding to the New York

route type choice model, justified the specification with all coefficients having the right sign and statistically significant.

- Several alternative specifications were tried with both the New York and Seattle data to capture the best cost sharing mechanisms for carpools statistically. They included cost scaling by the powered occupancy, as well as occupancy-specific cost coefficient. The scaling strategy prevailed in New York, while segmentation of the cost coefficient by occupancy was less successful. The scaling values of 0.8 for work tours and 0.7 for non-work tours were eventually adopted for New York, since that are in line with the route choice findings. The results for Seattle indicate that the cost sharing reflected in the Seattle RP data is perhaps less strong than in the New York data.
- With the New York dataset, a dummy variable that represents person status categorized by three major types (workers, adult non-worker, and child) proved to be statistically significant, and was included in the base model specification described above for non-work travel. A richer set of behavioral impacts with respect to person characteristics was found with the Seattle model specification, including some related effects of gender, age, and part-time worker status on VOT. In this regard, the New York model and Seattle model provide complementary examples of specifications that can be combined and hybridized in many ways.
- With the New York model, the shape of the distance-effect curves that is similar to the shape obtained for work trips in the route type choice framework was statistically confirmed in the more general mode choice framework. Depending on the highest order of polynomial function used in the model specification (squared or cubed), the inverted "U" effect can be less or more prominent, with a very small impact on the overall model fit. We can reiterate the explanation given above for the same effect in the route choice framework, that the lower VOT for long-distance commuters is a manifestation of restructuring the daily activity-travel pattern. We have obtained roughly the same shape for both HB Work and HB Other trip with the Seattle model, with VOT rising to a maximum at a distance of about 25 miles, and then decreasing, but the effect is much more pronounced for HB Other. For HB Other, the maximum VOT is about twice as high as the VOT for very short trips, while for HB Work, the maximum VOT is only about 20% higher than for very short trips.
- It is important to account for the main land-use and density effects in the mode choice framework to ensure a reasonable background for analysis of LOS impacts and to separate these effects from the pure effects of travel time, cost, and reliability. In the New York regional conditions, the primary effects were found by segmenting trips to and from Manhattan (strongly dominated by transit) and internal trips within Manhattan (dominated by transit, walk, and taxi). These effects were captured by stratified mode-specific constants without an impact on VOT. The Seattle data indicates a somewhat similar effect for trips to CBD.

3.4.2 Basic Specification, Segmentation, and Associated VOT

New York Model

An advanced tour-based mode choice model structure was adopted for the New York study. The same data source (New York Household Travel Survey, 1996) and the same method for generating synthetic travel time reliability measures was applied as was described above for the route type choice model. Each observation represents an entire tour that starts from home and ends at home with LOS variables (average time by components, cost, and travel time variability) calculated for both directions for the corresponding (actually observed) outbound and inbound departure hours. The actual (primary) destination of each tour and time of day were considered fixed at this stage. A more general choice framework that includes time-of-day choice as well will be described in the subsequent section. Travel time variability measures like STD were also calculated for the entire tour. Intermediate stops on the way to and from the primary destination were not considered at this stage.

When comparing the estimation results, in particular coefficients for time, cost, and reliability between the route type choice model and mode choice model it is important to bear in mind a general difference between trip-level and tour-level models. The values of such variables as travel time, cost, or standard deviation of travel time for tour are approximately as twice as greater than for trips. Thus, assuming that the same factors are captured in a consistent way, one can reasonably expect that the coefficients for these variables in a tour-level model like mode choice would be approximately equal to a half of the corresponding coefficients in a trip-level model like route type choice. This, however, should not affect VOT, VOR, and RR. When a measure of reliability like STD per mile is applied, it is directly comparable between tours and trips and is scaled automatically. With this measure of reliability, VOR and RR would be approximately as twice as higher for tour-level models comparing to trip-level models.

Overall, the New York Household Travel Survey included over 23,000 complete travel tours. Taking into account the focus of the study we considered only motorized tours and excluded fully non-motorized tours (where all trips were made by walk or bicycle). Further, we excluded tours for school purpose as well as at-work sub-tours (started and ended at the workplace) since they are characterized by a relatively short average distance and large share of non-motorized tours that makes these segments less relevant for the current study. The resultant tour dataset as divided into two major segments: 1) work and university commute tours (approximately 9,000 observations), and 2) non-work tours for various household maintenance and discretionary purposes (approximately 11,800 observations).

For both segments the same basic set of the following 13 modes and mode combinations was considered that are the most frequently observed in the New York Metropolitan Region:

- Single Occupancy Vehicle on Non-toll route (SOV-N)
- Single Occupancy vehicle on Toll route (SOV-T)
- High Occupancy Vehicle with 2 persons on Non-toll route (HOV2-N)

- High Occupancy Vehicle with 2 persons on Toll route (HOV2-T)
- High Occupancy Vehicle with 3 persons on Non-toll route (HOV3-N)
- High Occupancy Vehicle with 3 persons on Toll route (HOV3-T)
- High Occupancy Vehicle with 4 persons on Non-toll route (HOV4-N)
- High Occupancy Vehicle with 4 persons on Toll route (HOV4-T)
- Commuter Rail with Walk access and any additional transit modes (WCR)
- Commuter Rail with Drive access and any additional transit modes (DCR)
- Other Transit (bus, subway, ferry) with Walk access (WT)
- Other Transit (bus, subway, ferry) with Drive access (DT)
- Taxi cab (TX)

With this set of alternatives, the mode choice model incorporates also car occupancy choice and route type choice discussed above. This makes this structure fully compatible with the route-type choice in a sense that any finding or component of the highway utility function (generalized cost) tested in the route-choice framework can be tested again in the extended mode choice framework. Car occupancy in the mode choice framework becomes a dimension for structuring alternatives in explicit choice rather than an explanatory variable as it was in the route type choice framework.

Since the specified modes have a differential degree of similarity and can be grouped together in several ways, the corresponding hierarchical nested structures were tested during the model estimation. The following general three-level nested structure was identified as a starting point – see Figure 3.13. From this general structure, particular nested structures were derived by skipping some of the levels (either 1 or 2). This way, car occupancy and route type choice played a role of lower levels for mode choice. Highway LOS variables were skimmed separately by occupancy and route type (toll vs. non-toll). The existing highway network in the New York Metropolitan Region provides a rich dataset of LOS variables with a significant number of toll facilities and HOV facilities with distinctive time, cost, and reliability measures.

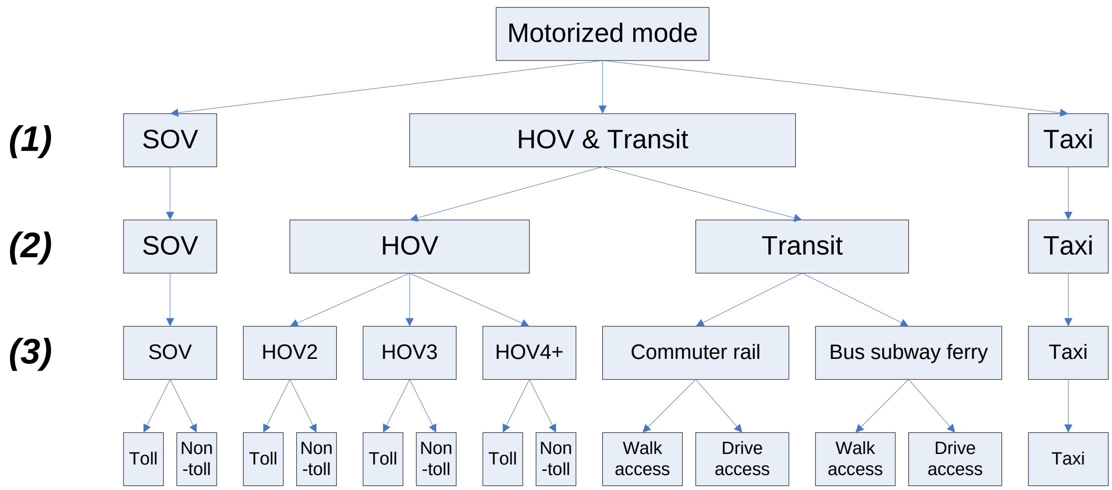


Figure 3.13. General nested structure of motorized mode choice for New York.

The following main explanatory variables were statistically tested for both segments (work and non-work):

- Travel time (min) subdivided into:
- In-vehicle time (IVT) for highway and transit modes subdivided for highway modes into:
- Free-flow time (IVTF)
- Congestion delay (IVTD)
- Out-of-vehicle time (OVT) subdivided into:
- Wait time (WAIT)
- Walk time (WALK)
- Drive-to-transit access time (DACC)
- Travel cost (COST) including parking cost and transit fare (cents)
- Highway distance (DIST) from the origin to destination (miles)
- Various distance effects on travel time and/or cost captured through interaction variables:
- $IVT\times DIST$, $IVT\times DIST^2$, $IVT\times DIST^3$
- $COST\times DIST$, $COST\times DIST^2$, $COST\times DIST^3$
- Travel time variability measures:
- Standard deviation (STD)
- Standard deviation per mile (STD/M)
- Difference between the 80^{th} or 90^{th} percentile of travel time distribution and median (80%/90%-50%)
- Toll bias (TOLLB) that is an additional constant that differentiates between toll and non-toll alternatives for the same occupancy category.
- Household relative auto-sufficiency dummies (0,1):
- No autos (A=0)

- Autos fewer than workers (A<W), assuming at least 1 auto
- Autos equal to workers (A=W), assuming at least 1 auto
- Autos more than workers (A>W)
- Household income group dummies (0,1):
- Low income (LOW) corresponding to 15% of households with lowest income
- High income (HIGH) corresponding to 15% of households with highest income
- Medium income (MED) corresponding to 70% of the other households
- Person type (applied for non-work tours only):
- Dummy for worker status (WORK)
- Dummy for non-worker staus (NWRK)
- Household composition and daily activity pattern details:
- Dummy for 2 or more adults with a non-work tour for maintenance purpose like shopping, banking, escorting, or visiting doctor (2*AD/M)
- Dummy for at least one adults and one child with a non-work tour for mintenance purpose (A+KID/M)
- Dummy for 2 or more adults with a non-work tour for discretionary purpose like recreation, entertainment, visiting relatives and friends, or eating out (2*AD/D)
- Dummy for at least one adults and one child with a non-work tour for discretionary purpose (A+KID/D)
- Dummies for location of tour origin and destination:
- Both origin and estination in Manhattan (INMANH)
- One tour end in Manhattan but the otherone is outside Manhattan (TOMANH)
- Informal parking lot (no organized parking at the station) dummy (INFL)

In the process of statistical analysis and model estimation many transformations have been applied to some particular variables. They are discussed below in the context of corresponding model segment.

The applied utility expressions for auto and non-auto can be written in the following general way that preserves consistency with the route type choice model described above:

$$U(i,t) = L(i,t) + S(i) + Z(i) + \Delta(i,t) \tag{3.42}$$

$$U(j) = L(j) + S(j) + Z(i) \tag{3.43}$$

where:

i	=	main highway modes before split between toll and non-toll route type,
$t = 1,2$	=	toll and non-toll route type dichotomy applied for highway modes,

j = non-auto modes (transit and taxi),

$L(i,t)$ = utility component that incorporates LOS variables for highway modes,

$L(j)$ = utility component that incorporates LOS variables for transit modes and taxi,

$S(i)$ = utility component that incorporates socio-economic variables,

$Z(i)$ = utility component that incorporates zonal location-specific variables,

$\Delta(i)$ = toll bias for highway sub-modes with toll route.

The utility component that incorporates LOS variables for highway mode is specified in the same way as for the route type choice model discussed above. In the base formulation discussed in the current sub-section it is a linear combination of average travel time and cost specific to toll and non-toll routed for each car occupancy category (Equation 3.29). In the subsequent sub-sections hi component will be explored through more advanced specifications and effects reflected in Equation 3.30 through Equation 3.39. In most specifications, the coefficients are generic across route types; thus the difference between toll and non-toll highway modes is due to LOS variables (average time, cost, reliability, distance, and interaction terms between them) as well as because of the toll bias.

The utility component for transit modes and taxi is specified once as a linear combination of travel time variables (in-vehicle time, wait time, walk time, auto access time, and transfer time) and cost (fare) variables. It is kept constant through the subsequent statistical analysis as discussed below.

Utility components that incorporate socio-economic household and person constants have the same additive form for all modes. The dummy variables (by which the constants are multiplied before summation) are sometimes specified as interactions (for example by household car-sufficiency & income group combinations).

Utility components that incorporate zonal (origin and/or destination) characteristics also have the same additive from fro all modes. In the current research these variables are limited to three main spatial markets: 1) tours with both origin and destination in Manhattan, 2) tours with one destination (either origin or destination) in Manhattan while the second one is outside Manhattan, and 3) tours with both origin and destination outside Manhattan. As explained below, Manhattan is characterized by unique travel conditions that have a crucial impact on mode choice.

The toll bias for highway sub-modes using a toll route is specified exactly in the same way as in the route type choice framework.

Some of the modes have a limited availability for particular population segments. The following general availability rules were assumed in the model estimation and application:

- SOV is not available for households without autos (A=0) as well as for children under 16
- Walk to transit modes (WCR, WT) are not available if the origin sub-zone has no walk access to transit
- All transit modes (WCR, DCR, WT, DT) are not available if the destination sub-zone has no walk access to transit
- Any particular transit mode (WCR, DCR, WT, DT) is not available if the corresponding transit path cannot be built in the network (skimmed in-vehicle time is equal to 0). For WCR and DCR modes, positive in-vehicle time for commuter rail was used as the criterion for mode availability. For WT and DT modes, total in-vehicle time for bus, subway, and ferry was used as the criterion for mode availability.

Application of these availability rules is based on the segmentation of the persons in each household into three types (children under 16 years, workers, and non-working adults) as well as geographical segmentation of each traffic zone into transit-accessible and transit-not-accessible parts. In the model estimation and application, each tour is associated with the household, person making the tour, and origin & destination sub-zones.

In addition to the model coefficients, the following most important statistics are shown for each model segment:

- Number of observation in the estimation file (NOBS); each observation corresponds to a tour that includes a pair of directional journeys (half-tours) – outbound and inbound,
- Final value of the log-likelihood (LL),
- Rho-squared with respect to 0 utilities (RHO).

Also, the following important relative characteristics are derived from the model coefficients and shown for each model segment:

- Value of Time (VOT) in $ per hour,
- Value of Reliability (VOR) in & per hour,
- Reliability Ratio (RR) that is equal to VOR/VOT,
- Out of vehicle time weight relative to in-vehicle time for various out-of-vehicle time components

In both model segments, HOV2 serves as the reference utility with all constants equal to zero. It was more convenient to choose HOV2 as the reference mode rather than SOV because HOV2 is an available alternative for all travelers while SOV has certain availability constraints.

Thus, all other modes' coefficients express relative attractiveness of the corresponding mode comparing to HOV2.

The adopted model structure and estimated coefficients for the base mode choice model for Work tours are presented in Table 3.26. This model includes only simple linear travel time and cost variables without travel time reliability measures. It serves as the basic structure with a certain configuration of constants and socio-economic variables from which the subsequent more elaborate structures were pivoted off. A robust basic structure had to be established first for a mode choice model of this level complexity since it is impossible to explore all possible model specifications across socio-economic and LOS variables at the same time. The subsequent analysis was focused on elaborating time, cost, and incorporation of travel time reliability variables while the configuration of most socio-economic variables and constants was kept the same. The reported coefficients are not scaled by the nesting coefficients. Thus, in order to compare the LOS coefficients to the previously estimated route type choice model, they have to be divided by the product of all nesting coefficients (and additionally they have to be doubled to scale for round tours when compared to on-directional trips).

Basic in-vehicle time and cost coefficients are generic across all modes. They lie in a reasonable range similar to most of the tour mode choice model estimated elsewhere (expected to be as twice as small compared to a typical trip mode choice model due to the round-trip variables). The VOT of $5.7 per hour resulting from these coefficients is quite low compared to average VOT for journeys to work adopted in most regions in US. It should be noted that the VOT for work tours obtained in the mode choice framework is systematically lower than the VOT obtained for work trips in the route type choice framework discussed above for the New York Region. This can be explained by the extension of the population from auto users to all-mode users. Seemingly, a better consistency could have been obtained by specifying mode-specific time and cost coefficients (and consequently VOT). However, the attempts to do that with the current dataset did not bring consistent results. It should also be noted that making the coefficients mode-specific but estimating the entire model on the pooled dataset that includes both auto and transit users is not equivalent to estimating a route choice type model on a truncated dataset that includes auto users only.

Table 3.26. Base Mode Choice Model for Work Tours

Variable	Mode								
	SOV	HOV2	HOV3	HOV4+	WCR	DCR	WT	DT	TX
IVT	-0.0137 (-14.49)								
COST	-0.1430 (-11.04)								
WAIT					-0.0273				
WALK					-0.0205				
DIST					0.0246 (7.78)				
DACC						-0.0137		-0.0137	
LOW/A=0	-99.000		-1.8615 (-4.71)	-1.8615 (-4.71)	4.2733 (5.22)	1.1342 (1.86)	3.3836 (13.79)	-0.7285 (-0.95)	
LOW/A<W	1.1691 (9.07)		-1.8636 (-19.5)	-1.8636 (-19.5)	1.000	-0.4006 (-0.58)	1.2326 (4.46)	-1.9651 (-1.86)	-2.8413 (-6.82)
LOW/A=W	2.2874 (8.56)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.500	-0.4006 (-0.58)	1.2326 (4.46)	-1.9041 (-2.49)	-2.8413 (-6.82)
LOW/A>W	3.473 (12.85)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.200	-0.4006 (-0.58)	0.226	-1.9041 (-2.49)	-3.5327 (-3.41)
MED/A=0	-99.000		-1.8615 (-4.71)	-1.8615 (-4.71)	3.6156 (6.55)	1.1342 (1.86)	3.3836 (13.79)	0.6662 (1.69)	
MED/A<W	1.1691 (9.07)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.9849 (2.36)	-0.474 (-1.36)	1.0406 (5.95)	-1.4405 (-4.51)	-2.8413 (-6.82)
MED/A=W	2.9424 (13.45)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.2602 (0.74)	-0.0933 (-0.42)	0.5651 (3.39)	-1.189 (-4.69)	-2.8413 (-6.82)
MED/A>W	3.473 (12.85)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.2111 (0.53)	-0.0933 (-0.42)	0.2255 (0.92)	-1.189 (-4.69)	-3.5327 (-3.41)
HIGH/A=0	-99.000		-1.8615 (-4.71)	-1.8615 (-4.71)	3.6156 (6.55)	-0.8869 (0)	2.7555 (6.59)	-1.2457 (-1.12)	
HIGH/A<W	1.5222 (5.74)		-1.8636 (-19.5)	-1.8636 (-19.5)	-0.242 (-0.38)	-0.474 (-1.36)	0.226 (0.74)	-1.9348 (-4.05)	-1.2585 (-2.57)
HIGH/A=W	2.9424 (13.45)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.1473 (0.33)	-0.0933 (-0.42)	-0.3018 (-1.17)	-1.4612 (-4.65)	-1.9768 (-3.75)
HIGHA>W	3.473 (12.85)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.2111 (0.53)	-0.0933 (-0.42)	-0.4984 (-1.45)	-1.4612 (-4.65)	-2.8286 (-2.73)
INMANH		0.9193 (1.51)	1.3951 (1.93)	1.3951 (1.93)			4.4057 (8.98)	2.9063 (4.73)	5.3596 (10.52)
TOMANH		0.4541 (1.65)	-0.0825 (-0.22)	-0.0825 (-0.22)	2.7025 (7.24)	2.8895 (9.29)	2.2939 (9.16)	2.8924 (9.08)	2.42 (4.34)
TOLLB	-0.3608 (-4.56)	-0.5971 (-4.59)	-0.7049 (-3.52)	-0.7049 (-3.52)					
NEST 1	0.8081								
NEST 3	0.9000								
NOBS	9002								
LL	-6901.3								
RHO	0.6051								
VOT	5.7								
WAIT/IVT	2								
WALK/IVT	1.5								
DACC/IVT	1								

Coefficients for out-of-vehicle time components and the corresponding weights relative to the in-vehicle time coefficient proved to be highly differential by modes. The extremely high weight for waiting time for taxi results from the synthetic specification of the taxi wait time. It was set to 2 min in Manhattan and 10 min elsewhere. It should be noted that the actual observed share of taxi in Manhattan is 7.7% while outside Manhattan it is less than 1%.

Unfortunately, in the framework of current research, only highway travel time reliability measures were generated and explored. Generation of transit reliability measures represents a complicated issue and requires a significant additional effort [*ITS, 2008; Li et al, 2010, Bates et al, 2002*]. Thus, the differential travel time reliability of transit modes was captured implicitly.

Transit wait and walk time coefficients were estimated as generic but even with this simplification, the estimation yielded either illogical or unstable values. Eventually, these coefficients as well as coefficient for drive access to transit were forced to be equal to the basic in-vehicle time coefficient with a specified weight (2.0 for wait, 1.5 for walk, and 1.0 for drive access).

Very interesting and strong behavioral phenomenon was captured by introducing a distance term into the utility of commuter-rail-based modes (WCR, DCR). It has a positive coefficient of 0.0246 that means that all else being equal each additional 10 miles of the journey distance would add approximately 20% to the relative share of commuter rail in the modal split. This term plays a role of an additional distance-based rail bias that favors commuter rail especially for long-distance commute since this mode offers additional convenience for long-trip makers.

The size of the sample for this purpose allowed for direct estimation of all 12 pair-wise combinations of the 4 auto-sufficiency categories by 3 income groups for all modes. Explicit considering of 12 pair-wise combinations rather than two sets of dummies linearly included into the utility function, is preferable since the impacts of income and car-ownership can be non-linearly combined. In particular, there is quite a unique group of high-income households residing in Manhattan that do not own cars. Travel behavior of such a group cannot be linearly combined from independent income and car-ownership variables.

The following main behavioral impacts were captured by the set of income and car-sufficiency constants:

- Lower income is logically associated with generally more frequent use of the shared ride and regular transit modes (bus, subway, ferry) while significantly less frequent use of taxi; also differences across car-sufficiency groups with respect to transit use are sharper for low incomes comparing to medium and high incomes. Higher propensity of low-income workers to HOV is an important feature that is frequently overlooked in analysis of congestion and pricing impacts. In general, it is more convenient for lower-income workers to carpool compared to higher-income workers because of the more regular (or fixed) work schedules as well as by virtue of clustering their residential and job locations in urbanized areas. This should be an important consideration in equity analysis that would mitigate to a certain extent, negative impacts of pricing on low-income population.
- Higher car-sufficiency is strongly associated with a lower propensity for shared ride and transit modes.
- Taxi has the highest bias constants for high and medium income groups in combination with the lowest car-sufficiency (no cars). For low income group as well as for higher car-sufficiency groups, taxi is very infrequent as the mode for journey to work.

The Manhattan-related dummies proved to be very strong variables. Travel conditions in Manhattan are unique in many respects. In particular, Manhattan is characterized by an extremely developed transit system, high level of congestion & driving inconvenience, very high parking cost & significant parking search time, as well as enhanced walkability compared to the rest of the New York region. Thus, this set of strong constants for Manhattan is necessary to replicate properly the observed shares of travel modes within and to/from Manhattan (where SOV constitutes less than 15%) comparing to the rest of the New York metropolitan region (where drive alone constitutes more than 70%). The model estimation results logically showed very strong positive constants for HOV, WT, and taxi for work tours within Manhattan and very strong positive constants for DT and DCR for tours to and from Manhattan. Specifically, tours with origin outside Manhattan and destination in Manhattan represent the most important travel segment of commuters.

Another interesting result is that the negative toll bias that was previously estimated for the route type choice model persisted in the more general mode choice framework. As was discussed above, this bias represents a general negative attitude towards tolls (or, stated otherwise, a subconscious search for non-toll route options) beyond time and cost trade-offs expressed in the VOT.

The adopted nested structure has two levels (level 1 and level 3 shown in Figure 3.13 above) corresponding to the following behavioral interpretation. At the upper level with a stronger nesting coefficient of 0.81, a traveler for work purpose considers three principal options – SOV, HOV or transit, and taxi. Since the principal choice has been made, a traveler consider lower level options for shared ride and transit with a weaker nesting coefficient of 0.90 for toll vs. non-toll route types, commuter rail access sub-modes (WCR, DCR), and transit access sub-modes (WT, DT). An interesting behavioral interpretation arises from this structure. Different from the majority of nested structures of mode choice estimated elsewhere where SOV and HOV are normally nested together, in the highly-urbanized conditions of New York travelers consider driving alone as a unique option while they may more frequently trade shared ride and transit for each other. Several attributes of HOV for work commute (dependence on the other persons' schedule, need to compromise the shortest path in order to collect and distribute all passengers) make it actually closer to transit than to driving alone.

The adopted base model structure and estimated coefficients for the mode choice model for Non-work tours are presented in Table 3.27. Again, as in the case of work tours discussed previously, the reported coefficients are not scaled by the nesting coefficients. Thus, in order to compare the LOS coefficients to the previously estimated route type choice model, they have to be divided by the product of all nesting coefficients (and additionally they have to be doubled to scale for round tours when compared to on-directional trips).

Non-work tours represent the biggest segment with 11,800 motorized journeys observed in the survey. However, non-work tours are characterized by a variety of travel purposes (including such maintenance activities as shopping, visiting doctor, or banking, and such discretionary activities as recreational, visiting, or eating out) and different traveler types (workers, non-working adults, and children). This internal heterogeneity in combination with a short average distance and comparatively low share of transit modes made the estimation of the model difficult and required several aggregations of coefficients in order to obtain stable estimates.

It proved to be impossible to estimate each of the components of out-of-vehicle time (wait and walk) separately and they were aggregated. Even after aggregation, the estimates for out-of vehicle time proved to be unstable and they were linked to the in-vehicle time in the final adopted structure in order to ensure predetermined relative weights – 2.00 for wait time for transit modes, 3.00 for walk time, and 1.00 for drive access time for the drive-to-transit modes (DCR, DT). The different target values for out-of-vehicle time weights comparing to the previously discussed model for work tours were chosen based on the preliminary estimation results by various partial segments.

Table 3.27. Base Mode Choice Model for Non-Work Tours

Variable	Mode								
	SOV	HOV2	HOV3	HOV4+	WCR	DCR	WT	DT	TX
IVT	-0.0126 (-12.1)								
COST	-0.1254 (-13.7)								
WAIT					-0.0252				
WALK					-0.0378				
DIST					0.0031 (0.3)				
DACC						-0.0126		-0.0126	
INFL							-2.3049 (-6.05)		
A=0	-99.000		-0.6439 (-3.02)	-0.9654 (-4.1)			2.6516 (9.2)		-0.3504 (-0.77)
A<W	-3.2917 (-12)		-0.9436 (-10.33)	-1.4278 (-7.8)			0.7312 (2.37)		-2.6286 (-4.92)
A=W	-3.0727 (-12.06)		-0.9436 (-10.33)	-1.5435 (-14.47)	-0.0957 (-0.1)		-0.0131 (-0.05)		-3.7659 (-7.67)
A>W	-2.5385 (-10.01)		-0.9436 (-10.33)	-1.5435 (-14.47)	-0.0957 (-0.1)		-0.5977 (-2.08)		-4.7089 (-8.4)
LOW					1.1294 (0.96)	-0.1097 (-0.09)	0.8313 (4.64)		
MED									
HIGH			-0.1531 (-2.26)	-0.1531 (-2.26)	-1.3347 (-1.25)		-0.1964 (-0.97)	-1.0664 (-2.23)	
WORK	4.5689 (17.99)		-0.9101 (-9.89)	-1.1654 (-10.95)	-3.1193 (-2.46)	-2.909 (-3.59)	-0.8426 (-3.51)		-0.5841 (-1.4)
NWRK	4.1014 (16.1)		-0.897 (-9.31)	-1.1462 (-10.3)	-2.7791 (-2.18)	-2.2003 (-2.71)	0.2574 (1.12)		-0.2771 (-0.65)
2*AD/M	-0.923 (-14.86)		-0.3579 (-4.53)	-0.1955 (-2.14)	-0.2565 (-0.25)	-2.0466 (-2.53)	-1.4608 (-8.69)	-1.9109 (-6.06)	-0.8555 (-2.8)
A+KID/M	-1.2539 (-14.83)		1.2425 (15.42)	1.4205 (14.94)	-3.6649 (-2.2)	-2.5814 (-2.04)	0.0879 (0.43)	-2.0746 (-2.8)	0.7137 (1.92)
2*AD/D	-0.7784 (-9.06)			0.3967 (3.28)	0.0447 (0.03)	-1.6563 (-1.33)	-0.6754 (-2.49)	-1.0319 (-1.83)	-0.6183 (-1.1)
A+KID/D	-0.8913 (-6.85)		0.8477 (8.82)	0.9303 (8.39)			0.1072 (0.36)	-1.7514 (-1.64)	-2.5341 (-1.98)
INMANH		0.6151 (1.77)	0.6974 (1.63)	0.6974 (1.63)			3.7489 (11.12)	2.8039 (3.74)	5.7546 (13.81)
TOMANH		-0.3384 (-1.29)	-0.3384 (-1.29)	-0.3384 (-1.29)	5.7035 (5.47)	4.6183 (5.5)	1.4746 (5.7)	1.1895 (3.57)	3.6764 (7.77)
TOLLB	-0.6495 (-5.01)	-0.5367 (-5.08)	-0.8494 (-6.51)	-0.8494 (-6.51)					

NEST 2	0.9000
NEST 3	0.9000
NOBS	11,800
LL	-12957.1
RHO	0.3967
VOT	6.0
WAIT/IVT	2.0
WALK/IVT	3.0
DIVT/IVT	1.0

Basic in-vehicle time and cost coefficients are generic across all modes. They lay basically in a reasonable range, but are somewhat lower than in the most of the models estimated elsewhere for non-work purposes. The VOT of $6.0 per hour resulting from these coefficients is also reasonable but somewhat lower than the VOT estimates for route type choice. One of the reasons that can explain the low VOT and low absolute values of the time and cost coefficients is that the average distance for non-work tours is comparatively short (less than 4 miles) and for short travel time and cost variables do not have enough variability and trade-offs to provide stable estimates.

Socio-economic constants for household car-sufficiency (4 categories) and income (3 groups) were set separately for this segment rather than in a multiplicative way that resulted in 12 combined categories for work tours described above. The following main behavioral impacts were captured by the set of household car-sufficiency and income constants:

- Higher car-sufficiency works logically in favor of SOV, while reducing propensity to use shared ride, walk-to-transit modes (WCR, WT) and taxi.
- Higher income is associated with a clear propensity to drive alone at the expense of shared ride, walk-to-transit sub-modes (WCR, WT), and drive to regular transit (DT). Interestingly, two modes – DCR and taxi proved to be practically insensitive to income.
- In general, car-sufficiency variables proved to be more important than income variables for most of the modes in relative terms. This can be interpreted as a relative uniformity of non-work activities across different income groups and the ways that travel modes are considered for this purpose.

Household maintenance errands and discretionary activities can be implemented by all three person types – workers, non-working adults, and children under 16 years of age. Person type of the traveler is important in the mode choice context because workers have a higher priority in using household cars comparing to non-workers, while children cannot drive alone at all. Person type dummies WORK and NWRK were included into the model while child served as the reference case. In a logical way, the corresponding coefficients showed a significantly higher propensity of workers and (to a smaller extent) non-working adults to use SOV at the expense of shared ride and most of the transit modes.

Maintenance and discretionary tours are characterized by a high percentage of joint travel (30-50% depending on the detailed trip purpose) that is expressed in a generally high share of HOV. In the mode choice context, it proved to be useful to introduce variables that indicate on maintenance or discretionary activities of several household members since these activities are frequently implemented jointly and mostly by the HOV modes. Two variables were added to the model for each activity type – a dummy that is equal to 1 if at least 2 adults from the household have maintenance tours (2*AD/M) or discretionary tours (2*AD/D); and dummy that is equal to 1 if at least one adult and one child from the household have maintenance tours (A+KID/M) or discretionary tours (A+KID/D). In a logical way, these indicators worked in favor of shared ride modes at the expense of SOV and most of the transit modes (A+KID/M is especially strong that includes escorting a child to doctor; hence taxi is also frequent for this case).

As in the previously discussed segment for work tours, the Manhattan-related dummies proved to be extremely strong variables. For internal travel within Manhattan, SOV is strongly suppressed while commuter rail is not available because of the single station (terminal) for each line in Manhattan. Taxi is strongly favored followed by transit sub-modes (WT and DT). For journeys to and from Manhattan, logically the commuter rail sub-modes WCR and DCR are strongly favored followed by transit sub-modes (WT and DT) and taxi. It essentially means that in most cases, when transit or (especially) commuter rail is available, travelers would not use auto modes (drive alone or shared ride) for maintenance or discretionary tours to Manhattan.

In a similar way to mode choice for work tours and route type choice models discussed above, strong negative toll biases were estimated for all highway sub-modes (car occupancy categories). This confirms the presence of general toll-averse attitude as was discussed above in the section on route type choice.

The adopted nested structure for non-work tours is slightly different from the nested structure for work tours described above. It includes levels 2 and 3 shown in Figure 3.18. The upper level corresponds to the combination of all three shared ride modes in one nest and all four transit modes in the other nest, while SOV and taxi proved to be unique modes. At the next level, occupancy for HOV and main transit mode (commuter rail versus the others) are modeled. Finally, the elemental mode alternatives include details of route type choice (toll vs. non-toll) and transit access sub-modes (walk vs. drive). The nesting coefficients are specified as generic across nests and not extremely strong – 0.9000. In the process of model estimation, these coefficients were unstable and taking different values between 0.8 and 1.2 depending on the model specification details. Thus, the whole structure is actually close to a simple multinomial logit model that indicates that most of the travelers for maintenance purposes consider all available modes as equally substitutable. In order to make the subsequent model estimation results comparable across different configurations of LOS variables and also in order to focus on the highway utility (generalized cost) function the values for both nesting coefficients were fixed.

Having these mode choice models as the starting point, we further explored various aspects of the highway utility in the same order as it was done before for route type choice. In this research, the entire model was re-estimated each time when the highway utility specification (with respect to time, cost, or reliability measures) had been changed. However, no additional analysis and exploration of the other variables such as socio-economic constants or transit time components was undertaken. In fact, these coefficients proved to be quite stable across the subsequent model estimation runs. Thus, only the relevant model components (i.e., relevant LOS variables) are reported for this focused analysis while the entire model estimation results for each run can be found in Appendices. Additionally, the parameters that were fixed (like out-of-vehicle transit time components and nesting coefficients) remained fixed at the same level across all subsequent runs.

Seattle Model

The Seattle 2006 Household survey RP data was used to estimate models of mode choice. This same data source was also used to estimate the time of day (TOD) choice models reported in the previous sections. In contrast to the TOD choice models, the mode choice models from this data allow the estimation of a cost coefficient, even with no tolling in the Puget Sound region. In this case, the travel costs are fare for the transit modes, and parking and operating costs for the auto modes. The transit fare is from TAZ-TAZ fare skim matrices provided by PSRC. The parking cost information is based on zonal averages and does not take account of employer parking subsidies or provision, and the auto operating cost is based solely on TAZ-TAZ auto distance skims. As the focus was not on transit in this project, no account was taken of transit pass ownership or age-related fare discounts, and the choice between different transit sub-modes such as local bus, premium/express bus, and commuter rail, was made in the transit assignment stage and not in the mode choice model itself. Walk access time to transit is also from the TAZ-TAZ transit skims. Note that the most recent PSRC regional model improvements address these possible inaccuracies—by including explicit models of transit sub-mode choice, transit pass ownership and employer parking subsidies, and by basing parking costs, driving distances, and transit walk access times on parcel-level location information. Those improvements are still rather rare, however, even among activity-based models, so the mode choice models presented here are nevertheless representative of advanced practice.

There are six different mode types distinguished as alternatives in the mode choice models:

1. SOV – Auto drive alone.
2. HOV2 – Auto drive with one passenger
3. HOV3+ - Auto drive with two or more passengers
4. Drive-Transit – Transit with auto access
5. Walk-Transit – Transit with non-auto (walk or bike) access
6. Non-motorized – Walk or bike

Auto occupancy is a key focus of this research, and thus the choice alternatives distinguish three different levels of occupancy. The PSRC regional models distinguish bicycle and walk as separate modes, but, as non-motorized travel is not a focus of this project, we have grouped them as a single alternative.

The SOV alternative is available only to persons of age 16+ in a household which owns one or more vehicles. The Drive-Transit and Walk-Transit alternatives are available only when a valid path is included in the transit skim matrices for the trip O-D, and Drive-Transit is only available for households owning one or more vehicles. The Non-motorized alternative is available only for trips with distance less than 15 miles. Otherwise, all alternatives are modeled as available.

The mode choice models were estimated conditional upon time of day (TOD) choice, so all levels of service are based on the actual time at the home end of the trip. Separate transit skim matrices were provided by PSRC for the AM peak and Midday periods, with the PM peak level of service specified to be the same as the AM peak level of service for the same O-D pair in the opposite direction. The Evening period transit level of service was assumed to be the same as for the Midday period, and transit was assumed to be unavailable in the Night period (11 PM to 5 AM). For auto, travel time and distance skims were available from PSRC for either 5 different periods or 17 different periods, as described in the earlier sections for the TOD models. Unless noted otherwise, the skims for 5 different periods were used for the models reported below.

Finally, before going into the detailed estimation results, we will describe the mode nesting structure adopted for all of the models reported here. After exploratory analysis, one nesting structure gave the best results. This includes the 4 auto-related modes (SOV, HOV2, HOV3+ and Drive-Transit) in a single auto nest, and the other two modes (Walk-Transit and Non-motorized) each in their own separate "nest" of a single alternative. For the HB Work models, the logsum coefficient is generally in the range 0.5-0.6, and for the HB Other models, the coefficient is generally in the range 0.6-0.7, always significantly lower than 1.0. (The exact logsum coefficients, along with the other estimated coefficients, can be found in the appendices.) The models contained the following types of variables:

- Level of service variables related to time, cost and distance
- Mode alternative-specific constants
- Mode preference variables related to household, person and trip characteristics

In the tables in this section, we only report the estimates for the level of service variables, although the results for the mode preference variables are discussed as well in the appropriate sections. Table 3.28 contains the results for the basic specification for HB Work and HB Other models. (HB Other includes home-based trips for the purposes shopping, personal business, eating at a restaurant, social, and recreation.) For each of the two purposes, models were estimated using auto skim matrices for 5 periods (AM peak, Midday, PM peak, Evening and Night) and using 17 different skim periods (one for each hour from 5 AM to 8 PM, plus one for 8-11 PM and one for 11 PM-5 AM).

Table 3.28. Trip Mode Choice, Seattle, RP, Basic Specification

Variable	HB Work – 5 skim per.	HB Work – 17 skim per.	HB Other - 5 skim per.	HB Other - 17 skim per.
	monlyw04	monlyw04x	monlyn04	routodn01e
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Travel cost, $	-0.300 (-14.9)	-0.294 (-14.6)	-0.181 (-4.5)	-0.186 (-4.6)
Auto in-vehicle time, min	-0.0339 (-8.9)	-0.0366 (-10.4)	-0.0372 (-4.3)	-0.0339 (-4.0)
Transit in-vehicle time, min	-0.0088 (-1.6)	-0.122 (-2.2)	-0.0044 (-0.3)	-0.0013 (-0.1)
Transit walk access time, min	-0.0713 (-9.4)	-0.0713 (-9.5)	-0.0688 (-5.1)	-0.0690 (-5.0)
Transit wait time, min	-0.0530 (-6.1)	-0.0553 (-6.3)	-0.104 (-4.1)	-0.105 (-4.0)
Transit number of transfers	-0.885 (-5.3)	-0.838 (-5.1)	-0.841 (-2.2)	-0.873 (-2.3)
Non-motorized distance, miles	-0.888 (-11.1)	-0.886 (-11.2)	-1.52 (-7.2)	-1.52 (-7.0)
VOT for auto in-vehicle time, $/hr	6.8	7.5	12.3	10.9
VOT for transit in-vehicle time, $/hr	1.8	2.5	1.5	0.4
VOT for transit walk acc. time, $/hr	14.3	14.6	22.8	22.3
VOT for transit waiting time, $/hr	10.6	11.3	34.5	33.9
Observations	11,798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.583	0.584	0.382	0.382
Final log-likelihood	-8192.6	-8178.2	-20416.7	-20418.0

All of the level-of-service variables for all modes in Table 3.28 have the expected negative sign, and all except transit in-vehicle time are strongly significant. This result in itself is quite an atypical success for RP data from household travel surveys—typically several coefficients need to be constrained at reasonable variables.

The estimated VOT for auto in-vehicle time is somewhat higher for HB Other than for HB Work, the same as was found from the Traffic Choices data. This result is not typical, and will be discussed further in later sections, after more different model specifications are investigated.

The transit LOS variables have significant estimates with reasonable variables, except that the transit in-vehicle time coefficient is quite low. In practice, auto and transit in-vehicle time are often constrained to have the same coefficient. The empirical evidence however, here and in many other data sets, typically shows transit in-vehicle time coefficient estimates that are less negative than for auto in-vehicle time, while transit out-of-vehicle time coefficients are more negative than for auto in-vehicle time. As the focus of this study is not on transit, we have not done further specification searches for transit LOS variables. In cases like this, however, we might recommend constraining the transit in-vehicle and out-of-vehicle time components to have the same ratios as used in transit path building (typically ratios of 2.0-2.5 for out-of-vehicle versus in-vehicle time), and using a composite, generalized transit time variable in estimation.

In contrast to the TOD choice models presented earlier, using 17 different skim periods instead of 5 to provide more information about variations in auto travel time across the day improves the models slightly for HB Work trips (although not for HB Other trips). The improvement is most notable in the estimates for auto and transit in-vehicle times for HB Work. However, as noted earlier, using 17 skim periods provides poorer estimates for auto in-vehicle time for TOD choice models. To facilitate comparison to joint TOD and mode choice models presented in later sections, all subsequent mode choice models reported below were estimated using skims from just 5 periods of the day.

Comparison and Synthesis: Seattle and New York

Both mode choice models have a rich set of explanatory variables including LOS variables, as well as various person and household variables. This provides a reasonable background for the further tests with different functional forms for the generalized cost. The overall scale of time and cost coefficients (specifically for auto time that is in the focus of the current study) is reasonable. It must be taken into account that the LOS variables in a tour model should be approximately doubled when compared to a trip mode choice model. Thus, the corresponding coefficients for time and cost should be halved for a trip mode choice model when directly compared to a tour mode choice model. This is the case for auto in-vehicle time, for example for work-relate travel, it is -0.014 for the New York tour mode model and -0.029 for the Seattle trip mode model.

VOT is directly comparable between tour and trip models. For work tours in New York and work trips in Seattle, the base model specifications showed a relatively low VOT for auto users of $6/h-$7/h. This value is not, however, recommended for use in other models. We decided not to enforce a more reasonable VOT at this stage but rather continue testing of more elaborate forms for generalized cost. For non-work travel, the VOT values are more reasonable although there is quite a significant difference between New York ($6/h) and Seattle ($11/h). This can be explained by the model specification differences. While the New York model has generic time coefficient, cost coefficient, and VOT, the Seattle model explicitly distinguishes between auto users and transit users by employing mode-specific time & cost coefficients. This has to be taken with caution, since, in the choice framework, utilities are not directly associated with mode users. In fact, every traveler is exposed to all modes. However, in reality, many auto users and transit users are repetitive in their choices. Thus, the chosen modes create a latent segmentation of the users themselves, which is partially captured by the estimated mode-specific coefficients.

3.4.3 Travel Time Segmentation by Congestion Levels and Facility Type

New York Model

With the New York tour mode choice model, multiple statistical trials previously implemented with the route type choice model, with travel time segmented by one or several attributes were repeated in order to capture possible differential perception of travel time by highway users depending on the driving conditions. In this regard, for the New York mode choice model, the same approaches to splitting travel time into components were tested statistically:

- Time on highways and freeways vs. time on arterial and local roads,
- Time under reasonable conditions where link Volume over Capacity (V/C) ratio is under 0.9 (would roughly correspond to level of service A-D) vs. time under congested conditions where V/C is equal to or greater than 0.9 (would roughly correspond to level of service E-F),
- Free flow time vs. travel time due to additional delay.

For the New York model, with respect to segmentation by facility type and link congestion levels, neither of the multiple trials brought a reasonable and statistically significant result that could be adopted. However, for both work and non-work trips, some of the estimation runs showed a logical effect expressed in a large negative coefficient for congestion delay versus free flow time as well as large negative coefficient for travel time spent on local roads vs. highways – see Table 3.29 for summary of coefficients for the highway LOS variables and variables like in-vehicle transit time that shared the same coefficient with one of the highway time variable.

Table 3.29. Tour Mode Choice, New York, RP, Travel Time Segmentation

Variable	Work		Non-work	
	Coefficient	T-Stat	Coefficient	T-Stat
Transit in-vehicle time, min	-0.0152	-8.03	-0.0082	-3.26
Free-flow time, min	-0.0152	-8.03	-0.0082	-3.26
Congestion delay, min	-0.0278	-7.64	-0.0290	-4.65
Cost, $	-0.1047	-15.66	-0.0913	-11.81
VOT/free-flow, $/hour	8.7		5.4	
VOT/delay, $/hour	15.9		19.1	
Perceived weight, delays	1.8		3.5	
Likelihood with constants only	-9682.4		-16782.0	
Final likelihood	-6860.6		-12858.4	

The effect for non-work travel was previously obtained in the route choice framework and becomes even stronger in the mode choice framework. Interestingly, for work travel it manifested itself in the mode choice framework only while the results were not conclusive in the route choice framework. The relative weight for congestion delay for non-work travel is very high (3.5) that is beyond the reasonable range 2.0-2.5 adopted in many other studies [*Wardman,* *2008; NCHRP 431, 1999*]. For work tours the results are very reasonable and the VOT estimates improved compared to the base run.

The fact that the specific impact of travel time delay vs. free-flow time proved to be more prominent in the mode choice framework compared to route choice framework is not surprising although it is not immediately obvious. One of possible behavioral explanations is that in extreme congested conditions combined with high cost of parking, choice of transit may becomes a dominant option while auto modes are rather used under special circumstances. Transit in New York is characterized by a high share of rail modes (commuter rail and subway) that are not subject to highway congestion (although they experience somewhat unique phenomena of rail congestion and crowding). As the result, when transit share comes into play, it is strongly correlated with the highway delay which makes them statistically significant. When auto trips are singled out in the route choice framework this effect is largely lost (for work travel) or mitigated (for non-work travel).

It might look counter intuitive that the congestion delay weight for non-work trips proved to be stronger than for work trips. The prevailing stereotype that travel time reliability (and any direct or indirect measure if it) should be more significant for work-related travel than for non-work related travel may not be that relevant anymore due to a large share of workers with flexible work schedules and presence of such non-work activities as visiting doctor or going to a show where schedule adherence is crucial. It should be noted that for trips to and from Manhattan that are characterized by longest highway delays the share of workers with flexible schedules and non-work activities with fixed schedules will probably quite high.

Another possible explanation relates to average tour length. Work tours in New York are characterized by almost as twice as higher average distance (7 miles) compared to non-work tours (4 miles). Previously, in the context of such measure of reliability as STD per unit distance in the route type choice section, we discussed the concept of relative perception of travel time reliability along with absolute perception of average travel time. If we accept this concept, unreliability of travel time (and any related measure of it) should obtain a relatively high weight for shorter distances. This means, however, that tour purpose in this particular context just serves as a crude proxy for tour distance.

In the mode choice framework, as was previously discussed for the route type choice framework, segmentation of highway time into differently perceived components can be used as a partial proxy for travel time reliability. The main advantage of this method is simplicity in both model estimation and application, since it does not require any direct measure of travel time variability (like standard deviation or buffer time) to be generated. It can be equally applied in 4-step and Activity-Based models with both STA and DTA. This method can be put into practice immediately as a temporary solution until more advanced methods that operate with direct measures of reliability have become available. However, as was explained above, for the current research, this result is rather peripheral since the main focus of the project is on advanced modeling approaches.

Seattle Model

With the Seattle RP data, we tested segmenting the auto travel time variable into two parts – the extra time spent in congested conditions on links where the travel time was greater than 1.2 times the free flow time versus the remaining travel time. The method for creating skims of the "extra time" spent in congestion was described above in Section 4.3.2. Our thought was that while the method did not seem to offer much benefit for TOD models, except for use in TOD shift variables, it may provide more benefit for mode choice modeling. Table 3.30 compares the base specification from above for HB Work and HB Other, using 5 skim periods, to a model that is identical except for segmenting the travel time variable by two components with different congestion levels. For the HB Work model, the results show virtually no change from the non-segmented model, with very similar coefficients on both travel time components. For the HB Other model, the results show a much lower value for time spent in very congested conditions, contrary to what one would expect. Again, this particular travel time segmentation approach provides no benefit to the models. (In Section 4.3.2, we described how the "extra time" variable can be used as a shift variable in a TOD choice model context.)

Table 3.30. Trip Mode Choice, Seattle, RP, Segmentation by Congestion Level

Variable	HB Work monlyw04 Coefficient (T-Stat)	HB Work monlyw04a Coefficient (T-Stat)	HB Other monlyn04 Coefficient (T-Stat)	HB Other monlyn04a Coefficient (T-Stat)
Travel cost, $	-0.300 (-14.9)	-0.300 (-16.7)	-0.181 (-4.5)	-0.152 (-4.2)
Auto in-vehicle time, min	-0.0339 (-8.9)		-0.0372 (-4.3)	
Auto in-vehicle, extra time on links above 1.2*free flow time, min		-0.0327 (-6.6)		-0.0017 (-0.2)
Auto in-vehicle, time on links below 1.2* free flow time, min		-0.0351 (-6.9)		-0.0841 (-8.4)
Observations	11,798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.583	0.583	0.382	0.383
Final log-likelihood	-8192.6	-8192.6	-20416.7	-20386.5

Comparison and Synthesis: Seattle and New York

Segmentation of travel time by congestion levels brought very different results in the two regions. With the New York data, a statistically significant effect was confirmed and actually manifested itself in the mode choice framework, much more strongly than in the route type choice framework. The congestion delay component of travel time proved to be weighted as 1.8-3.5 versus the free-flow time. It is logical that mode choice framework provides a better statistical support for this phenomenon compared to route type choice framework. In the New York region, transit share for trips to and from Manhattan constitutes 80%, while it is less than 10% for the rest of the region, and the corresponding auto trips have the biggest congestion delay. Thus, in the mode choice framework we capture a congestion-averse attitude of transit users in addition to auto users.

A similar test with the Seattle data did not bring such reasonable results. It should be noted that the Seattle model operates with a different segmentation of time compared to the New York model. In the Seattle model, links are broken into two categories (over-congested and others) while in the New York model, entire trip travel time is broken into a free-flow component and congestion delay. However, in both specifications we capture the same phenomenon, and in general, the trips with a greater number of links with V/C>1.2 should have the biggest congestion delay. Thus, although the two segmentation schemes are not equal, the results should be very much correlated. We believe that the failure of this particular component with the Seattle data is the consequence of very different regional conditions compared to New York. We may conclude that travel time segmentation by congestion levels works well in extremely congested areas, but is questionable for less congested regions where the differences between different trips in terms of congestion are somewhat blurred by the crudeness of synthetic skims.

As was mentioned before in the route type choice context, we do not propose this method as the main vehicle for the current research, despite the strong statistical evidence from the New York data. In general, highway travel time segmentation is only a proxy for direct measures of travel time reliability.

3.4.4 Incorporation of Travel Time Reliability and VOR

New York Model

For the New York tour mode choice model, all travel time reliability measures analyzed previously in the route type choice framework were statistically tested again including travel time standard deviation for the entire trip, standard deviation per unit of distance, difference between 80th or 90th percentile of travel time distribution and the median, etc. All tests previously implemented with the route type choice model were repeated to see if the effect changes in a more general choice framework. The results proved to be interesting and, in general, in line with the main finding for route type choice. LOS coefficient estimates from the most successful model forms in terms of statistical significance and behavioral interpretation are presented in Similar to the route type choice framework, model estimation with such measures of reliability as standard deviation (STD) of travel time and difference between the 80/90th percentile and median failed to produce reasonable and statistically significant results. The major reason for this general problem was a high level of correlation between average travel time, STD and any travel time distribution percentile between 50 and 100 as was discussed before for route type choice. Table 3.31.

Similar to the route type choice framework, model estimation with such measures of reliability as standard deviation (STD) of travel time and difference between the 80/90th percentile and median failed to produce reasonable and statistically significant results. The major reason for this general problem was a high level of correlation between average travel time, STD and any travel time distribution percentile between 50 and 100 as was discussed before for route type choice.

Table 3.31. Tour Mode Choice, New York, RP, Reliability Measures

Variable	Work	Non-work	
	1st form	1st form	2nd form
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Travel time, min	-0.0171 (9.20)	-0.0095 (3.72)	-0.0094 (3.66)
Travel cost, $	-0.110 (16.99)	-0.095 (12.25)	-0.095 (12.39)
STD time, min		-0.025 (0.56)	
STD time per unit distance, min/mile	-0.024 (0.11)		-0.140 (0.51)
VOT, $/hour	9.3	6.0	5.9
VOR, $/hour		16.0	
VOR/10 miles, $/hour	1.3		8.8
Reliability ratio		2.6	
Reliability ratio/10 miles	0.1		1.5
Likelihood with constants only	-9682.4	-16782.0	-16782.0
Final likelihood	-6866.4	-12858.2	-12858.3

For both segments (work and non work) the best and most stable results were achieved with a standard deviation of time per distance unit. This measure has a significant practical advantage of generally having a low correlation with travel time. It proved to be quite significant statistically and resulted in reasonable ranges for all other model coefficients for non-work tours. A behavioral interpretation of this measure, as was discussed before, is that people perceive (and remember) variation in speed more strongly than variation in journey time itself. It should be stressed that this variable makes sense only in combination with the average travel time.

For work tours, the mode choice framework currently brought some inconclusive results. The only utility form that had all coefficients signs logical was the specification with STD of travel time per unit distance. Even with this form, the statistical significance of the reliability term proved to be quite low that also had a reflection on a very low reliability ratio. This result has to be taken in the proper context of the entire model specification and estimation. The mode choice model, from the base run on, exhibited very strong and statistically significant mode preferences by socio-economic groups (income, car sufficiency) and urban density. It was essentially dominated by these stratified constants while even the basic average time and cost variables were difficult to estimate. In particular, the coefficients for out-of-vehicle time components for transit had to be enforced to be equal to the in-vehicle time coefficient with predetermined multipliers.

This apparent model insensitivity to travel time and cost can be partially attributed to the quality of transit LOS skims. In the New York region, the transit network is extremely complicated and the existing transit network procedures are not always adequate to explain the behavior of transit passengers in a multimodal network. However, we also believe that to a certain extent, we are dealing with a valid behavioral phenomenon when *a priori* mode preferences captured by socio-economic and location constants are so strong that LOS variables do not come into play in statistical terms. For example, it has been long recognized by practitioners that commuter rail is by far the most preferred mode in the region for medium and high income commuters to Manhattan. There are many factors that relate to the quality of transit service beyond (average) travel time and cost that are currently not modeled but recognized as very important and specifically for daily commuters. They include comfort and convenience in the cars and at stations, schedule adherence, parking arrangement for Park-and-Ride, etc. For many commuter rail users this is a part of the self-chosen lifestyle package that includes their residential living conditions, job type and location choice, and commuting arrangements. We believe that some significant improvements on the transit side are needed to enrich mode choice models. This represents an important avenue for future research.

For non-work purposes, the estimation results were more successful. In the second form for work-related purposes, STD of travel time per unit distance was used as the measure of reliability. This form yielded reasonable results in general with a significant RR of 1.5 calculated at distance of 10 miles. VOT proved to be quite stable and similar to the previously estimated value of $6/hour with the base form without reliability. This form was selected as the seed for the subsequent analysis.

The first form for non-work purpose was the only formulation with (non-scaled) STD where all coefficients obtained the right sign. However, statistical significance of the STD coefficient proved to be also quite low and it was unstable when additional terms were added. Thus, this structure could not be used as the main source for further analysis. It also had a very high reliability ratio of 2.6 for non-work travel although as was explained before this might be a valid consequence of the short average tour distance.

The second form for non-work purpose mimics the adopted form for work-related purpose. It is based on the STD of time per distance unit. All three coefficients obtained the right negative sign and reasonable values although the coefficient for reliability proved to be not extremely significant. VOT was quite stable and similar to the previously estimated value of $6/hour with the base form without reliability. This formulation was adopted as the source for the final synthesis in parallel with the model for work-related purposes.

For the rest of the statistical tests reported below, we adopted STD per mile as the main reliability measure. It was routinely included in all model formulations. The same decision was made and supported by statistical evidence for route type choice as discussed before.

Seattle Model

With the Seattle RP data, we repeated the tests of estimating with travel time reliability variables reported above in Section 4.3.3, but this time using mode choice models instead of TOD choice models, which also allows inclusion of a cost variable. The results are presented below in Table 3.32. Compared to the TOD models discussed above, the inclusion of the travel-time variability variables appears more promising, mainly in the case of the buffer travel time (90^{th} percentile minus median).

For the HB Work models in Table 3.32, the reliability variables all have the incorrect sign, except when included as the buffer time divided by distance, which has a significant negative coefficient. For trips of less than 2 miles, the reliability variable would have a stronger contribution to the utility than the travel time variable (RR over 1.0), while for longer trips, it would generally have a weaker contribution, depending on how high the buffer time is relative to the median/expected time. For example, if the buffer time were as large as the median time for a trip of 10 miles, the utility contribution of the reliability variable would be a factor of (-0.0816/-0.0347 * 1/10) or about 25% of the contribution of the median travel time variable.

For the HB Other models in the bottom half of Table 3.32, the buffer travel time (90^{th} percentile minus median) variable is again the only reliability variable with a significant negative coefficient, but this time when not divided by trip distance. The coefficient on the buffer time is about 25% as high as the main travel time coefficient, meaning that the variability in terms of the buffer time would have to be quite high to reach a reliability ratio of over 1.0.

Table 3.32. Trip Mode Choice, Seattle, RP, Inclusion of Reliability Variables

Trip type:	**HB Work**	**HB Work**	**HB Work**	**HB Work**
Model – with 5 broad skim periods	**monlyw04b**	**monlyw04c**	**monlyw04d**	**monlyw04e**
	Coefficient (T-Stat)	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**
Travel cost ($)	-0.300 (-14.8)	-0.300 (-14.9)	-0.299 (-14.8)	-0.299 (-14.8)
Auto travel time (min)	-0.0441 (-8.9)	-0.0340 (-8.1)	-0.0402 (-7.5)	-0.0347 (-9.2)
Std. deviation of travel time (min)	0.154 (3.3)			
Std. dev.travel time / distance (min/mile)		0.068 (0.1)		
Buffer (90^{th} % - median) time (min)			0.0067 (1.7)	
Buffer (90^{th} % - median) / distance (min/mile)				-0.0816 (-3.8)
Trip type:	**HB Other**	**HB Other**	**HB Other**	**HB Other**
Model – with 5 broad skim periods	**monlyn04b**	**monlyn04c**	**monlyn04d**	**monlyn04e**
	Coefficient (T-Stat)	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**
Travel cost ($)	-0.175 (-4.5)	-0.180 (-4.5)	-0.187 (-4.5)	-0.222 (-4.6)
Auto travel time (min)	-0.0559 (-4.8)	-0.0359 (-3.8)	-0.0281 (-3.1)	-0.0337 (-3.6)
Std. deviation of travel time (min)	0.257 (2.3)			
Std. dev.travel time / distance (min/mile)		-0.331 (-0.3)		
Buffer (90^{th} % - median) time (min)			-0.0072 (-3.3)	
Buffer (90^{th} % - median) / distance (min/mile)				0.033 (2.9)

It is interesting to note that the different measures of travel time variability and reliability tested thus far seem to work well in some models for some travel purposes and not for others. This is one of the few studies to attempt to measure the effect of travel time variability on choice behavior using disaggregate OD level measures, so it is too soon to provide any general rules or expectations. For the Seattle data, however, it is interesting that the measure of standard deviation seems to work better in route choice and time of day modeling, while the measure of the buffer time appears to work better for mode choice modeling. It is possible that mode choice behavior is more sensitive to the extreme cases of delay, while route choice behavior is more sensitive to recurrent delays.

Comparison and Synthesis: Seattle and New York

Introduction of direct reliability measures in both models proved to be not simple, and many model attempted specifications failed to produce reasonable and statistically significant results. In general, it was difficult to simultaneously obtain the right (negative) sign on average travel time, cost, and travel time reliability measure.. This model specification is inherently fragile with the RP data, because of the correlation between all three variables (although using a standard deviation per unit distance significantly alleviates this problem). As was mentioned in the discussion above, part of the problem is the synthetic nature of the reliability measures and the quality of the other LOS skims. However, with some particular specifications, it proved possible to generate a logical model structure with all three variables in place.

The most promising model estimated with the New York data is the model for non-work tours where a standard deviation of travel time per unit distance was used. The corresponding reliability ratio is about 1.5 at a 10-mile distance. The most promising models estimated with the Seattle data included a formulation with buffer time per unit distance for work and non-work trips although a formulation with standard deviation of travel time per unit distance for non-work trips had the right sign for all LOS variables. At this stage the decision was made to continue with the most promising specifications and to explore additional effects and impacts that could interact with the impacts of LOS variables.

3.4.5 Impact of Household Car Availability

New York Model

The tour mode choice models based on the New York RP data included household car-sufficiency variables in all mode utility expressions. Car sufficiency was defined relative to the number of workers in the household and categorized by four mutually exclusive categories: 1) households without cars, 2) households with cars fewer tan workers, 3) households with cars equal to workers, 4) household with cars greater than workers. For work tours, 4 car-sufficiency dummies were interacted with 3 income group dummies leading to 12 combined household categories. For non-work tours, 4 car-sufficiency dummies were separately estimated. The basic impacts of car sufficiency on mode choice were discussed above for the base mode choice structure and estimation results along with the all other variables. In this sub-section we single out the car-sufficiency constants for a focused discussion. They are summarized in Table 3.33.

There are several general effects associated with car ownership and sufficiency that are common across almost all mode choice models. They include a general positive impact of high car sufficiency on use of highway modes and negative impact on use of transit. There are, however, many specific effects that have been less discussed in literature. They relate to impacts of car sufficiency on carpooling, on choice between transit modes and access sub-modes, as well as on use of special modes like taxi (we remind at this point that non-motorized tours were excluded from this exercise; thus only mode choice between motorized modes was modeled). In this regard, the following main findings of this study can be mentioned:

- For both work and non-work tours, there is a common tendency for carpooling being negatively correlated with car sufficiency. The impact is stronger for higher car occupancy categories. In this sense, if we consider a sub-choice between highway modes, the least frequent case will be an HOV4+ mode chosen by a household with number of cars greater than workers. Conversely, the most frequent case will be HOV2 for zero-car households.
- For both work and non-work tours, drive to transit requires a car. Thus, for a sub-choice between transit modes, zero-car households are logically characterized by a strong propensity to use walk to transit rather than drive to transit access.
- For both work and non-work tours, there is a strong negative impact of higher car sufficiency on use of taxi. Thus generally confirms that taxi is used only as an occasional mode for special trips if auto is not available or inconvenient to use. Taxi has an unusually high share in modal split in Manhattan (around 8% for work tours and 7% for non-work tours) because of a large share of households that do not own cars. Limousine services that are widely used in Manhattan were also considered as taxi.

Table 3.33. Tour Mode Choice, New York, RP, Impact of Car Sufficiency

Variable	Mode								
	SOV	HOV2	HOV3	HOV4+	WCR	DCR	WT	DT	TX
For Work Tours									
LOW/A=0	-99.000		-1.8615 (-4.71)	-1.8615 (-4.71)	4.2733 (5.22)	1.1342 (1.86)	3.3836 (13.79)	-0.7285 (-0.95)	
LOW/A<W	1.1691 (9.07)		-1.8636 (-19.5)	-1.8636 (-19.5)	1.000	-0.4006 (-0.58)	1.2326 (4.46)	-1.9651 (-1.86)	-2.8413 (-6.82)
LOW/A=W	2.2874 (8.56)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.500	-0.4006 (-0.58)	1.2326 (4.46)	-1.9041 (-2.49)	-2.8413 (-6.82)
LOW/A>W	3.473 (12.85)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.200	-0.4006 (-0.58)	0.226	-1.9041 (-2.49)	-3.5327 (-3.41)
MED/A=0	-99.000		-1.8615 (-4.71)	-1.8615 (-4.71)	3.6156 (6.55)	1.1342 (1.86)	3.3836 (13.79)	0.6662 (1.69)	
MED/A<W	1.1691 (9.07)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.9849 (2.36)	-0.474 (-1.36)	1.0406 (5.95)	-1.4405 (-4.51)	-2.8413 (-6.82)
MED/A=W	2.9424 (13.45)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.2602 (0.74)	-0.0933 (-0.42)	0.5651 (3.39)	-1.189 (-4.69)	-2.8413 (-6.82)
MED/A>W	3.473 (12.85)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.2111 (0.53)	-0.0933 (-0.42)	0.2255 (0.92)	-1.189 (-4.69)	-3.5327 (-3.41)
HIGH/A=0	-99.000		-1.8615 (-4.71)	-1.8615 (-4.71)	3.6156 (6.55)	-0.8869 (0)	2.7555 (6.59)	-1.2457 (-1.12)	
HIGH/A<W	1.5222 (5.74)		-1.8636 (-19.5)	-1.8636 (-19.5)	-0.242 (-0.38)	-0.474 (-1.36)	0.226 (0.74)	-1.9348 (-4.05)	-1.2585 (-2.57)
HIGH/A=W	2.9424 (13.45)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.1473 (0.33)	-0.0933 (-0.42)	-0.3018 (-1.17)	-1.4612 (-4.65)	-1.9768 (-3.75)
HIGHA>W	3.473 (12.85)		-1.8636 (-19.5)	-1.8636 (-19.5)	0.2111 (0.53)	-0.0933 (-0.42)	-0.4984 (-1.45)	-1.4612 (-4.65)	-2.8286 (-2.73)
For Non-Work Tours									
A=0	-99.000		-0.6439 (-3.02)	-0.9654 (-4.1)			2.6516 (9.2)		-0.3504 (-0.77)
A<W	-3.2917 (-12)		-0.9436 (-10.33)	-1.4278 (-7.8)			0.7312 (2.37)		-2.6286 (-4.92)
A=W	-3.0727 (-12.06)		-0.9436 (-10.33)	-1.5435 (-14.47)	-0.0957 (-0.1)		-0.0131 (-0.05)		-3.7659 (-7.67)
A>W	-2.5385 (-10.01)		-0.9436 (-10.33)	-1.5435 (-14.47)	-0.0957 (-0.1)		-0.5977 (-2.08)		-4.7089 (-8.4)

While the results obtained with the current specification are reasonable and can be adopted for the subsequent analysis, there are several additional aspects of car ownership that should be explored further and deserve a special focused research. One of them is a better understanding of casual linkages between mode choice and car ownership. In the current research, household car ownership is considered as upper-level choice and mode choice is modeled conditional upon the number of cars available for the household. This causation can be questioned for commuting in the U.S. and some alternative model system designs can be considered where (usual) commuting mode and car ownership are modeled simultaneously. Some compromise solutions will be described below where car ownership is still considered as an upper-level choice but is fed by accessibility measures that essentially represent simplified mode choice logsums for travel between the residential and work places.

Seattle Model

The mode choice models based on the Seattle RP data and discussed in previous sections also contain several variables to explain mode preferences related to certain household, person and trip characteristics. These variables are generally specified as mode-specific “dummy” (0/1) variables. Specified as such, these variables do not modify the LOS coefficients and related VOT directly. Nonetheless, it is important to include important mode preference variables in the model specification in order to avoid spurious results for the LOS-related variables, as there may be correlations between the different types of variables.

As we are not concerned so much with the exact results for the mode preference variables, but more with the types of variables to include and the general estimates to expect, the results for the mode choice models on the Seattle data are presented qualitatively in Table 3.34. Negative coefficients are represented with minus signs, and positive coefficients with plus signs, and the general strength of effect is indicated by the number of positive signs, from one to three. One plus or minus means that the coefficient tends to be marginally significant, while three pluses or minuses means that the variable tends to be very strong. N/A indicates that the alternative is not available for certain cases. The exact estimated values of the coefficients in the various mode choice models can be found in the appendices.

Vehicle availability is the strongest of the mode “preference” variables, although in this case the effects may reflect constraints more than preferences. Households with no vehicles tend to choose non-motorized modes and (particularly) walk-to-transit over shared ride (HOV). In contrast, household that own one or more vehicles but have fewer vehicles than workers in the household tend to also choose walk-to-transit and non-motorized, but are also more likely to choose shared ride (HOV). These findings apply to both HB Work and HB Other trips.

Gender and age also show consistent effects across the purposes, with females more likely to choose HOV and less likely to choose non-motorized modes relative to males. (Typically, this gender difference is found to be stronger for the bicycle mode than the walk mode.) As adults grow older, they become less likely to use non-motorized modes. Typically, this effect of age applies to both bike and walk modes, and is likely to reflect physical effects of aging, perhaps as well as some cohort-related preferences as well (i.e., older people in the future may be more or less willing to walk and bike than people who are that same age today).

Although we attempt to capture spatial effects as completely as possible with the level of service variables, there are often specific scale characteristics of central business districts (CBD) that are difficult to capture with such variables. This is particularly the case in regions such as Puget Sound, where the Seattle CBD is much denser and qualitatively different than any other area. The table shows that for both HB Work and HB Other trips, trips to the CBD are more likely to go by transit than what the models would predict only on the basis of time and cost. This may be due somewhat to the density of routes serving the CBD, and the choice of routes that this represents. Also, the LOS data may not fully reflect the difficulty of driving and finding a parking space in the CBD, particularly for those not used to driving in such a dense street network. The latter may be particularly true for HB Other trips, where non-motorized trips are also more attractive relative to the auto alternatives.

Finally, as the HB Other model covers a variety of non-work purposes, Table 10 also shows different mode preferences related to specific trip purposes, relative to Personal Business, which was set as the "base" purpose. Shopping trips appear somewhat less likely to use transit, perhaps due to the necessity of carrying purchased items. Social and recreation trips are more likely to use walk and bike, as outdoor exercise and physical activity may be a purpose of some such trips. They are more likely to use HOV also, as such trips often involve multiple household members. Finally, trips to eat out at restaurants are somewhat more prone to use all modes relative to SOV--particular HOV in the case of household members going out to eat together.

Table 3.34. Trip Mode Choice, Seattle, RP, Qualitative Results for Mode Preference Variables HB Work Models	**SOV**	**HOV**	**Drive-Transit**	**Walk-Transit**	**Non-motorized**
No vehicles in HH	n/a		n/a	+++	++
Fewer vehicles than workers in HH		+		++	++
Fewer people in HH than occupancy level		–			
Female		+			—
Age (years over 18)					—
Destination is in Seattle CBD			+	++	
HB Other Models	**SOV**	**HOV**	**Drive-Transit**	**Walk-Transit**	**Non-motorized**
No vehicles in HH	n/a		n/a	+++	+++
Fewer vehicles than workers in HH		+		++	++
Fewer people in HH than occupancy level		– –			
Female		+			—
Age (years over 18)					—
Destination is in Seattle CBD			++	++	+
Trip purpose is shopping			—	—	
Trip purpose is eating at restaurant		++	+	+	+
Trip purpose is social visit or		+			++

Table 3.34. Trip Mode Choice, Seattle, RP, Qualitative Results for Mode Preference Variables HB Work Models	**SOV**	**HOV**	**Drive-Transit**	**Walk-Transit**	**Non-motorized**
No vehicles in HH	n/a		n/a	+++	++
recreation					

Note: +/- for higher/lower preference, number of + or – for strength of effect

Comparison and Synthesis: Seattle and New York

There are many logical impacts of congestion and pricing on mode choice as described above, since both the New York and Seattle models have a rich set of explanatory variables. The main common effects that relate to the impact of car ownership on the mode choice with respect to auto and transit modes can be summarized as follows:

- For both work and non-work travel, there is a common tendency for carpooling to be negatively correlated with car sufficiency. Bigger households (in terms of number of workers and in terms of overall size) with fewer cars are the most frequent carpoolers. It is important to note that about 80% of the observed carpools are intra-household in both regions.
- For both work and non-work travel, drive to transit requires a car. Thus, for a sub-choice between transit modes, zero-car households are logically characterized by a strong propensity to use walk to transit, rather than drive to transit access.
- For both work and non-work travel, walk to transit is highly related to the absence of cars or low car sufficiency. Households from these categories provide majority of transit users, many of them are being transit captives since they either do not have cars at all or have fewer cars than workers; hence at least some of them become transit captives.

The New York model described above provides some interesting behavioral insights about using taxi that is a very frequently used mode in Manhattan. However, taxi is not a frequent mode in Seattle, and it was not included in the Seattle model formulation. The Seattle model includes non-motorized modes and provides some additional insights with regard to them. The New York mode choice model includes only motorized modes, because the split between motorized and non-motorized travel is modeled in the NYBPM by a separate model,. added to the New York model system due to a large proportion of walk trips in Manhattan. It was found that a mode choice framework that includes motorized and non-motorized modes is less effective in the extreme conditions of New York, where many trips are generated as non-motorized and not subject to mode choice per se. However, these special modes are not in the focus of the current research.

3.4.6 Impact of Household or Person Income

New York Model

As was mentioned in the corresponding subsection for the Route Type Choice model estimated with the New York RP data, there is no argument that under the most general circumstances household and/or person income should positively affect VOT. The remaining technical issue is what will be most suitable analytical form of the highway utility function (generalized cost) to capture this impact. The statistical exploration of route choice above resulted in a simple scaling of the cost variable by a power function of household income with the power parameter between

0.5 and 0.8. This scaling means that VOT will grow with income but not proportionally. A doubling of income would result in VOT growing by a factor of 1.5-1.8 approximately. This is also in line with many research works where a constant elasticity of VOT with respect to income (or GDP per capita) was found either in cross-sectional or longitudinal type of analysis [*Abrantes & Wardman, 2008; Borjesson et al, 2008*],

Mode choice framework, however, is different from highway route choice framework with respect to income effects since it includes many additional mode preferences associated with income in addition to perception of cost. Thus, the normal practice that has been fully reflected in the base mode choice model specification adopted for the current study is to fully segment mode-specific constants by income.

When the mode-specific constants are segmented by income and cost variable is scaled by income at the same time, each component has a specific role. Mode-specific constants by income represent differential attitude to travel modes beyond the immediate trip time, cost, and reliability. A good example of such factor is a higher propensity of low-income workers to carpool for commuting that was discussed above. This stem from the fact that for low income workers it is easier to find a partner since they normally work fixed schedules and have both residential and work locations most frequently in urbanized areas. This effect is independent of say, HOV/HOT lane policy. In addition to this type of effects, there is a LOS effect that has to be properly captured in that higher income travelers are generally willing to pay more for travel time (and reliability) improvements. This can be done by scaling the cost coefficient by income. This would make the mode choice model realistically sensitive to HOV/HOT lane policy. In particular, this would generate a greater shift to carpooling amongst low-income commuters in addition to the higher baseline share.

Another example of income-specific mode preferences that can be better expressed through constants rather than cost scaling is the preference for commuter rail of mid/high-income commuters that was discussed above. Such attributes as comfort and convenience, in particular, possibility to use the in-vehicle time productively for reading or using a laptop is beyond a simple time-cost trade-off. However, it does not mean that the commuters are not sensitive to cost policies at all. Thus, sensitivity to cost has to be modeled properly and with respect to the income-specific willingness to pay for travel time improvements in addition to fixed mode preferences.

Some of the most interesting statistical trials with different scaling parameters are summarized in Table 3.35. Again, only the LOS variables and associated effects are presented while there is also a full set of stratified mode-specific constants included that were discussed above. Essentially, different scaling parameters on the reasonable range between 0.5 and 1.0 have been tested with a full model re-estimation for each test.

Table 3.35. Tour Mode Choice, New York, RP, Income Impact

Variable	Work				Non-Work		
	1st form	2nd form	3rd form	4th form	1st form	2nd form	3rd form
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	(T-Stat)	(T-Stat)	(T-Stat)	(T-Stat)	(T-Stat)	(T-Stat)	(T-Stat)
Travel time, min	-0.0171 (9.20)	-0.0172 (9.36)	-0.0172 (9.31)	-0.0172 (9.32)	-0.0094 (3.66)	-0.0088 (3.53)	-0.0091 (3.58)
Travel cost, $	-0.1102 (16.99)				-0.0949 (12.39)		
Travel cost divided by income , $/($)		-4462.4582 (14.54)				-2277.5078 (9.37)	
Travel cost divided by income to the power of 0.6, $/($)$^{0.6}$			-75.5045 (16.93)				-46.4852 (10.74)
Travel cost divided by income to the power of 0.8, $/($)$^{0.8}$				-589.9664 (15.89)			
STD time per unit distance, min/mile	-0.0241 (0.11)	-0.0642 (0.29)	-0.0340 (0.15)	-0.0497 (0.22)	-0.1399 (0.51)	-0.1674 (0.61)	-0.1527 (0.56)
VOT, $/hour	9.3				5.9		
VOT/$12.5K, $/hour		2.9	3.9	0.5		2.9	3.4
VOT/$37.5K, $/hour		8.7	7.6	8.0		8.7	6.5
VOT/$62.5K, $/hour		14.5	10.3	12.0		14.5	8.8
VOT/$87.5K, $/hour		20.2	12.6	15.7		20.4	10.8
VOT/$125K, $/hour		28.9	15.7	20.9		29.1	13.4
VOT/$175K, $/hour		40.5	19.2	27.3		40.7	16.4
VOR/10 miles, $/hour	1.3				8.8		
VOR/10 miles/62.5K, $/hour		5.4	2.0	3.5		27.6	14.9
Reliability ratio	0.1				1.5		
Reliability ratio/10 miles/62.5K		0.4	0.2	0.3		1.9	1.7
Likelihood with constants only	-9682.4	-9682.4	-9682.4	-9682.4	-16782.0	-16782.0	-16782.0
Final likelihood	-6866.4	-6894.9	-6860.7	-6876.3	-12858.3	-12887.5	-12872.6

A scaling parameter value of 0.8 was finally established for work tours and 0.6 for non-work tours that is in line with the previously discussed findings for route type choice (0.6 and 0.5 respectively) although not identical. As was already explained then, there are valid behavioral reasons why the household income effect on VOT is more direct for work-related trips and less direct for non-work trips. Work-related trips are implemented by workers whose personal earnings directly contribute to the household income. Non-work trips are implemented by both workers and non-workers. The personal VOT for non-workers might be less correlated with the household income.

Also, the fact that the VOT elasticity with respect to income proved to be somewhat higher in the mode choice framework compared to route type choice framework can be explained. The mode choice framework includes transit users that in general have a lower VOT and income. Thus, with the generic specification of the LOS variables and cost scaling parameters, this might result in the higher sensitivity to cost. This means that the constant elasticity to cost across a wide range of income groups and modes is still an analytically convenient simplification, and some more elaborate cost scaling forms should be explored.

Seattle Model

In this section, the mode choice models for the Seattle RP data set were specified with effects of household income and vehicle occupancy on the travel cost coefficient. This was done in two ways: (a) by segmenting the sample into 4 income groups with a separate cost coefficient for each income group and using a separate cost coefficient modifier for the two HOV mode alternatives (HOV 2 and 3+), and (b) by using the assumed power functions of income and occupancy to divide cost, as specified for the New York data in the previous sections.

The main estimation results are shown in Table 3.36 and plotted in Figure 3.14. In the segmented model (1), additive cost coefficients are estimated for three income groups relative to a "base" income group of $30-60K per year. We would expect the lowest income group to be most cost-sensitive, so the additive cost coefficient for the $0-30K income group should be negative. This is true for the HB Work model, with the coefficient negative and marginally significant, although it is only about 20% as large as the base cost coefficient, so will only reduce VOT for that group by about 20% relative to the base income group. For the HB Other model, the additive cost coefficient for the low income group has a positive sign, but is not significant.

We would expect the additive cost coefficients for the two higher income groups to be positive, reducing the total cost coefficient and increasing VOT. This is the case for HB Work, with the coefficient for the $60-100K income group significant and increasing VOT by about 12%, and the coefficient for the over $100K income group very significant and increasing VOT by about 50% relative to the base group. For the HB Other model 1, the result for the $60-100K group is not of the expected positive sign, but also quite small and insignificant. Similar to the HB Work model, the coefficient for the highest income group is significantly positive and increases VOT by about 150% relative to the base group.

Model 2 for each purpose uses the assumed income adjustment to the cost coefficient explained and tested in previous chapters – dividing cost by income to the power 0.6 for HB Work and by income to the power 0.5 for HB Other. In terms of model fit, this model has fewer degrees of freedom than model 1, so one would expect a lower fit. For HB Work, including the five income and occupancy modifiers on cost improves model fit by 85 log-likelihood units. The simpler model for comparison is the model shown in Table 3.28, with final likelihood of -8192.6. By contrast, model 2 with no additional degrees of freedom, but a different specification of the cost variable, improves the log-likelihood by 63 units over the simpler model. So, the assumed cost function achieves about 75% of the likelihood improvement of the segmented model. For the HB Other models, model 1 is a likelihood improvement of 15 units, while model 2 actually has a somewhat worse model fit than the simpler model.

When looking at the plots in Figure 3.14, it is clear that the approach for model 2 yields higher VOT than the segmentation approach of model 1, except at the very lowest income levels. This is particularly true for the HB Other model. The main reason for this is that the exponents on income of 0.6 for HB Work and 0.5 for HB Other appear to be somewhat higher than can be supported by the Seattle data. Better model fits may be obtained using lower exponents (or by searching for other types of functional specifications).

Another reason for higher VOT with the second approach is that using the income and occupancy modifiers on cost somewhat reduces the correlation between the travel-time and cost variables, both of which are a function of distance to some extent. This produces estimates of the travel time coefficients that are somewhat larger in magnitude and more significant, as can be seen for both HB Work and HB Other in Table 3.36. This is a positive benefit of the approach, and should produce estimates of VOT ratios that are closer to reality. (Note that reduced correlation may not always cause VOT estimates to increase, although that is the result in this case.)

Table 3.36. Trip Mode Choice, Seattle, RP, Effect of Income and Occupancy on Cost Coefficient

Trip type:	**HB Work**	**HB Work**	**HB Other**	**HB Other**
Model – with 5 broad skim periods	**(1) monlyw04g**	**(2) monlyw04h**	**(1) monlyn04g**	**(2) monlyn04h**
	Coefficient (T-Stat)	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**
Travel cost – all cases ($)	-0.376 (-14.9)		-0.257 (-4.2)	
Travel cost – income is less than $30K ($)	-0.0696 (-1.6)		0.0686 (1.1)	
Travel cost – income is $60K to $100K ($)	0.0416 (2.1)		-0.017 (-0.3)	
Travel cost – income is more than $100K ($)	0.132 (6.7)		0.157 (2.8)	
Travel cost – 2 occupants in veh. ($)	0.123 (9.1)		0.028 (2.5)	
Travel cost – 3+ occupants in veh. ($)	0.150 (7.2)		0.0072 (0.6)	
Travel cost (toll) divided by income to the power 0.6 and occupancy to the power 0.8, $\$/[(\$)^{0.6}(O^{0.8}]$		-214 (-17.8)		
Travel cost (toll) divided by income to the power 0.5 and occupancy to the power 0.7, $\$/[(\$)^{0.5}(O^{0.7}]$				-23.1 (-5.3)
Auto travel time (min)	-0.0283 (-7.5)	-0.0343 (-9.3)	-0.0342 (-3.8)	-0.0386 (-4.5)
Observations	11,798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.588	0.587	0.383	0.382
Final log-likelihood	-8107.4	-8129.1	-20401.2	-20417.5

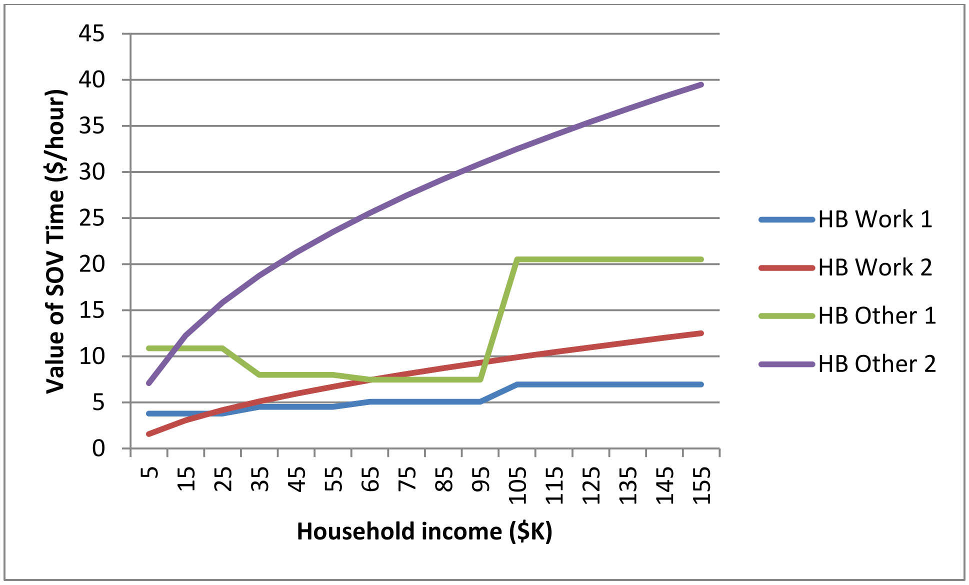


Figure 3.14. Seattle RP, VOT versus household income for different model specifications.

Comparison and Synthesis: Seattle and New York

Several different approaches were explored with models in both regions, including the scaling the cost variable by income, and the segmentation of cost variable coefficient by income group. Although segmentation by income group resulted in many cases in a better likelihood values (as illustrated with the Seattle model above), we believe that the income scaling version is more behaviorally appealing. Segmentation by income group requires an arbitrary setting of income categories that can be quite broad. Also, it does not guarantee a smooth monotonic effect across all categories as shown in Figure 3.14 above.

With the New York model, a scaling parameter value of 0.8 was established for work tours and 0.6 for non-work tours that is in line with the previously discussed findings for route type choice (0.6 and 0.5 respectively) although not identical. The fact that the VOT elasticity with respect to income proved to be somewhat higher in the mode choice framework compared to route type choice framework can be explained. The mode choice framework includes transit users that in general have a lower VOT and income. Thus, with the generic specification of the LOS variables and cost scaling parameters, this might result in the higher sensitivity to cost. This means that the constant elasticity to cost across a wide range of income groups and modes is still an analytically convenient simplification, and some more elaborate cost scaling forms should be explored.

The corresponding version of the Seattle model, with the coefficients values corresponding to the New York route type choice model, justified the specification with all coefficients having the right sign and statistically significant. Thus, this scaling strategy for income was adopted as the main approach in the further statistical tests. As was mentioned above, this functional form is also consistent with the prevailing view on VOT elasticity with respect to income [*Abrantes & Wardman, 2008; Borjesson et al, 2008*]. This formula corresponds to the constant elasticity with the coefficient less than 1 (i.e., weaker than a liner function).

3.4.7 Impact of Joint Travel and Car Occupancy

New York Model

With the adopted specification of the tour mode choice model for New York, car occupancy is explicitly accounted as mode alternative with a full set of socio-economic and zonal variables as well as toll biases specified for each car occupancy category separately. In this formulation, we consider each individual tour as a separate decision-making unit. A more sophisticated approach is possible where joint travel is considered explicitly as a separate segment from individual travel. This, however, can be done for intra-household carpools only. In the current research we did not segmented tours by joint and individual and combined car occupancy choice with mode choice. While many carpooling factors are accounted through the mode-specific constants as discussed above, there is also a need to properly scale the cost variables by occupancy to account for (partial) cost sharing for HOV.

The situation is similar to impact of income hat also is modeled through segmented mode-specific constants and cost scaling in parallel. In this case, mode-specific constants represent a static part of the model driven by the socio-economic characteristics of the traveler while cost scaling allows for properly modeling sensitivities to pricing policies. Each policy can be characterized by occupancy-specific cost variables (tolls), for example in case of a HOT-3 lane carpools with 3 or more persons can be made free of charge, carpools with two person can have a half price, while SOV will have to pay a full toll value. This is an advantage of the choice structure with occupancy as part of the choice tree. However, in addition to the cost variables themselves, a proper coefficient is needed to reflect the cost-sharing mechanism (in the case of HOV3 lane it will be applied to HOV2 half-toll) as discussed above in the route type choice context.

Several alternative specifications were tried to capture the best cost sharing coefficient statistically as reported in Table 3.37. The values of 0.8 for work tours and 0.7 for non-work tours were eventually adopted since they are in line with the route choice findings although their statistical advantage over all other values in the range between 0.5 and 1.0 was minimal.

Although, with the New York dataset, the difference between the scaling factors for occupancy between work-related travel (0.8) and non-work travel (0.7) proved to be not extremely significant we found it is logical to expect that cost sharing for work carpools should be somewhat lower than for non-work carpools. This can be explained by a significantly large share of intra-household carpools and travel parties with children for non-work trips. As was mentioned before in the route type choice context, this model feature can be refined in further research by explicitly considering different types of carpools and travel party compositions for both work and non-work purposes.

Table 3.37. Tour Mode Choice, New York, RP, Occupancy Effect on Cost

Variable	Work		Non-Work
	1st form	2nd form	1st form
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Travel time, min	-0.0176 (9.42)	-0.0175 (9.42)	-0.0095 (3.69)
Travel cost divided by income to the power of 0.6, and occupancy to the power 0.8, $/[($)$^{0.6}$,O$^{0.8}$]	-82.4799 (17.65)		-52.9424 (11.37)
Travel cost divided by income to the power of 0.8, and occupancy to the power 0.8, $/[($)$^{0.8}$,O$^{0.8}$]		-644.7535 (16.55)	
STD time per unit distance, min/mile	-0.0204 (0.09)	-0.0369 (0.17)	-0.1403 (0.51)
VOT/$12.5K, $/hour	3.7	3.1	3.1
VOT/$37.5K, $/hour	7.1	7.4	6.0
VOT/$62.5K, $/hour	9.6	11.2	8.1
VOT/$87.5K, $/hour	11.8	14.6	9.9
VOT/$125K, $/hour	14.6	19.5	12.3
VOT/$175K, $/hour	17.9	25.5	15.0
VOR/10 miles/62.5K, $/hour	1.1	2.4	12.0
Reliability ratio/10 miles/62.5K	0.1	0.2	1.5
Likelihood with constants only	-9682.4	-9682.4	-16782.0
Final likelihood	-6842.7	-6860.0	-12861.5

Seattle Model

With the Seattle RP data, we did not explicitly model the effects of joint travel on mode choice. These are models of individual trips, and we do not include explicit variables related to the household members traveling together (although we did test the effect of household size on the choice of shared ride mode alternatives, mentioned above in 4.4.4).

We did, however, include cost coefficient modifiers related to vehicle occupancy for the auto modes. Each of the auto-only alternatives—SOV, HOV2, and HOV3+ has a different occupancy level implicitly associated with it, and one would expect some degree of cost sharing to be associated with ride sharing, especially for work trips. The results in Table 3.36 show that in the HB Work model 1, the cost modifiers for HOV2 and HOV3+ are both positive and significant, and increase VOT for those modes by about 50%. For HB Other model 1, the results are less dramatic, with about a 20% higher VOT for 2 occupants relative to drive alone, but very little increase for 3+ occupants.

Figure 3.15 plots the results for computed VOT as a function of vehicle occupancy for the models in Table 3.36. As the cost coefficient also depends on household income, an income of $25K was used to compute the values in the chart (although similar relative trends would be found at other income levels). The results indicate that the cost sharing reflected in the Seattle RP data is perhaps less strong than is assumed with the occupancy exponents of 0.8 for HB Work and 0.7 for HB Other. Just as was found for income, those exponents appear somewhat too high to fit the Seattle data, leaving one to question whether lower values would be more appropriate, or whether other changes to the model specification could be found to better match the sensitivity found in the New York data.

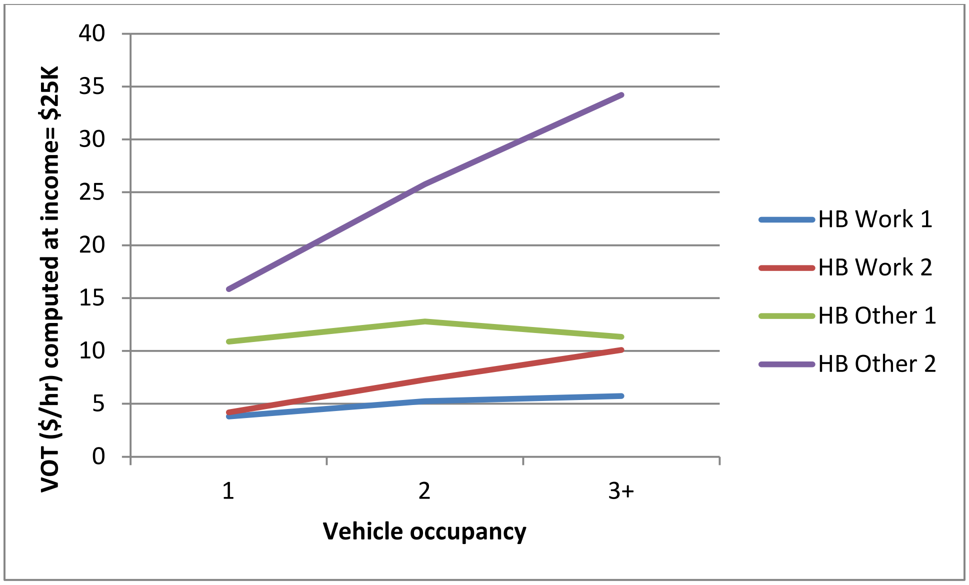


Figure 3.15. Seattle RP: VOT versus vehicle occupancy for different model specifications.

Comparison and Synthesis: Seattle and New York

Several alternative specifications were tried with both the New York and Seattle in order to capture the best cost sharing coefficient statistically. They included cost scaling by the powered occupancy as well as occupancy-specific cost coefficient. The scaling strategy prevailed in New York while segmentation of the cost coefficient by occupancy was less successful. The values of 0.8 for work tours and 0.7 for non-work tours were eventually adopted for New York since that are in line with the route choice findings.

The results for Seattle indicate that the cost sharing reflected in the Seattle RP data is perhaps less strong than in the New York data. Just as was found for income, those exponents appear somewhat too high to fit the Seattle data, leaving one to question whether lower values would be more appropriate, or whether other changes to the model specification could be found to better match the sensitivity found in the New York data.

As was discussed in the corresponding section on impact of car occupancy on route type choice (Section 3.2.7), there can be some additional dimensions within this effect that could be further explored. In particular, intra-household and inter-household carpools can have different cost-sharing mechanisms. It is expected that cost sharing should be higher for inter-household carpools (that means the power coefficient close to 1.0) and lower for intra-household carpools (power coefficient close to zero). Additionally, cost sharing between adults might be stronger than between adults and children.

3.4.8 Impact of Gender, Age, and Other Person Characteristics

New York Model

For the New York tour mode choice model, various specification were tried to explore impacts of such person characteristics as gender and age. The results in general proved to be inconclusive and unstable, thus neither of model specifications including these variables is reported. However, a dummy variable that represents person status categorized by three major types (workers, adult non-worker, and child) proved to be statistically significant and was included in the base model specification described above for non-work travel. The relevant coefficients are singled out in Table 3.38.

Table 3.38. Non-Work Tour Mode Choice, New York, RP, Effect of Person Type

Variable	Mode								
	SOV	HOV2	HOV3	HOV4+	WCR	DCR	WT	DT	TX
WORK	4.5689 (17.99)		-0.9101 (-9.89)	-1.1654 (-10.95)	-3.1193 (-2.46)	-2.909 (-3.59)	-0.8426 (-3.51)		-0.5841 (-1.4)
NWRK	4.1014 (16.1)		-0.897 (-9.31)	-1.1462 (-10.3)	-2.7791 (-2.18)	-2.2003 (-2.71)	0.2574 (1.12)		-0.2771 (-0.65)

It can be seen that all else being equal workers are characterized by higher propensity to use household cars for solo driving while non-workers carpool and use transit more frequently except for commuter rail that workers use more frequently (since it is also the commuting mode for many of them). Children are most frequent carpool and taxi passengers compared to both workers and non-workers.

Seattle Model

Beginning with the Model 2 specification from the previous section, with cost divided by functions of income and vehicle occupancy, we also included additive travel time variables specific to females and part-time workers, as well as an additive travel time variable multiplied by age minus 18 (set at a minimum of 0 to apply only to those over 18). The results shown in Table 3.39 indicate the effects of adding those additional travel time variables. For both HB Work and HB Other, females have a marginally significant negative coefficient which, when added to the main travel time coefficient, results in VOT for females about 20-25% higher than for males. This difference may be due to tighter scheduling constraints for females (on average) related to household and childcare roles.

As age increases from a base of 18 years old, we see a slight increase in VOT for HB Work trips and a slight decrease in VOT for non-work trips in Table 3.39, with neither effect very significant statistically. The total magnitude of the age effect is similar to that of the gender effects when the value of (age -18) is about 40-50 years, meaning that people are age 60 or so. The fact that VOT for older people is somewhat lower for HB Other trips could be related to somewhat laxer schedules (on average) after their children leave the household.

For part-time workers, we see a somewhat lower VOT for HB Work trips, with a magnitude similar to the gender effect, but in the opposite direction and less significant. On average, part-time workers may have laxer activity schedules than full-time workers, which would explain a lower VOT. For HB Other trips, virtually no effect of part-time employment is found.

Note that when these VOT modifiers are added to the models, the mode preferences related to age and gender that were previously described in Section 3.4.8 retain similar value (as can be seen from the detailed model estimation results in the appendices). This means that the mode preference results are essentially independent from any differences in VOT. Nevertheless, if one wishes to capture differences in travel time or cost sensitivity in mode choice models, it is important to also include any mode preference variables related to the same characteristics, in order to avoid spurious results.

Table 3.39. Trip Mode Choice, Seattle, RP, Effect of Age, Gender and Employment Status on Travel Time Coefficient

Trip type:	**HB Work**	**HB Work**	**HB Other**	**HB Other**
Model – with 5 broad skim periods	**monlyw04h**	**monlyw04i**	**monlyn04h**	**monlyn04i**
	Coefficient (T-Stat)	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**
Travel cost (toll) divided by income to the power 0.6 and occupancy to the power 0.8, $\$/[(\$)^{0.6}(O^{0.8}]$	-214 (-17.8)	-213 (-17.7)		
Travel cost (toll) divided by income to the power 0.5 and occupancy to the power 0.7, $\$/[(\$)^{0.5}(O^{0.7}]$			-23.1 (-5.3)	-23.0 (-5.2)
Auto travel time (min)	-0.0343 (-9.3)	-0.0296 (-6.4)	-0.0386 (-4.5)	-0.0427 (-3.5)
Auto travel time - female (min)		-0.0054 (-2.5)		-0.0112 (-1.5)
Auto travel time – age (min * (age-18))		-0.00011 (-1.2)		0.00030 (1.4)
Auto travel time – part time worker (min)		0.0058 (0.7)		-0.0026 (-0.4)
Observations	11,798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.587	0.587	0.382	0.382
Final log-likelihood	-8129.1	-8124.8	-20417.5	-20414.9

Comparison and Synthesis: Seattle and New York

With the New York dataset, a dummy variable that represents person status, categorized by three major types (workers, adult non-worker, and child), proved to be statistically significant and was included in the base model specification described above for non-work travel. Workers are characterized by higher propensity to use household cars for solo driving, while non-workers carpool and use transit more frequently, except for commuter rail that workers use more frequently (since it is also the commuting mode for many of them). Children are most frequent carpool and taxi passengers, compared to both workers and non-workers.

A richer set of behavioral impacts with respect to person characteristics was found with the Seattle model specification, including some related effects of gender, age, and part-time worker status on VOT. For both HB Work and HB Other, females have a marginally significant negative coefficient which, when added to the main travel time coefficient, results in VOT for females about 20-25% higher than for males. As age increases from a base of 18 years old, we see a slight increase in VOT for HB Work trips and a slight decrease in VOT for non-work trips. For part-time workers, we see a somewhat lower VOT for HB Work trips, with a magnitude similar to the gender effect, but in the opposite direction and less significant.

In this regard, the New York model and Seattle model provide complementary examples of specifications that can be combined and hybridized in many ways. We preserved the best existing specifications for the further testing. It is difficult to recommend one particular model structure that would fit all possible regional conditions. Person variables can be effectively used to stratify mode choice constants (as the New York model has shown) and/or stratify VOT (as the Seattle model has shown).

3.4.9 Effect of Tour/Trip Length

New York Model

As was described above in detail for the route type choice model estimated for New York, impact of trip length on VOT (and possibly VOR) has been analyzed in several interesting past studies from both theoretical and empirical perspectives. There is no full consensus regarding the direction of impact. Positive, negative, and non-monotonic effects all have been considered and found at least with some datasets and forms of analysis. However, probably in the majority of previous studies, the authors arrived at the conclusion that VOT should grow monotonically with trip length. However, for long distance commuters in the New York metropolitan area a certain decrease in VOT was substantiated that resulted in “inverted U” parabolic function for VOT. This result, however, was not confirmed for non-work trips.

These findings and multiple possible specifications of the highway generalized cost function were explored again in the more general framework of tour mode choice based on the New York data. The same technique of using interactional variables of time and distance (as well as cost and distance) was employed since it is very convenient analytically and essentially results in linear-in-parameters utility functions. For tours we used the distance between the origin and primary destination as the “tour length”.

Estimation results for the most interesting and reasonable model specification forms are presented in Table 3.40. For each travel purpose, we present two forms that differ only by the distance function. The first form includes a linear and squared distance terms. The third form includes also a cubed distance term that allows for more elaborate curvature for the entire distance multiplier on VOT.

Table 3.40. Tour Mode Choice, New York, RP, Tour Length Impact

Variable	Work	
	Coefficient	**(T-Stat)**
Travel time, min	-0.0119	(12.01)
Travel time multiplied by distance, min×mile	-0.000319	(6.00)
Travel time multiplied by squared distance, min×mile^2	0.0000020	(5.34)
Travel cost (toll) divided by income to the power 0.6 and occupancy to the power 0.8, $\$/[(\$)^{0.6}(O^{0.8}]$	-804.0888	(11.12)
STD time per unit distance, min/mile	-0.2096	(0.77)
VOT/10 miles /$12.5K, $/hour	2.1	
VOT/10 miles /$37.5K, $/hour	5.1	
VOT/10 miles /$62.5K, $/hour	7.6	
VOT/10 miles /$87.5K, $/hour	10.0	
VOT/10 miles /$125K, $/hour	13.3	
VOT/10 miles /$175K, $/hour	17.4	
VOR/10 miles/62.5K, $/hour	10.7	
Reliability ratio/10 miles/62.5K	1.4	
Likelihood with constants only	-9682.4	
Final likelihood	-6893.3	

Models estimated for work-related purpose have reasonable values for all coefficients, and this resulted in VOT, VOR, and reliability ratio with a generally high statistical significance. These models hold promise as seed structures for further research. Models for non-work purposes are more problematic. They are characterized by unreasonably high VOT that cannot be adopted. However, we keep these models for a specific analysis of distance effects presented below.

The entire additional multiplier on the travel time that collects all distance terms is of special interest since it directly expresses the impact of distance on VOT. It is shown for work-related purposes in Figure 3.9. This multiplier is bound to be equal to 1 at zero distance by specification (Equation 3.37).

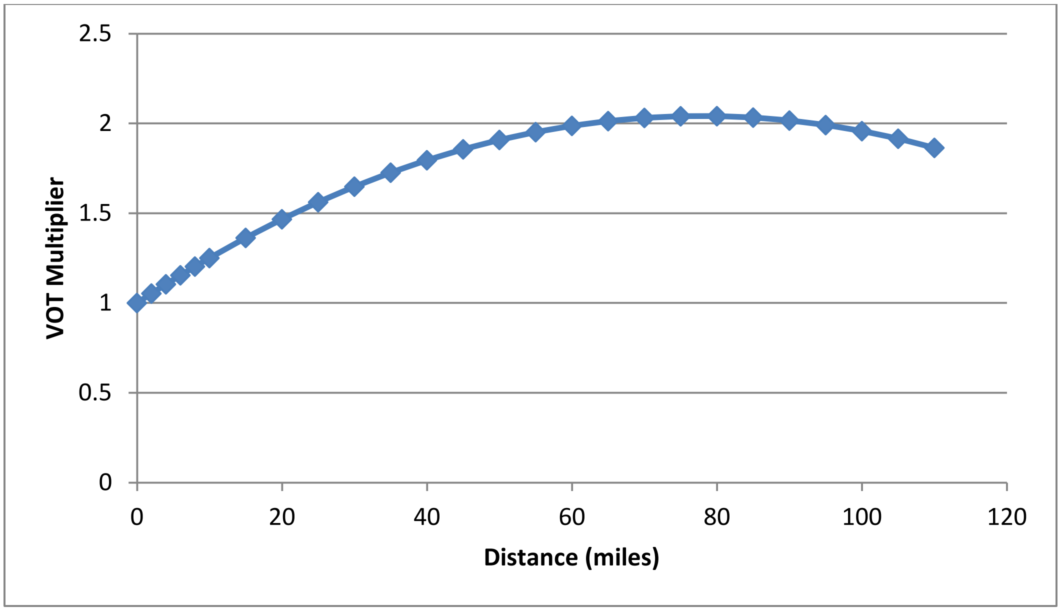


Figure 3.16. Tour length effect on VOT – work tours.

The shape of the distance-effect curves in Figure 3.9 is similar to the shape obtained for work trips in the route type choice framework. Depending on the highest order of polynomial function used in the model specification (squared or cubed) the inverted "U" effect can be less or more prominent with a very small impact on the overall model fit. We can reiterate the explanation given above for the same effect in the route choice framework that the lower VOT for long-distance commuters is a manifestation of restructuring the daily activity-travel pattern. Long-distance commuters tend to simplify their patterns and not to have many additional out-of-home activities on the day of regular commute since the work activity and commuting would take the lion share of the daily schedule. To compensate for this, they tend to have compressed work weeks or telecommute more frequently that gives them an opportunity to combine non-work activities in one particular day of the week (most frequently, Friday) when they do not commute to work. Contrary to that, short-distance commuters tend to have multiple additional out-of-home activities that add pressure to the daily schedule. In a certain sense, there are also lifestyle and residential self-choices embedded here, i.e., long-distance commuters are willing to sacrifice out-of-home non-work activities for better living conditions (and presumably more intensive in-home activities).

An additional factor that may result in higher tolerance to long travel times for commuters is the possibility to use the commuting time productively (especially if convenient transit modes like commuter rail are used). Using cell phones and laptops or reading a newspaper/book reduces the burden of travel time. This is somewhat less relevant for auto trips, although cell phone usage in auto travel is becoming quite common as well.

At this stage of analysis we prefer the more conservative Form 1 that is characterized by a smaller impact of trip distance on VOT compared to Form 2. This is more in line with the previous research. Also, in the absence of a consensus in the literature regarding the shape of the curve it is reasonable to avoid extreme cases and model formulations that might be oversensitive to distance.

Similar to the route choice model described above, distance effects for non-work travel did not produce a reasonable and statistically significant result in the mode choice framework either. Thus, no distance effect was included in the final model specification for non-work tours.

Seattle Model

Using the Seattle RP data, we estimated mode choice models allowing the travel time coefficient to vary as a quadratic function of distance, as described in earlier sections. Two additive travel time coefficients were included in addition to the base specification reported above in Table 3.28. In Table 3.41, the relevant estimates for the new model are compared alongside those of the basic specification for the HB Work and HB Other models. For HB Work, the addition of two variables provides only a slight improvement in log-likelihood, and the estimates are not very significant. For HB Other, the t-statistics and the improvement in model fit are higher.

Table 3.41. Trip Mode Choice, Seattle, RP, Variation of VoT with Distance

Variable	HB Work monlyw04 Coefficient (T-Stat)	HB Work monlyw04f Coefficient (T-Stat)	HB Other monlyn04 Coefficient (T-Stat)	HB Other monlyn04f Coefficient (T-Stat)
Travel cost, $	-0.300 (-14.9)	-0.300 (-14.8)	-0.181 (-4.5)	-0.176 (-4.6)
Auto in-vehicle time, min	-0.0339 (-8.9)	-0.0302 (-3.1)	-0.0372 (-4.3)	-0.0242 (-1.3)
Auto in-vehicle * O-D distance (min-mile)		-4.00 e-4 (-0.9)		-0.0021 (-1.8)
Auto in-vehicle * O-D distance squared (min-mile-mile)		7.40 e-6 (1.2)		4.60 e-5 (2.4)
Observations	11,798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.583	0.584	0.382	0.383
Final log-likelihood	-8192.6	-8190.8	-20416.7	-20412.1

[Originally Table B13.]

When the resulting VOT is plotted as a function of distance in Figure 3.17, we see roughly the same shape for both HB Work and HB Other, with VOT rising to a maximum at a distance of about 25 miles, and then decreasing, but the effect is much more pronounced for HB Other. For HB Other, the maximum VOT is about twice as high as the VOT for very short trips, while for HB Work, the maximum VOT is only about 20% higher than for very short trips. The possible behavioral reasons for such a relationship with distance are described in detail in other sections of this report.

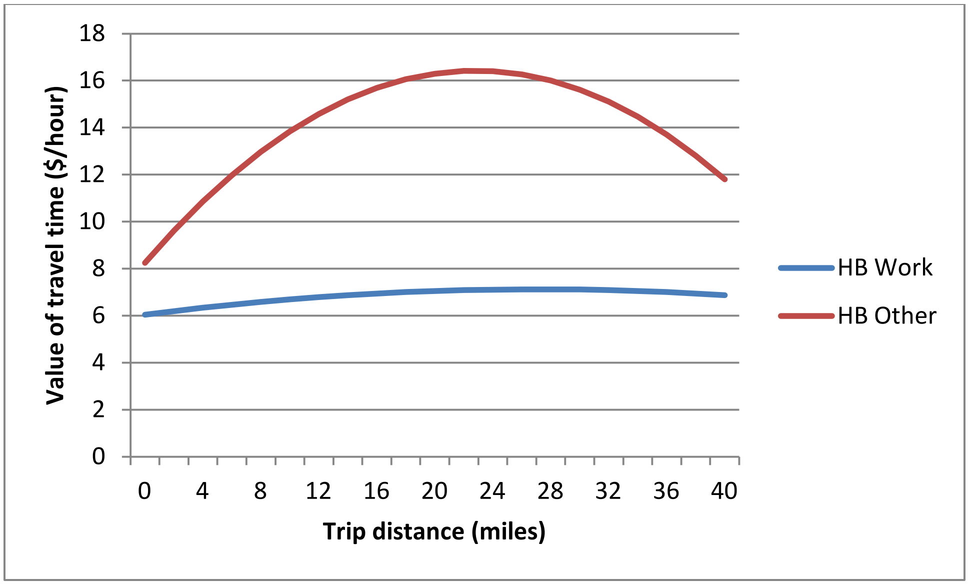


Figure 3.17. Seattle RP mode choice: VOT versus trip distance.

Comparison and Synthesis: Seattle and New York

With the New York model, the shape of the distance-effect curves was estimated to be similar to the shape obtained for work trips in the route type choice framework, and was statistically confirmed in the more general mode choice framework. Depending on the highest order of polynomial function used in the model specification (squared or cubed), the inverted "U" effect can be less or more prominent with a very small impact on the overall model fit. We can reiterate the explanation given above for the same effect in the route choice framework, that the lower VOT for long-distance commuters is a manifestation of restructuring the daily activity-travel pattern. Long-distance commuters tend to simplify their patterns and not to have many additional out-of-home activities on the day of regular commute, since the work activity and commuting would take the lion share of the daily schedule. To compensate for this, commuters tend to have compressed work weeks or telecommute more frequently that provides an opportunity to combine non-work activities in one particular day of the week (most frequently, Friday) when they do not commute to work.

We have obtained roughly the same shape for both HB Work and HB Other trip with the Seattle model, with VOT rising to a maximum at a distance of about 25 miles, and then decreasing, but the effect is much more pronounced for HB Other. For HB Other, the maximum VOT is about twice as high as the VOT for very short trips, while for HB Work, the maximum VOT is only about 20% higher than for very short trips.

Given the consistent statistical evidence from both regions with respect to work, travel we adopted the polynomial (quadratic) form as the main structure for the subsequent tests. Adoption of the same form for non-wok travel was problematic given its failure with the New York data.

3.4.10 Impact of Urban Density and Land Use

New York Model

With the adopted specification of the New York tour Mode choice model, the impact of urban density and land-use was limited to mode-specific dummies for internal tours within Manhattan and tours to and from Manhattan while the rest of travel outside Manhattan served as the reference case. The correspondent estimated coefficients are singled out in Table 3.42.

Table 3.42. Tour Mode Choice Model, New York, RP, Manhattan Effects

Variable	Mode								
	SOV	HOV2	HOV3	HOV4+	WCR	DCR	WT	DT	TX
Work tours:									
		0.9193 (1.51)	1.3951 (1.93)	1.3951 (1.93)			4.4057 (8.98)	2.9063 (4.73)	5.3596 (10.52)
		0.4541 (1.65)	-0.0825 (-0.22)	-0.0825 (-0.22)	2.7025 (7.24)	2.8895 (9.29)	2.2939 (9.16)	2.8924 (9.08)	2.42 (4.34)
Non-work tours:									
INMANH		0.6237 (1.8)	0.7235 (1.69)	0.7235 (1.69)			3.8228 (11.17)	3.0018 (3.88)	6.0371 (14.07)
TOMANH		-0.3646 (-1.73)	-0.3646 (-1.73)	-0.3646 (-1.73)	5.877 (5.5)	4.9403 (5.63)	1.5577 (5.76)	1.8277 (4.62)	3.8624 (8.02)

The Manhattan-related dummies proved to be very strong determinants of mode choice. Travel conditions in Manhattan are unique in many respects. In particular, Manhattan is characterized by an extremely developed transit system, high level of congestion & driving inconvenience, very high parking cost & significant parking search time, as well as enhanced walkability compared to the rest of the New York region. Thus, this set of strong constants for Manhattan is necessary to replicate properly the observed shares of travel modes within and to/from Manhattan (where SOV constitutes less than 15%) comparing to the rest of the New York metropolitan region (where drive alone constitutes more than 70%). The model estimation results for work tours logically showed very strong positive constants for HOV, WT, and taxi for work tours within Manhattan and very strong positive constants for DT and DCR for tours to and from Manhattan. Specifically, work tours with origin outside Manhattan and destination in Manhattan represent the most important travel segment of commuters.

For non-work tours, the effects are similar. For internal travel within Manhattan, SOV is strongly suppressed while commuter rail is not available because of the single station (terminal) for each line in Manhattan. Taxi is strongly favored followed by transit sub-modes (WT and DT). For journeys to and from Manhattan, logically the commuter rail sub-modes WCR and DCR are strongly favored followed by transit sub-modes (WT and DT) and taxi. It essentially means that in most cases, when transit or (especially) commuter rail is available, travelers would not use auto modes (drive alone or shared ride) for maintenance or discretionary tours to Manhattan.

Seattle Model

Land use variables related to urban design and densities can be important in determining mode choice, but primarily related to the feasibility and attractiveness of using transit and non-motorized modes rather than auto. High employment density may also facilitate ridesharing, making it easier to find a carpool partner with similar trip end locations. For the Seattle RP data, we discussed in Section 3.4.4 that all of the non-auto modes were more attractive for trips to the Seattle CBD, although no effect was found for the ride sharing mode. The focus of this project was not on the utility for non-auto modes, but in the PSRC regional model, there are detailed parcel-level variables related to intersection density, land use densities, mixed use ratios ("entropy"), transit accessibility and parking availability that help to explain the prevalence of transit, walk and bike trips and make the use of CBD dummy variables or other area type dummy variables less necessary.

Comparison and Synthesis: Seattle and New York

This component is somewhat peripheral to the main purpose of the current research. However, it was important to account for the main land-use and density effects in the mode choice framework inorder to ensure a reasonable background for the analysis of LOS impacts, and to separate these effects from the pure effects of travel time, cost, and reliability. In the New York region, the primary effects were found by segmenting trips to and from Manhattan (strongly dominated by transit) and internal trips within Manhattan (dominated by transit, walk, and taxi). These effects were captured by stratified mode-specific constants without an impact on VOT. The Seattle data indicate a somewhat similar effect for trips to the CBD, but this region does not have a metropolitan core comparable to Manhattan; thus further analysis for internal trips within the CBD did not make much sense.

3.4.11 Preferred Model Specifications with Deterministic Coefficients

New York Model

After numerous statistical trials and comparison of the several most promising specifications for the New York tour mode choice model that combine the best features discussed above we adopted the forms for highway generalized cost component similar to the previously established forms for route type choice. These specifications can be written now in the following more specific way that will be further investigated in more general frameworks of joint mode and time-of-day choice:

$$\begin{aligned} L(i) = \quad & \Delta(i) + a_1 \times T(i) + a_2 \times T(i) \times D(i) + a_3 \times T(i) \times D(i)^2 + \\ & b \times \left[C(i) / \left(I^{0.6} \times O^{0.8} \right) \right] + c \times R(i) \end{aligned} \tag{3.44}$$

$$L(i) = \Delta(i) + a \times T(i) + b \times \left[C(i) / \left(I^{0.5} \times O^{0.7} \right) \right] + c \times R(i) \tag{3.45}$$

The entire (final) mode choice model that corresponds to the adopted specifications for highway generalized cost functions is presented in Table 3.43 for work tours and Table 3.44 for non-work tours.

Table 3.43. Final Mode Choice Model for Work Tours, New York, RP

Variable	Mode								
	SOV	HOV2	HOV3	HOV4+	WCR	DCR	WT	DT	TX
IVT	-0.0119 (-12.01)								
COST [$Inc^{0.8}$,$Occ^{0.8}$]	-804.0888 (-11.12)								
TIME×DIST	-0.00032 (-6)								
TIME×$DIST^2$	0.00000205 (5.35)								
STD/D	-0.2096 (-0.77)								
WAIT					-0.0238				
WALK					-0.0179				
DIST					0.0229 (7.13)				
DACC						-0.0119		-0.0119	
LOW/A=0	-99.000		-1.9799 (-5.01)	-1.9799 (-5.01)	4.599 (4.91)	1.0729 (1.77)	3.1754 (12.65)	-0.7409 (-0.96)	
LOW/A<W	1.1721 (8.9)		-1.8471 (-19.33)	-1.8471 (-19.33)	1.000	-0.1302 (-0.18)	0.8723 (2.71)	-2.1485 (-1.99)	-3.0654 (-7.07)
LOW/A=W	2.8143 (9.03)		-1.8471 (-19.33)	-1.8471 (-19.33)	0.500	-0.1302 (-0.18)	0.8723 (2.71)	-2.1264 (-2.71)	-3.0654 (-7.07)
LOW/A>W	3.4219 (12.91)		-1.8471 (-19.33)	-1.8471 (-19.33)	0.200	-0.1302 (-0.18)	-0.119	-2.1264 (-2.71)	-3.9637 (-3.7)
MED/A=0	-99.000		-1.9799 (-5.01)	-1.9799 (-5.01)	3.3358 (6.07)	1.0729 (1.77)	3.1754 (12.65)	0.4406 (1.1)	
MED/A<W	1.1721 (8.9)		-1.8471 (-19.33)	-1.8471 (-19.33)	0.5755 (1.36)	-0.878 (-2.47)	0.8481 (4.67)	-1.7286 (-5.29)	-3.0654 (-7.07)
MED/A=W	2.895 (13.53)		-1.8471 (-19.33)	-1.8471 (-19.33)	-0.1653 (-0.46)	-0.435 (-1.88)	0.3066 (1.75)	-1.5376 (-5.9)	-3.0654 (-7.07)
MED/A>W	3.4219 (12.91)		-1.8471 (-19.33)	-1.8471 (-19.33)	-0.1686 (-0.41)	-0.435 (-1.88)	-0.1194 (-0.47)	-1.5376 (-5.9)	-3.9637 (-3.7)
HIGH/A=0	-99.000		-1.9799 (-5.01)	-1.9799 (-5.01)	3.3358 (6.07)	-0.8869 (0)	3.2445 (7.39)	-0.8516 (-0.76)	
HIGH/A<W	1.3527 (5.12)		-1.8471 (-19.33)	-1.8471 (-19.33)	-0.7666 (-1.2)	-0.878 (-2.47)	0.2186 (0.72)	-2.0592 (-4.34)	-2.0766 (-4.32)
HIGH/A=W	2.895 (13.53)		-1.8471 (-19.33)	-1.8471 (-19.33)	-0.2277 (-0.51)	-0.435 (-1.88)	-0.2818 (-1.07)	-1.625 (-5.1)	-2.9251 (-5.39)
HIGHA>W	3.4219 (12.91)		-1.8471 (-19.33)	-1.8471 (-19.33)	-0.1686 (-0.41)	-0.435 (-1.88)	-0.4589 (-1.32)	-1.625 (-5.1)	-3.9725 (-3.71)
INMANH		1.2845 (2.04)	1.865 (2.52)	1.865 (2.52)			4.8189 (9.37)	3.3749 (5.32)	5.7315 (10.83)
TOMANH		0.7773 (2.63)	0.3302 (0.85)	0.3302 (0.85)	3.0398 (7.69)	3.2476 (9.86)	2.5957 (9.52)	3.1877 (9.51)	2.0318 (3.49)
TOLLB	-0.5372 (-6.71)	-0.754 (-5.72)	-0.7305 (-3.6)	-0.7305 (-3.6)					
NEST 1	0.7849								
NEST 3	0.9000								
NOBS	9002								
LL	-6892.4								
RHO	0.6059								
VOT (62.5K, 10 miles)	7.6								
WAIT/IVT	2								
WALK/IVT	1.5								
DIVT/IVT	1								

Table 3.44. Final Mode Choice Model for Non-Work Tours, New York, RP

Variable	Mode								
	SOV	HOV2	HOV3	HOV4+	WCR	DCR	WT	DT	TX
IVT	-0.0128 (-12)								
COST/ [$Inc^{0.6}$,$Occ^{0.8}$]	-62.5577 (-11.31)								
STD	-3.8536 (-0.78)								
WAIT					-0.0256				
WALK					-0.0384				
DIST					0.0019 (0.19)				
DACC						-0.0128		-0.0128	
INFL					-2.3535 (-6.19)				
A=0	-99.000		-0.6804 (-3.19)	-1.0207 (-4.32)			2.697 (9.32)		-0.3577 (-0.79)
A<W	-3.3304 (-12.15)		-0.9354 (-10.24)	-1.4106 (-7.71)			0.7013 (2.28)		-2.9656 (-5.63)
A=W	-3.123 (-12.26)		-0.9354 (-10.24)	-1.518 (-14.26)	-0.047 (-0.05)		-0.0869 (-0.33)		-4.1605 (-8.55)
A>W	-2.6064 (-10.29)		-0.9354 (-10.24)	-1.518 (-14.26)	-0.047 (-0.05)		-0.6801 (-2.38)		-5.2219 (-9.35)
LOW					1.4318 (1.22)	0.1986 (0.17)	0.7074 (3.78)		
MED									
HIGH			-0.0947 (-1.39)	-0.0947 (-1.39)	-1.333 (-1.26)		-0.0684 (-0.35)	-1.0321 (-2.18)	
WORK	4.5598 (17.97)		-0.9085 (-9.88)	-1.1594 (-10.9)	-3.2922 (-2.58)	-3.0043 (-3.75)	-0.8716 (-3.63)		-0.6652 (-1.61)
NWRK	4.1189 (16.17)		-0.897 (-9.31)	-1.1462 (-10.3)	-2.8956 (-2.29)	-2.3452 (-2.92)	0.2848 (1.24)		-0.137 (-0.32)
2*AD/M	-0.9258 (-14.92)		-0.3646 (-4.61)	-0.2064 (-2.26)	-0.3329 (-0.32)	-2.0245 (-2.55)	-1.4894 (-8.83)	-1.9991 (-6.34)	-0.8424 (-2.75)
A+KID/M	-1.2456 (-14.75)		1.2392 (15.38)	1.4159 (14.9)	-3.7179 (-2.24)	-2.7024 (-2.15)	0.0818 (0.4)	-2.2127 (-2.86)	0.7498 (2.04)
2*AD/D	-0.7823 (-9.12)			0.3921 (3.24)	-0.1249 (-0.1)	-1.7224 (-1.4)	-0.638 (-2.36)	-1.0596 (-1.88)	-0.6206 (-1.14)
A+KID/D	-0.8905 (-6.85)		0.8437 (8.78)	0.9261 (8.36)			0.1053 (0.36)	-1.7822 (-1.67)	-2.2646 (-1.79)
INMANH		0.779 (2.25)	0.9288 (2.18)	0.9288 (2.18)			3.9642 (11.83)	3.0197 (4.04)	5.8376 (13.93)
TOMANH		-0.1604 (-0.61)	-0.1604 (-0.61)	-0.1604 (-0.61)	5.7755 (5.55)	4.7182 (5.61)	1.5548 (5.77)	1.2239 (3.58)	3.4362 (7.31)
TOLLB	-0.816 (-6.38)	-0.5743 (-5.38)	-0.7264 (-5.66)	-0.7264 (-5.66)					
NEST 2	0.9000								
NEST 3	0.9000								
NOBS	11,800								
LL	-12982.2								
RHO	0.3986								
VOT	6.0								
WAIT/IVT	2.0								
WALK/IVT	3.0								
DIVT/IVT	1								

Seattle Model

The final specification of the Seattle mode choice model is presented in Appendix A-2. The adopted form of the generalized cost function is similar to the New York model described above. This form is further tested in a more general framework of joint mode & TOD choice.

3.4.12 Incorporating Unobserved Heterogeneity (New York Model)

At the final stage of mode choice analysis with the New York model, we explored possibilities to improve the model specification and statistical fit by accounting for unobserved user heterogeneity, i.e., randomness of the coefficients. The choice set for the mode choice model included thirteen mode and toll/access combinations as shown in Figure 3.18 that is identical to the adopted deterministic-coefficient version described above.

- SOV – Toll
- SOV – Free
- HOV 2 Occupants – Toll
- HOV 2 Occupants – Free
- HOV 3 Occupants – Toll
- HOV 3 Occupants – Free
- HOV4+ Occupants – Toll
- HOV4+ Occupants – Free
- Walk to Commuter Rail (CR)
- Drive to Commuter Rail (CR)
- Walk to Subway/Transit (TR)
- Drive to Subway/Transit (TR)
- Taxi

The dataset was identical to the one used for estimation of the deterministic-coefficient version of the New York model. After many model specifications were tested on the full sample, the one yielding the best results are shown partially in Table 3.45 and fully in Appendix A-3. Only coefficients and t-statistics of LOS variables and alternative specific constants are shown below, since car ownership variables are discussed elsewhere in this report.

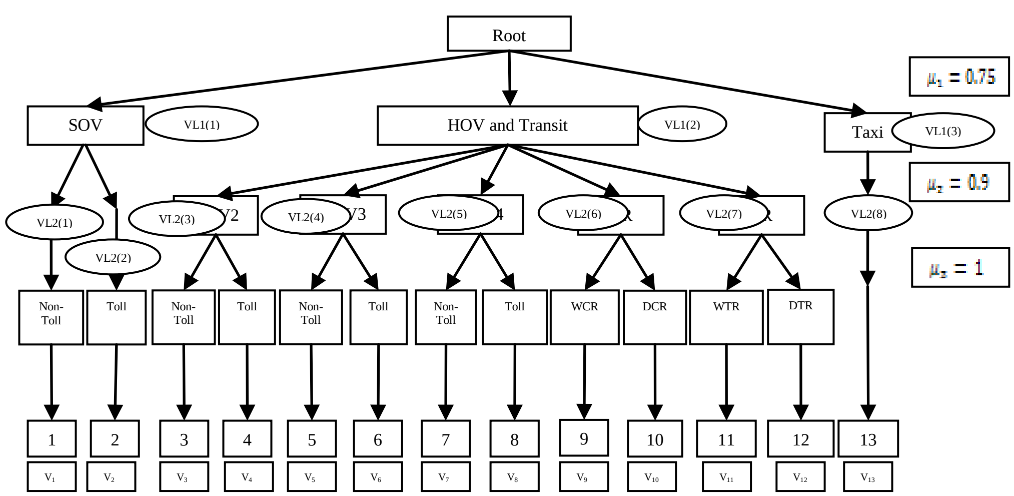


Figure 3.18. Mode choice nesting structure

Table 3.45. Estimation Results for Mode Choice Model

Model Type	MNL		Mixed Logit Log-Normal	
Number of Observations	9002		9002	
Log-Liklihood at Zero Coefficients	-9682.4245		-9682.4245	
Log-Liklihood at Convergence	-6891.2985		-6890.8239	
	Coefficient	**t-statistic**	**Coefficient**	**t-statistic**
Alternative Specific Constants				
SOV Toll	-0.5415	-6.6970	-0.5349	-6.1437
HOV2 Toll	-0.7691	-6.0208	-0.7521	-5.4695
HOV3+ Toll	-0.7387	-3.5549	-0.7300	-3.4737
HOV4	-1.1844	-7.1522	-1.1886	-7.2582
LOS Variables				
IVTT (min)	-0.0120	-9.6024	-0.0107	-114.2647
Distance * IVTT	-0.0003	-9.0062	-0.0003	-7.0324
Distance Square * IVTT	0.0000	8.1205	0.0000	5.7358
Standard Deviation per mile for Highway Modes	-0.2097	-0.8456	-0.2071	-0.6485
Cost by (Occupancy^0.8 * Income^0.8) (cents)	-7.7833	-16.3343	-8.0401	-16.3266
Others				
Scale Parameter	0.7374	39.2660	0.7001	18.5994
Variance IVTT	---	---	8.59E-06	1.9221
VOT ($/hr) Mean	14.44		12.52	
VOT ($/hr) Variance	---		3.42	

MEAN (β_i^{time}) = Orange; VARIANCE (β_i^{time}) = Purple

The results above for the mode choice model show similarities and differences from the previous model of route type choice. First the estimation results show an improvement in the log-likelihood value when heterogeneity is added, but that improvement is not significant statistically. One noticeable difference is that although an unbounded log-normal distribution was used, a reasonable estimated variance for the value of time was obtained. One possible explanation for this is that the mode choice model is really a joint model where users are choosing both free vs. toll and mode. It may be that by accounting for correlations due to the mode dimensions, through a nested logit model, you reduce the variance associated with the value of time. The high variance for VOT in Table 3.45 may be attributed to not capturing any correlation between alternatives. The only choice dimensions modeled were free vs. toll. Had an additional dimension been captured, such as time of day, the variance may be smaller and distributions may not require truncation.

Additionally, whereas the mean VOT increased when unobserved heterogeneity was added in the choice between route types, as shown in Table 3.45, in the mode choice case, the value of time decreased slightly. One possible explanation for this is only highway users were included in the sample for route type. In the mode choice, the sample of users included transit and taxi users as well. Thus, there may be a fundamental difference between the VOT for highway users only and highway and transit users.

3.5 Joint Mode and TOD Choice – Revealed (RP) Framework

3.5.1 Overview of Section, Approach, and Main Findings

Linkage between Mode & TOD Choice

In practice, mode choice models are often estimated separately from time of day choice models. Typically, the mode choice models are estimated using the auto and transit level of service variables for the actual chosen time of day. Then, in model application, the mode choice model can be applied conditional on the choice from the time of day choice model and, ideally, mode choice logsums for each time of day alternative are passed up to the time of day model as well. Several of the activity-based model systems in use have applied this approach. Alternatively, a time of day outcome can be drawn stochastically from the aggregate shares prior to application of the the mode choice model, and then the time of day model can be applied conditional on the prediction from the mode choice model, predicting the time of day using the level of service for the predicted mode. The activity-based models used in Denver and Sacramento use this latter approach. As it is not obvious whether time of day should be predicted conditional on mode choice or vice-versa, the best approach is to estimate joint time of day and mode choice models and empirically investigate nesting structures between mode and time of day. That is the approach used for this research, with the results described in this section.

Bot this model structure and the way in which utility components related to time-of-day choice were formed are discussed step by step below.

Seed Hybrid Time-Of-Day Choice-Duration Structure

The seed structure used in this research with the New York data is a model for scheduling travel tours that can predict departure-from-home and arrival-back-home time for each tour with enhanced temporal resolution. The model formulation is fully consistent with the tour-based modeling paradigm, and is designed for application within an individual micro-simulation framework. Time-of-day choice models of this type has been estimated and applied as a part of the Activity-Based travel demand model system developed in regions of US such as Columbus, Atlanta, San-Francisco Bay Area, Sacramento, and San-Diego.

The model is essentially a discrete choice construct that operates with tour departure-from-home and arrival-back-home time combinations as alternatives [*Vovsha & Bradley, 2004*]. The utility structure is based on “continuous shift” variables represents an analytical hybrid that combines the advantages of a discrete choice structure (flexible in specification and easy to estimate and apply), with the advantages of a duration model (parsimonious structure with a few parameters that support any level of temporal resolution including continuous time). The model is applied with a temporal resolution of 1 hour. It is expressed in 20 alternatives for departure and arrival time from 5:00 AM through 11:00 PM while the remaining hours are collapsed together in the following way:

1. Earlier than 5:00 AM
2. 5:00-5:59 AM
3. 6:00-6:59 AM
4. 7:00-7:59 AM
5. 8:00-8:59 AM
6. 9:00-9:59 AM
7. 10:00-10:59 AM
8. 11:00-11:59 AM
9. 12:00-12:59 PM
10. 1:00-1:59 PM
11. 2:00-2:59 PM
12. 3:00-3:59 PM
13. 4:00-4:59 PM
14. 5:00-5:59 PM
15. 6:00-6:59 PM
16. 7:00-7:59 PM
17. 8:00-8:59 PM
18. 9:00-9:59 PM
19. 10:00-10:59 PM
20. 11:00 PM or later

This is expressed in 20×21/2=210 hour-by-hour departure-arrival time alternatives. Only feasible combinations where arrival hour is equal to or later than the departure hour are considered.

Analogue between Discrete Choice and Duration Models through "Shift" Variables

Consider a discrete set of time-related alternatives, for example, alternative duration for some activity in hours $t = 1,2,3...$. A general form for the probabilistic model that returns the probability of activity duration is:

$$P(t) = f(t) \tag{3.46}$$

where $f(t)$ represent a probability density function for duration. This general form is not really operational because it incorporates any possible parametric or non-parametric density function and does not suggest any constructive method for model estimation.

Duration models operate with a special function $0 < \lambda(t) < 1$ that represents a termination rate (frequently called "hazard" in the literature) at time t assuming that the activity has not been terminated before, i.e., at one of the time points $1,2...,t-1$. The probability density function for a duration model in discrete space takes the following form:

$$P(t) = \lambda(t)\prod_{s=1}^{t-1}\left[1-\lambda(s)\right] \tag{3.47}$$

There is a direct correspondence between the general-form density function and the continuous duration model. Any duration model has the correspondent density function calculated by the formula (Equation 3.47), and any density function has the underlying termination rate calculated by the following formula:

$$\lambda(t) = \frac{f(t)}{1-\sum_{s=1}^{t-1} f(s)} \tag{3.48}$$

The duration-type formulation (Equation 3.47) has both operational and meaningful advantages over the general model formulation (Equation 3.59), because the termination-rate function $\lambda(t)$ is frequently easier to parameterize, estimate, and interpret than the density function itself. These advantages are especially clear when modeling processes with duration-related conditionality. Also having the termination-rate $\lambda(t)$ as an analytical function of t makes the duration model equally practical for any units of t.

Formulation of the duration model as a discrete choice model employs the following analytical form, assuming a multinomial logit model in this case:

$$P(t) = \frac{\exp(V_t)}{\sum_s \exp(V_s)} \tag{3.49}$$

where V_t denotes the utility function that is a linear-in-parameters function of independent variables:

$$V_t = \sum_k \beta_{kt} x_{kt} \tag{3.50}$$

where:

$k \in K$	=	household, person, zonal, and duration-related variables,
x_{kt}	=	values of the variables for each alternative,
β_{kt}	=	coefficients for the variables.

There is again a direct correspondence between the choice model (Equation 3.49) and the general-form density function (Equation 3.46). Any choice model has the corresponding density function calculated by formula (Equation 3.49), and also any density function (Equation 3.46) has an underlying set of utilities that are calculated by the following formula:

$$V_t = \ln f(t) \tag{3.51}$$

As in the case of duration models, discrete choice models (Equation 3.49) have advantages over the general formulation (Equation 3.46) because utility expressions (Equation 3.50) are easier to parameterize, estimate, and interpret than the density function itself. However, when the utility expression (Equation 3.50) is formulated in a general way with all alternative-specific coefficients and variables, the choice model (Equation 3.49) is getting more complex with the addition of temporal resolution, which is not the case with the duration model (Equation 3.47). Also, the multinomial-logit formulation with independent alternative-specific variables suffers from the IIA (independence from the irrelevant alternatives) property with respect to those variables, ignoring the fact that the duration alternatives are naturally ordered.

Both of these deficiencies of the discrete choice formulation can be overcome using a certain specification of the utility function (Equation 3.50). This specification stems from an analogy that can easily be established between the duration model (Equation 3.47) and discrete choice model (Equation 3.49). Consider a ratio of densities for two subsequent points in time stemming from the two models and restrict it to be equal in both cases:

$$\frac{P(t+1)}{P(t)} = \frac{\lambda(t+1) \times [1 - \lambda(t)]}{\lambda(t)} = \exp(V_{t+1} - V_t) \tag{3.52}$$

Formula (Equation 3.52) contains several interesting and analytically convenient particular cases that lead to operational models that can be equally written and estimated in either duration form (Equation 3.47) or discrete choice form (Equation 3.49). We will consider only one (actually, the simplest) case that corresponds to a duration model with a constant termination rate λ. With this assumption, the expression (Equation 3.52) is simplified to the following formula:

$$\exp(V_{t+1} - V_t) = 1 - \lambda \tag{3.53}$$

This means that there is a constant decrement in the utility function for each subsequent time point compared to the previous one and it is equivalent of the constant termination rate parameter of the duration model. Negative utility increment corresponds to the value of $1-\lambda$ that is less than 1. To ensure that the utility increment is independent of the time point, we should set variables x_{kt} and coefficients β_{kt} in the utility expression (Equation 3.50) in a specific way. One of the possible ways to do it is to define all coefficients as generic across duration alternatives ($\beta_{kt} = \beta_k$) while the variables are assumed to have the following form:

$$x_{kt} = t \times x_k \tag{3.54}$$

This formulation for the variables is not very restrictive since most of the household, person, and zonal characteristics in the time-of-day choice model are naturally generic across time alternatives. However, it is not true for network level-of-service variables that vary by time-of-day and should be specified as alternative-specific. These variables, which are essentially time-specific, violate the constant termination-rate assumption. However, the discrete choice framework allows for easy hybridization of both types of variables (generic and time-specific).

Using generic coefficients and variables of the type (Equation 3.54) creates a compact structure of the choice model where the number of alternatives can be arbitrarily large (depending on the chosen time unit scale) but the number of coefficients to estimate is limited to the predetermined set K. These variables can be interpreted as "continuous shift" factors that parameterize the termination rate in such a way that a positive coefficient means the termination rate is getting lower and the whole distribution is shifted to the longer durations. Negative values work in the opposite direction, collapsing the distribution towards shorter durations.

In the current research, we also considered a non-linear generalization of shift variables in the following forms:

$$x_{kt}^1 = t \times x_k; \quad x_{kt}^2 = t^2 \times x_k \tag{3.55}$$

Where x_{kt}^1 and x_{kt}^2 are used in the utility function as independent variables with estimated coefficients β_k^1 and β_k^2 consequently. This extension of model structure allows for capturing some non-linear effects, in particular saturation effects where the impact of a certain variable x_k is expressed in differential shifts along the duration time line. Essentially, the resulted multiplier for original variable x_k in the utility function $\left(t \times \beta_k^1 + t^2 \times \beta_k^2\right)$ represents the timing profile for impact of this variable.

In addition to non-linear shifts in the current research we also applied various referencing and constraining schemes for shifts variables. Referencing means that the shift is calculated relative to a certain point in time and differential shifts can be applied for being earlier or later. Referencing can be formalized in the following way:

$$x_{kt}^3 = \min(t - t_k, 0) \times x_k; \quad x_{kt}^4 = \max(t - t_k, 0) \times x_k \tag{3.56}$$

where:

t_k	=	reference time point (alternative) for the variable,
x_{kt}^3	=	variable corresponding to shifts to earlier time than the reference alternative,
x_{kt}^4	=	variable corresponding to shifts to later time than the reference alternative.

Constrained shifts are only applied for a certain subset of adjacent alternatives, rather than for all 20 alternatives. For example, some peak-spreading effects can be localized within the specific peak period like 6:00-10:00 AM and are not be relevant to the later hours.

In the process of model estimation, all types of shift variable transformations are applied in combination including non-linear effects, referencing, and constraining. The best combined form is defined by statistical fit and also by meaningful behavioral interpretations. The resulted impact of each variable x_k is referred as “timing profile”. It essentially singles out the impact of this variable on time-of-day choice. If the variable itself is a dummy (like female gender or income group indicator) the timing profile is expressed in utility units. This is the most common case with a straightforward interpretation. If the variable is continuous (like travel time or distance), then the interpretation of timing profile is more complicated and expressed in as a relative impact of each min or mile of travel on time-of-day choice.

Time-of-Day Model Formulation for a Tour

Scheduling of an entire travel tour requires that the choice alternatives are formulated as tour departure-from-home and arrival-at-home hour combinations (g,h). Then, tour duration is derived as the difference between the arrival and departure hours ($h-g$). In the current research, tour duration incorporates both the activity duration and travel time to and from the main tour activity, including intermediate stops.

The tour time-of-day choice utility for single tour can be operationalized in the following general form [*Vovsha & Bradley, 2004; Abou-Zeid et al, 2006; Popuri et al, 2008*]:

$$V_{gh} = V_g + V_h + D_{h-g} \tag{3.57}$$

where:

g,h	=	departure from home and arrival back home times,
V_g	=	departure time choice specific component,
V_h	=	arrival time choice specific component,
D_{h-g}	=	duration-specific component,

Departure and arrival hour-specific components are estimated using generic "shift-type" variables (household, person, and zonal characteristics) according to the formulas (Equation 3.54-Equation 3.55) with a limited set of time-of-day period-specific constants. Just as duration "shift" variables are multiplied by the duration of the alternative, departure "shift" variables are multiplied by the departure alternative and arrival "shift" variables are multiplied by the arrival alternative.

Note that the index of the duration component is (*h*-*g*) rather than ($g \times h$), making the estimation procedure much simpler, since the number of duration alternatives is much less than the number of departure/arrival combinations. It should also be noted that none of the estimated components of the utility function (Equation 3.55) has an index with dimensionality ($g \times h$). Thus, the number of coefficients that have to be estimated is in general fewer than number of alternatives. This parsimonious structure, however, outperformed a model with a full set of ($g \times h$) alternative specific constants [*Vovsha & Bradley, 2004*].

Joint Time-of-Day & Mode Model Formulation

Model generalization to incorporate the mode choice dimension is straightforward and results in adding one more component to the utility function:

$$V_{ghm} = V_g + V_h + D_{h-g} + W_m(gh) \tag{3.58}$$

where:

V_{ghm}	=	combined utility function for time-of-day and mode choice,
m	=	travel modes, car occupancy categories, and route types,
$W_m(gh)$	=	mode utility component with time-of-day specific LOS variables.

Although the combined structure has a very large number of alternatives (210×13=2,730) the complexity of model estimation is approximately equal to the sum of efforts corresponding to time-of-day choice and mode choice due to the additive utility function. The mode-related component structures with all pertinent variables were adopted from the final version of estimated mode choice model discussed above. Thus, this mode choice construct is used as the starting point. All coefficients however, were re-estimated in the more general choice framework including travel time, cost, and reliability coefficients. It should be noted that all mode choice coefficients in the previously discussed mode choice model and this combined model, were specified as generic across time-of-day periods to keep the model structure manageable. The mode-related utility components $W_m(gh)$ differ across time-of-day periods because the LOS variables were generated for each time of day (*gh*) specifically.

The mode choice coefficients were estimated simultaneously with the coefficients related to time-of-day choice. Despite the complexity of joint estimation, it has a significant advantage of possibility to explore different nested structures between the time-of-day and mode dimensions, as well as within each of them. Previously estimated tour time-of-day models of this type were fed by pre-calculated mode choice logsums for each time-of-day period. In the process of joint mode estimation, lower-level logsums are calculated automatically and adjusted according to the mode choice coefficient estimates.

Main Findings

In this subsection, we summarize the main model components and corresponding behavioral impacts that proved to be common for the New York and Seattle models. The main research question at this stage was whether adopting the more general framework of joint mode & TOD choice would change the main findings of the previous sections with respect to the seed form of generalized cost of highway modes. The previously substantiated functional forms were subject to a series of additional statistical tests, where the utility function included both mode and TOD components. In this regard, the following main findings can be summarized:

- The main conclusion that can be made at this stage is, that for both New York and Seattle models, the extension of the model to include TOD choice dimension in addition to mode dimension,did not violate the main impacts of LOS and other variables. In, particular, all main LOS components previously substantiated for more limited frameworks of route type choice and mode choice, proved to be statistically significant, with the right sign, and mostly with a similar magnitude in the more general choice context that includes the TOD dimension. This confirms the main hypothesis of the C04 reserach project, that there is a generic form of highway generalized cost that can combine mean travel time, cost, and travel time reliability measure (standard deviation of travel time per unit distance), and that this form can be used as a seed component in the utility function through the entire hierarchy of main travel choices. This is encouraging, because using the same seed formulation for generalized cost from bottom up in the travel model system ensures consistency of the model system elasticities and responses to congestion and pricing.
- In both New York and Seattle models, the mode choice part of the utility for highway modes included trip-length effects on VOT through the interaction terms between travel time and distance substantiated previously for the route type choice and mode choice frameworks. In this regard, all effects associated with trip distance captured in the mode choice framework discussed above in Sections 3.2 and 3.4 (including non-linear impact on VOT) were preserved in the more holistic framework of integrated time-of-day & mode choices.
- Several interesting direct effects of tour distance on time-of-day choice were captured with the New York data. The composite effect on departure time from home shows that with each additional mile of commuting, the probability of earlier departure will grow across all hours with the strongest shift between hours 11am and 6am. In a similar vein,

each additional commuting mile proved to stretch the departure time for the return trip to home towards later hours, with the highest elasticity between 2pm and 6pm.

- With respect to impact of car availability, the results with the New York model and Seattle model proved to be very similar. Impact of household car availability on combined choice of TOD & mode has been captured through the mode utility component, which proved to be very similar to the impact on pure mode choice. With the New York data, adding the TOD dimension did not change the main effects that are expressed through mode preferences by four car-sufficiency groups. In the same vein, the mode preference effects that were included in the mode choice models based on the Seattle RP data were once again included in the mode and TOD choice models, and the results were much the same.
- Income has several important impacts on joint choice of TOD & mode. The first effect relates to mode preferences. With the New York model, these impacts in the joint choice framework proved to be very similar to the mode preferences discussed in Section 3.2 above for the pure mode choice model. In the same vein, for the Seattle models, we repeated the same tests that were done for the mode choice models reported in Section 3.4: segmenting the cost coefficient by income and vehicle occupancy versus assuming the same power function that was adopted for the analyses on the New York data. Similar to the tests with the New York model, the results were virtually unchanged from what was found for the mode choice only models. The second income impact relates to schedule preferences. For example, the New York data showed that low-income commuters tend to have later schedules (departure from home after 9am) more frequently than medium and high income workers. The most prominent feature of high-income commuters is that they avoid very early starts (before 7am) compared to medium-income and low-income workers.
- Similar to the income variable, joint travel variable has two intertwined effects on combined mode & TOD choice. The first effect is captured by the mode-specific utility components that enter each TOD choice alternative with the corresponding LOS variables. These effects are explained by the mode choice component ,and they remain very similar in the joint mode & TOD choice formulation to the mode choice effects (specifically the sub-split between SOV and HOV) as was discussed above in Section 3.4. However, in the joint mode & TOD formulation, a second (direct) effect of car occupancy on TOD choice has been captured with the New York model,. that is more related to carpool organization factors and associated schedule constraints of the participants. Carpooling commuters are characterized by a later departure from home when very early hours from 5am to 7am are avoided. In a similar vein, carpoolers avoid very late arrival times back home (after 7pm), since it might not be convenient for at least some members of the travel party.
- With respect to additional person characteristics, we first summarize the impacts of person and household characteristics on the mode choice component comparing it to the

previously estimated pure mode choice formulations in Section 3.4 above. For the Seattle model, with cost divided by functions of income and vehicle occupancy, we also included additive travel time variables specific to females and part-time workers, as well as an additive travel time variable multiplied by age minus 18 (set at a minimum of 0 to apply only to those over 18). The results were somewhat less significant than was found in the mode choice only models, with no significant differences in VOT related to gender, age or part-time employment status. Secondly, there are significant mode preferences and TOD shift variables related to these characteristics, as reported in previous sections. Similarly, with the New York model, several TOD-related effects of person characteristics have been captured in addition to person variables included in the mode choice portion of the combined utilities. The most important distinction that strongly affects TOD choice for commuters is worker status. Part-time workers are characterized by later departure-from-home time compared to full-time workers. With respect to work tour duration, part-time workers are characterized by significantly shorter schedules compared to full-time workers. For arrival time back home, most of the effects will be derived as a composition of departure time and duration effects. For example, longer durations for full time workers, will naturally create later arrivals all else being equal.

- Travel time reliability is a factor that was explored with respect to impacts on two travel dimensions. As was discussed earlier in Section 3.4, travel time unreliability, measured as a standard deviation of travel time per unit distance, affects choice of modes as it was found statistically significant in mode choice utilities for highway modes, in adtion to the mean travel time. With the New York data, this effect becomes even more statistically significant when mode choice is considered jointly with TOD choice. In general, the greater the level of unreliability of highway travel time, the lower is the share of highway modes versus transit and other modes, all else being equal. It was also important to explore a possible direct impact of travel time reliability on time-of-day choice, in addition to the effect incorporated in mode choice logsums. For this purpose, with the New York model, travel time reliability measure was explored statistically as a shift variable in the time-of-day portion of the utility. The results confirmed two logical and statistically significant effects. The first effect relates to the shift of commuting departure time to hours earlier than 8AM that is progressively stronger for each earlier hour. This statistical evidence fully confirms the fact that commuters have to take into account a certain extra (buffer) time in presence of travel time unreliability. A similar symmetric effect was found for arrival time back home after work. Travel time unreliability resulted in later arrivals with a progressive effect between 5pm and 9pm.
- Several effects associated with urban density and land-use type were explored with the New York data. Some of effects were already incorporated in the mode choice utilities as discussed in Section 3.4. The effects remained stable after extension of the choice dimensions to include TOD in addition to mode. The additional direct effect on time-of-day choice captured by the Manhattan dummy is associated with a significantly longer

duration of work tours. Manhattan jobs are characterized primarily by office and managerial occupations that are associated with longer durations and more flexible arrangements like a compressed work week.

3.5.2 Basic Specification, Segmentation, and Associated VOT

New York Model

With the New York RP data, a combined tour time-of-day and mode choice model was estimated and the highway travel utility (generalized cost function) forms were explored in this broad framework of choice alternatives. The choice model structure included all 13 mode-, car occupancy-, and route-type- choice alternatives included in the mode choice framework for New York discussed above. These alternatives were combined with 210 tour time-of-day alternatives to form a complicated choice structure with 210×13=2,730 joint alternatives.

The base formulation for joint time-of-day and mode choice model includes only baseline constants and generic shifts for time-of-day choice model combined with a fully-specified mode choice model. The estimated coefficients are presented in Table 3.46 (mode-related part) and Table 3.47 (time-of-day related part).

It can be seen from Table 3.46 that all main LOS components previously substantiated for more limited frameworks of route type choice and mode choice, proved to be statistically significant and with the right sign in a more general choice context that includes the TOD dimension. This confirms the main hypothesis of the current project that there is a generic form of highway generalized cost that combined mean travel time, cost, and travel time reliability measure (standard deviation of travel time per unit distance) and that this form can be used as a seed component in the utility function through the entire hierarchy of main travel choices. This is encouraging because using the same seed formulation for generalized cost from bottom up in the travel model system ensures consistency of the model elasticities and responses to congestion and pricing. The basic in-vehicle time coefficient as well as the resulted VOT proved to be somewhat low for work travel but this can be overcome by constraining some of the coefficients (or ratios between them).

It is important that the travel time reliability measure in the context of joint mode & TOD choice proved to be more significant compared to the pure mode choice framework discussed above (Section 3.4). This means that the impact of travel time reliability on travel behavior can be better understood when both mode and TOD choice dimensions are considered. When a pure mode choice model is estimated (with fixed TOD for each observation) the advantage of more reliable modes (for example, rail transit or HOV on Managed Lanes) is less prominent due to the fact that a large share of SOV trips (least reliable mode) has been moved to the off-peak periods. In the extended choice framework of mode & TOD, this shift becomes a part of the (endogenously) modeled choice preferences.

It is also encouraging that all stratified mode-specific constants that express the impact of income, car sufficiency, and geography, proved to be statistically significant and with the right sign. This means that the corresponding impacts of the socio-economic variables on mode preferences discussed above are still valid in a more general choice framework. The negative toll-averse bias proved to be significant for all HOV categories; however it lost its significance for SOV. This can be explained by the fact that SOV in the peak periods is significantly penalized in the TOD choice framework through LOS variables.

The model structure at this stage is MNL. More elaborate nested structures with TOD choice at the upper level and mode choice at the lower level were explored at later stages.

Table 3.46. Mode and TOD Choice, New York, RP, Base Structure, Mode-Related Coefficients

Variable	Mode								
	SOV	HOV2	HOV3	HOV4+	WCR	DCR	WT	DT	TX
IVT	-0.0069 (-9.05)								
COST $[Inc^{0.8},Occ^{0.8}]$	-799.3067 (-17.72)								
TIME×DIST	-0.00022 (-4.14)								
TIME×$DIST^2$	0.00000113 (3.14)								
STD/D	-0.2452 (-2.41)								
WAIT					-0.0138				
WALK					-0.0104				
DIST					0.0074 (5.93)				
DACC						-0.0069		-0.0069	
LOW/A=0	-99.000		-1.042 (-2.95)	-1.042 (-2.95)	5.6553 (5.74)	1.8834 (2.85)	3.7877 (17.43)	1.3624 (1.25)	
LOW/A<W	0.9037 (9.83)		-1.6775 (-19.48)	-1.6775 (-19.48)	1.000	0.6135 (0.93)	0.8464 (2.97)	-2.126 (0)	-3.7464 (-14.75)
LOW/A=W	2.2592 (12.06)		-1.6775 (-19.48)	-1.6775 (-19.48)	0.500	0.6135 (0.93)	0.8464 (2.97)	-2.126 (0)	-3.7464 (-14.75)
LOW/A>W	2.3884 (32.46)		-1.6775 (-19.48)	-1.6775 (-19.48)	0.200	0.6135 (0.93)	-0.282	-2.126 (0)	-4.5816 (-6.36)
MED/A=0	-99.000		-1.042 (-2.95)	-1.042 (-2.95)	4.557 (7.99)	1.8834 (2.85)	3.7877 (17.43)	1.1765 (1.53)	
MED/A<W	0.9037 (9.83)		-1.6775 (-19.48)	-1.6775 (-19.48)	0.6467 (1.55)	-0.7525 (-2.11)	0.6833 (4.25)	-1.494 (-2.69)	-3.7464 (-14.75)
MED/A=W	2.0287 (34.7)		-1.6775 (-19.48)	-1.6775 (-19.48)	0.1445 (0.42)	-0.0587 (-0.26)	0.1748 (1.09)	-0.8406 (-2.48)	-3.7464 (-14.75)
MED/A>W	2.3884 (32.46)		-1.6775 (-19.48)	-1.6775 (-19.48)	0.0586 (0.15)	-0.0587 (-0.26)	-0.2817 (-1.15)	-0.8406 (-2.48)	-4.5816 (-6.36)
HIGH/A=0	-99.000		-1.042 (-2.95)	-1.042 (-2.95)	4.557 (7.99)	-0.8869 (0)	2.9197 (8.67)	1.9149 (1.54)	
HIGH/A<W	0.9128 (4.91)		-1.6775 (-19.48)	-1.6775 (-19.48)	-0.4906 (-0.79)	-0.7525 (-2.11)	0.0532 (0.2)	-2.2586 (-2.02)	-2.0161 (-5.69)
HIGH/A=W	2.0287 (34.7)		-1.6775 (-19.48)	-1.6775 (-19.48)	0.0532 (0.12)	-0.0587 (-0.26)	-0.2836 (-1.2)	-0.8304 (-1.86)	-3.0492 (-7.81)
HIGHA>W	2.3884 (32.46)		-1.6775 (-19.48)	-1.6775 (-19.48)	0.0586 (0.15)	-0.0587 (-0.26)	-0.3729 (-1.14)	-0.8304 (-1.86)	-3.6745 (-5.08)
INMANH		0.2355 (0.56)	0.6842 (1.23)	0.6842 (1.23)			3.5812 (12.86)		4.0609 (12.54)
TOMANH		0.1631 (1.03)	-0.2793 (-0.99)	-0.2793 (-0.99)	3.3377 (10.42)	3.9615 (16.22)	2.0166 (13.36)	2.6868 (7.12)	0.4926 (0.97)
TOLLB	0.0648 (0.67)	-0.5165 (-4.39)	-0.608 (-3.24)	-1.1062 (-8.01)					
Number of observations	8,803								
LL with Constants only	-43202.1								
LL	-42332.8035								
VOT (62.5K, 10 miles)	4.6								

Table 3.47. Mode & TOD Choice, New York, RP, Base Structure, TOD-Related Constants

Variable	Departure	Arrival	Duration
CONSTANTS			
Before 5 am	-3.2412 (-21.55)	-9.0000	
5 am to 6 am	-2.1889 (-23.16)	-2.3415 (-2.18)	
6 am to 7 am	-0.7375 (-14.91)	-1.8037 (-3.46)	
7 am to 8 am	0.0000	-2.4794 (-5.3)	
8 am to 9 am	0.0783 (1.73)	-2.0640 (-5.59)	
9 am to 10 am	-0.9164 (-11.37)	-1.6733 (-5.36)	
10 am to 11 am	-1.7589 (-14.54)	-2.0793 (-7.29)	
11 am to 12 pm	-2.0088 (-12.91)	-1.4836 (-6.5)	
12 pm to 1 pm	-2.3517 (-12.2)	-0.9598 (-5.1)	
1 pm to 2 pm	-2.3343 (-10.28)	-1.0782 (-6.87)	
2 pm to 3 pm	-1.8251 (-7.23)	-0.7432 (-6.12)	
3 pm to 4 pm	-1.6309 (-5.65)	-0.2462 (-2.99)	
4 pm to 5 pm	-1.4105 (-4.38)	-0.2276 (-4.55)	
5 pm to 6 pm	-1.5248 (-4.23)	0.0000	
6 pm to 7 pm	-1.7114 (-4.29)	-0.3988 (-7.87)	
7 pm to 8 pm	-1.8170 (-3.95)	-0.9005 (-10.64)	
8 pm to 9 pm	-2.1166 (-4.08)	-1.3047 (-10.94)	
9 pm to 10 pm	-2.7958 (-3.72)	-1.4657 (-9.67)	
10 pm to 11 pm	-2.4052 (-3.15)	-1.7459 (-9.2)	
After 11 pm	-3.0560 (-2.72)	-1.1749 (-5.62)	
0 to 2 hours			-2.5397 (-9.06)
3 to 4 hours			-1.6236 (-8.29)
5 to 6 hours			-1.3216 (-10.2)
7 hours			-1.2620 (-14.44)
8 hours			-0.7961 (-14.82)
9 hours			0.0000
10 hours			-0.0925 (-1.91)
11 hours			-0.4351 (-5.31)
12 to 13 hours			-0.9018 (-7.05)
14 to 19 hours			-2.2407 (-10.03)

The TOD choice component of the utility function at this stage is combined of three sets of constants. These constants reflect the observed frequencies of commuting by departure time from home, arrival time back home, and duration of the work tour. The reference points in each dimension were chosen for the most frequent case (peak frequency). It is 7-8am for departure time from home, 5-6pm for arrival back home, and 9 hours of tour duration (including work activity duration and travel to and from work). Logically, all other constants are negative and statistically significant reflecting on the observed work schedule preferences in the region.

Seattle Model

The trip level mode & TOD models estimated on the Seattle RP data include 102 alternatives, 6 different modes for each of 17 different time periods, with the modes and time periods the same as described in the preceding sections. For these models, we tested eight different possible nesting structures, using various combinations of within-mode and within-TOD nesting (nesting the 17 detailed periods into the 5 broader periods), along with different nesting structures between mode and TOD. For both HB Work, and HB Other, the bottom-most level of nesting is within-mode, nesting together all of the auto-related alternatives (SOV, HOV2, HOV3+ and Drive-Transit), the same as described for the mode choice model results.

The mode nesting coefficients are approximately 0.75 for HB Work and 0.65 for HB Other, all significantly different from 1.0. (The exact results are shown in Appendix A-3). For HB Other, the best results were obtained by further nesting the 3 mode types (auto, walk to transit, non-motorized) under each of the 17 time periods, with a nesting coefficient of roughly 0.7 (also significantly lower than 1.0). This nesting structure supports the approach commonly used in practice of predicting mode choice conditionally on TOD choice. However, it is often difficult to obtain good estimates of the mode choice logsum parameter in TOD models using sequential estimation methods. Also, the flexibility for specifying mode-specific LOS effects in a TOD choice model may be somewhat limited using sequential estimation. These are two reasons to recommend the estimation of joint mode and TOD choice models for practical forecasting systems. For the HB Work model, once we had nested the auto modes together, we could not find any further nesting structure with logsum parameters significantly below 1.0. Thus, the same nesting structure was used as for HB Other, but with the logsum parameter for mode types nested under TOD periods constrained at 1.0. In other words, the simultaneous choice of TOD period and mode type has an MNL structure. This finding of simultaneity further supports the joint, full information modeling of time of day and mode choice.

The impact of using joint mode & TOD model estimation on the estimation of time and cost coefficients is shown in Table 3.48, with the joint model estimates shown alongside the mode choice-only estimates reported earlier in Section 3.4.2. The coefficients and imputed values of time remain quite similar, with the main difference being somewhat higher t-statistics and more significant estimates for transit in-vehicle time. (The difference in transit travel times between peak and off-peak services influencing TOD choice for transit trips may improve the model in this way.) For HB Other, the auto in-vehicle time coefficient is now somewhat higher, giving a higher imputed VOT of $15.1/hour, while the VOT for HB Work remains quite a bit lower. Note that the log-likelihood rho-squared values cannot be directly compared between the mode choice and mode & TOD models, as the latter were estimated using a much larger choice set of alternatives.

Table 3.48. Trip Mode and TOD Choice, Seattle, RP, Basic Specification

Variable	HB Work – mode choice	HB Work – mode & TOD	HB Other - mode choice	HB Other - mode & TOD
	monlyw04	motodw04	monlyn04	motodn04
	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)	Coefficient (T-Stat)
Travel cost, $	-0.300 (-14.9)	-0.260 (-14.9)	-0.181 (-4.5)	-0.169 (-5.0)
Auto in-vehicle time, min	-0.0339 (-8.9)	-0.0296 (-10.2)	-0.0372 (-4.3)	-0.0425 (-6.6)
Transit in-vehicle time, min	-0.0088 (-1.6)	-0.119 (-2.7)	-0.0044 (-0.3)	-0.0079 (-0.7)
Transit walk access time, min	-0.0713 (-9.4)	-0.0518 (-10.4)	-0.0688 (-5.1)	-0.0630 (-5.8)
Transit wait time, min	-0.0530 (-6.1)	-0.0512 (-7.2)	-0.104 (-4.1)	-0.0876 (-4.3)
Transit number of transfers	-0.885 (-5.3)	-0.724 (-5.7)	-0.841 (-2.2)	-0.757 (-2.3)
Non-motorized distance, miles	-0.888 (-11.1)	-0.682 (-14.6)	-1.52 (-7.2)	-1.42 (-9.3)
VOT for auto in-vehicle time, $/hr	6.8	6.8	12.3	15.1
VOT for transit in-vehicle time, $/hr	1.8	2.8	1.5	2.8
VOT for transit walk acc. time, $/hr	14.3	12.0	22.8	22.4
VOT for transit waiting time, $/hr	10.6	11.8	34.5	31.1
Observations	11,798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.583	0.376	0.382	0.207
Final log-likelihood	-8192.6	-33109.7	-20416.7	-72520.1

Comparison and Synthesis: New York and Seattle

The main conclusion that can be made at this stage is that, for both New York and Seattle models, the extension of the model to include TOD choice dimension in addition to mode dimension, did not violate the main impacts of LOS and other variables. In, particular, all main LOS components previously substantiated for more limited frameworks of route type choice and mode choice, proved to be statistically significant, with the right sign, and mostly with a similar magnitude, in a more general choice context that includes the TOD dimension. This confirms the main hypothesis of the C04 reserach project that there is a generic form of a highway generalized cost function that can combin mean travel time, cost, and travel time reliability measure (standard deviation of travel time per unit distance), and that this form can be used as a seed component in the utility function through the entire hierarchy of main travel choices. This is encouraging because using the same seed formulation for generalized cost from bottom up in the travel model system ensures consistency of the model system elasticities and responses to congestion and pricing.

There are some particular subtle effects associated with a joint consideration of mode and TOD choice compared to a pure mode choice model with fixed TOD. The primary difference that manifests itself more strongly in a congested area like New York, is that when the TOD choice dimension becomes endogenous, it makes congestion-averse behavior more explicit. In the New York model it resulted in a stronger impact of travel time reliability. In general, due to a strong interdependence between mode and TOD choice, it is desirable to estimate these models jointly rather than sequentially. The current research has proven that this is both possible and practical, even though this results in a complicated choice structure, with a large number of alternatives, a large number of coefficients in the combined utility functions, and several nesting levels to explore,. In the model application, the model can still be broken into a sequence of sub-models by nesting levels, that is equivalent to a fully joint model if the lower-level logsums are properly carried up.

3.5.3 Non-Linear LOS, Trip Length, and Location Effects

New York Model

In the New York model, the mode choice part of the utility for highway modes includes trip-length effects on VOT through the interaction terms between travel time and distance. In this regard, all effects associated with trip distance captured in the mode choice framework discussed above (including non-linear impact on VOT) were preserved in the mode holistic framework of integrated time-of-day & mode choices. In additional to that, several interesting direct effects of tour length on time-of-day choice were captured as reported in Table 3.49 and illustrated in Figure 3.19.

Commuting distance proved to have a direct impact on departure time from home and arrival time back home that was captured by linear and squared shift variables. The composite effect on departure time from home shows that with each additional mile of commuting, probability of earlier departure will grow across all hours with the strongest shift between hours 11am and 6am. The effect is somewhat mitigated between very early hours 5-7am and non-conventional late work activity schedules that start after 12am. In a similar vein, each additional commuting mile proved to stretch the departure time home towards later hours with the highest elasticity between 2pm and 6pm. The effect was mitigated for vey early arrival home (before 2pm) and late arrival home (after 6pm). These effects are logical since commuting time is included in the tour time-of-day choice definition (from departure from home until arrival back home). Mitigation effects stem from the natural daily schedule constraints. For example, for very long commuting, workers would tend to compensate by later arrivals at work or earlier departure from work rather than by very earlier departure from home or late arrival back home since the latter would put them on an unconventional schedule that would affect their family and social life.

Table 3.49. Mode and TOD Choice, New York, RP, Trip Length Effect on TOD

Variable	Departure	Arrival	Duration
TRAVEL TIME			
Linear Shift for Departure before 8 am	-0.0052 (-4.64)		
Squared Shift for Departure before 8 am	0.0009 (2.17)		
Linear Shift for Departure after 9 am	-0.0063 (-12.72)		
Linear Shift for Arrival before 5 pm		0.0077 (6.64)	
Squared Shift for Arrival before 5 pm		0.0002 (0.44)	
Linear Shift for Arrival after 6 pm		0.0009 (2.89)	
NOBS	8803		
LL with Constants only	-43202.1		
LL	-41980.1794		

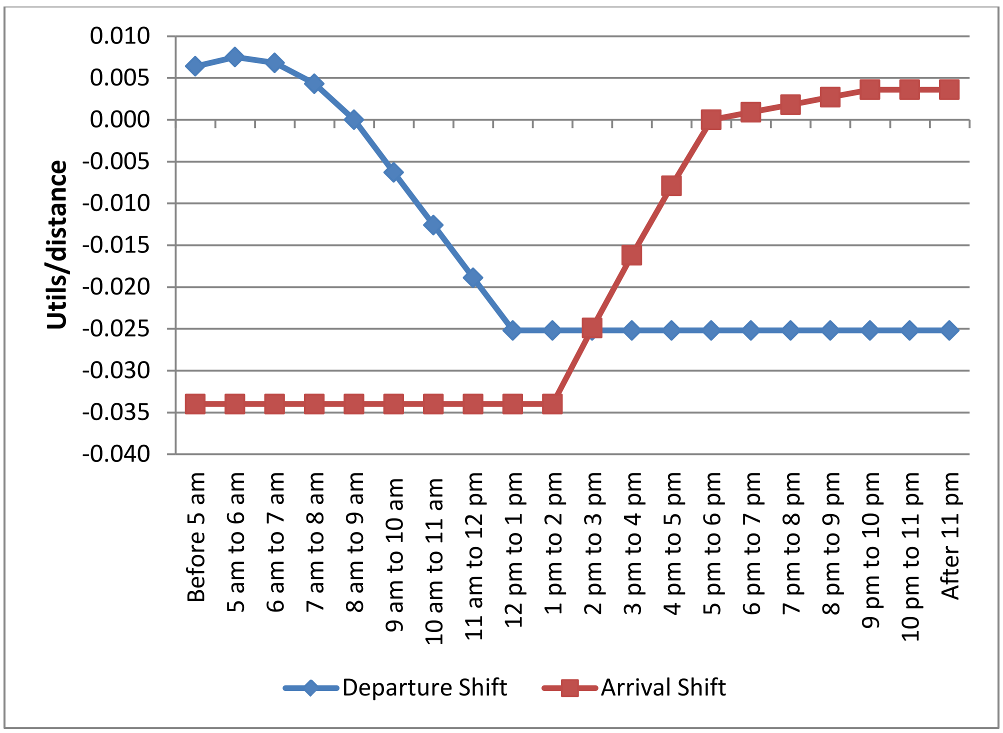


Figure 3.19. Mode and TOD choice, New York, RP, trip length effect on TOD.

Seattle Model

With the Seattle RP data, we once again tested the estimation of the time coefficient as a function of trip distance. The coefficients are shown in Table 3.50 and then the resulting VOT is plotted as a function of distance in Figure 3.20. Once again, we see roughly the same shape for both HB Work and HB Other, but, compared to the mode choice models results the curve is less pronounced for HB Other, and reaches a maximum at a higher distance for HB Work- at around 40 miles. For both purposes, the effect is not very pronounced, with the maximum VOT only 3 or 4 $/hour higher than the minimum VOT for very short trips.

Table 3.50. Trip Mode and TOD Choice, Seattle, RP, Variation of VOT with Distance

Variable	HB Work motodw04 Coefficient (T-Stat)	HB Work motodw04f Coefficient (T-Stat)	HB Other monlyn04 Coefficient (T-Stat)	HB Other monlyn04f Coefficient (T-Stat)
Travel cost, $	-0.260 (-14.9)	-0.255 (-14.5)	-0.169 (-5.0)	-0.179 (-5.1)
Auto in-vehicle time, min	-0.0296 (-10.2)	-0.0142 (-2.1)	-0.0425 (-6.6)	-0.0384 (-3.2)
Auto in-vehicle * O-D distance (min-mile)		-8.80 e-4 (-2.6)		-5.30 e-4 (-0.9)
Auto in-vehicle * O-D distance squared (min-mile-mile)		1.10 e-5 (2.5)		9.90 e-6 (1.7)
Observations	11,798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.376	0.376	0.207	0.207
Final log-likelihood	-33109.7	-33106.3	-72520.1	-72517.0

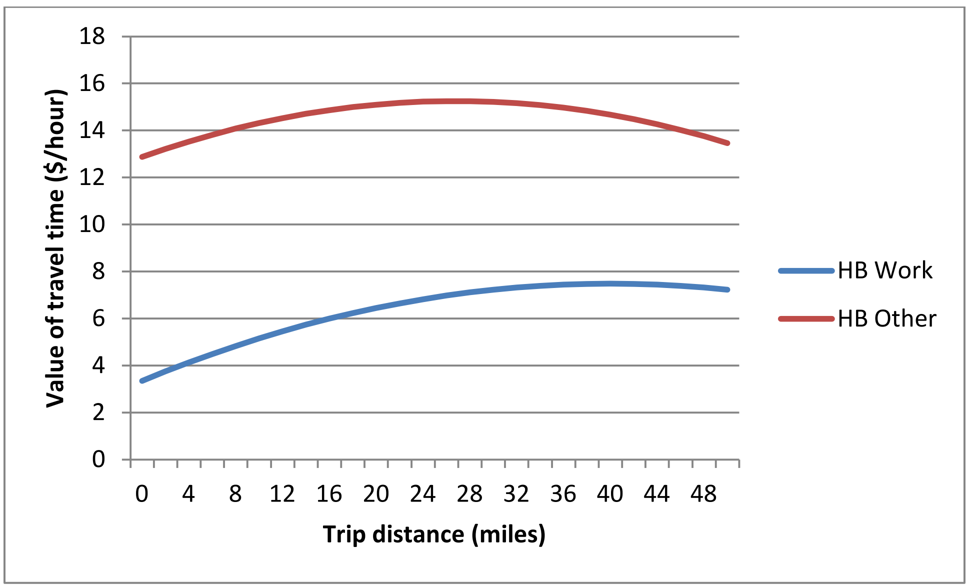


Figure 3.20. Seattle RP TOD and mode choice: VOT versus trip distance.

Comparison and Synthesis: Seattle and New York

In both New York and Seattle models, the mode choice part of the utility for highway modes included trip-length effects on VOT through the interaction terms between travel time and distance, substantiated previously for the route type choice and mode choice frameworks. In this regard, all effects associated with trip distance captured in the mode choice framework discussed above in Sections 3.2 and 3.4 (including non-linear impact on VOT) were preserved in the more holistic framework of integrated time-of-day & mode choices. With the Seattle RP data, compared to the mode choice models results, the curve is less pronounced for HB Other, and reaches a maximum at a higher distance for HB Work – at around 40 miles.

In additional to that, several interesting direct effects of tour distance on time-of-day choice were captured with the New York data. Commuting distance proved to have a direct impact on departure time from home and arrival time back home that was captured by linear and squared shift variables. The composite effect on departure time from home shows that with each additional mile of commuting, probability of earlier departure will grow across all hours with the strongest shift between hours 11am and 6am. In a similar vein, each additional commuting mile proved to stretch the departure time home towards later hours with the highest elasticity between 2pm and 6pm.

3.5.4 Impact of Congestion Levels

New York Model

As was mentioned above for mode choice model analysis, a direct impact of congestion level proved to be statistically unstable and an explicit measure of travel time reliability like STD or STD of time per unit distance was preferred. Since LOS variables are incorporated in the combined TOD & mode choice primarily through mode choice utility components no additional investigation if this impact was conducted. However, it should be noted that even if a certain effect manifested itself in the mode choice framework it does not automatically mean that it would be identical in a more general TOD & mode choice framework. Thus, in other cases all coefficients in the mode utility function were completely re-estimated for a combined TOD-mode formulation. In most cases, the mode-choice-related effects discussed above proved to be stable in the presence of upper-level TOD dimension. Cases where a mode choice effect proved to be dependent on TOD dimension are discussed specifically.

Seattle Model

As we did previously in the TOD choice and mode choice models on the Seattle RP data, we tested segmenting the auto travel time variable into two parts – the extra time spent in congested conditions on links where the travel time was greater than 1.2 times the free flow time versus the remaining travel time. The method for creating skims of the “extra time” spent in congestion was described above in Section 4.3.2. Table 3.51 compares the base specification from above for HB Work and HB Other, using 5 skim periods, to a model that is identical except for segmenting the travel time variable by two components with different congestion levels. Just as we found for the mode choice models in Section 4.4.2, the results show virtually no change from the non-segmented model, with very similar coefficients on both travel time components.

Table 3.51. Trip Mode and TOD Choice, Seattle, RP, Segmentation by Congestion Level

Variable	HB Work motodw04 Coefficient (T-Stat)	HB Work motodw04a Coefficient (T-Stat)	HB Other monlyn04 Coefficient (T-Stat)	HB Other monlyn04a Coefficient (T-Stat)
Travel cost, $	-0.260 (-14.9)	-0.253 (-14.3)	-0.169 (-5.0)	-0.169 (-4.9)
Auto in-vehicle time, min	-0.0296 (-10.2)		-0.0425 (-6.6)	
Auto in-vehicle, extra time on links above 1.2*free flow time, min		-0.0236 (-6.5)		-0.0424 (-5.9)
Auto in-vehicle, time on links below 1.2* free flow time, min		-0.0373 (-8.8)		-0.0426 (-4.5)
Observations	11;798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.376	0.376	0.207	0.207
Final log-likelihood	-33109.7	-33106.5	-72520.1	-72520.1

The shift variables related to extra time on congested links now show somewhat less significant effects than previously discussed for the TOD-only models in Section 3.3. People on HB Work trips who travel on ODs with very high AM peak congestion still tend to leave home earlier in the morning, but we now find that high PM peak congestion is related to arriving home earlier from work rather than later. In reality, people are likely to avoid the peak congestion in both directions, with some people shifting earlier and some later, particularly in the PM. This can be captured using more detailed shift variable functions described elsewhere in this report.

Comparison and Synthesis: Seattle and New York

In both the New York and Seattle regions- extension of the choice dimensions to TOD and mode did not significantly change the previous results with respect to auto time segmentation by congestion levels. Overall, the results were statistically unstable and/or insignificant. Thus, these results only reinforced the decision to apply direct measures of travel time (un)reliability like standard deviation of travel time per unit distance, rather than use indirect measures like auto time weights differentiated by congestion levels.

3.5.5 Impact of Household Car Availability

New York Model

Impact of household car availability on combined choice of TOD & mode has been captured through the mode utility component that proved to be very similar to the impact on pure mode choice as discussed in Section 3.4.5 – see Table 3.33. Adding the TOD dimension did not change the main effects that are expressed through mode preferences by four car-sufficiency groups. The full estimation results for the combined TOD & mode choice model for New York are presented in Appendix A-1.

Seattle Model

The mode preference effects that were included in the mode choice models based on the Seattle RP data were once again included in the mode and TOD choice models, and the results were much the same, with the exception that many of the effects are now estimated more significantly. Thus, the pattern shown below in Table 3.52 is much the same as that shown previously in Table 3.34 and discussed in Section 3.4.5, except there are now more pluses or minuses in some columns corresponding to somewhat more significant estimates.

Table 3.52. Trip Mode and TOD Choice, Seattle, RP, Qualitative Results for Mode Preference Variables

HB Work Models	**SOV**	**HOV**	**Drive-Transit**	**Walk-Transit**	**Non-motorized**
No vehicles in HH	n/a		n/a	+++	++
Fewer vehicles than workers in HH		++		+++	+++
Fewer people in HH than occupancy level		– –			
Female		+ +			– –
Age (years over 18)					–
Destination is in Seattle CBD			++	++	–
HB Other Models	**SOV**	**HOV**	**Drive-Transit**	**Walk-Transit**	**Non-motorized**
No vehicles in HH	n/a		n/a	+++	+++
Fewer vehicles than workers in HH				++	+++
Fewer people in HH than occupancy level		– – –			
Female		++			–
Age (years over 18)					– –
Destination is in Seattle CBD			++	++	+
Trip purpose is shopping			–	–	
Trip purpose is eating at restaurant		+++	+	+	+
Trip purpose is social visit or recreation		++			+++

Note: +/- for higher/lower preference, number of + or – for strength of effect

Comparison and Synthesis: Seattle and New York

With respect to impact of car availability, the results with the New York and Seattle models proved to be very similar. The impact of household car availability on combined choice of TOD & mode has been captured through the mode utility component in a way that proved to be very similar to the impact on pure mode choice. With the New York data, adding the TOD dimension did not change the main effects that are expressed through mode preferences by four car-sufficiency groups. In the same vein, the mode preference effects that were included in the mode choice models based on the Seattle RP data were once again included in the mode and TOD choice models, and the results were much the same, with the exception that many of the effects were estimated even more significantly.

3.5.6 Impact of Household or Person Income

New York Model

Income has several important impacts on joint choice of TOD & mode. The first set of impacts relates to mode preferences. These impacts in the joint choice framework proved to be very similar to the mode preferences discussed in Section 3.2 above for the pure mode choice model – see Table 3.35. Thus, in this section we focus on the second set of impacts that directly relate to TOD choice dimension. The full joint TOD & mode choice model estimation results are presented in Appendix A-3. In the joint model, both set of impacts are intertwined in a sense that income differences manifest themselves in mode preferences, TOD preferences, and interactions between these effects through differential mode LOS attributes by TOD periods. For example, high income commuters have a preference for commuter rail among transit modes and have preference for later departure hours (8am or later). If the commuter rail LOS (in particular, service frequency) is maximum between 8am and 10am this would reinforce both impacts. However, if the commuter rail frequency is maximum between 6am and 8am this would mitigate both impacts (that is closer to the actual situation in New York where commuter rail schedules are defined taking into account interests of all income groups). The specific TOD-related effects are presented in Table 3.53 (specification of all shift variables) and Figure 3.21 (composite effect of all shift variables on departure time from home as an example).

Table 3.53. Mode and TOD Choice, New York, RP, Income Effect on TOD

Variable	Departure	Arrival	Duration
INCOME			
Low Income Group			
Linear Shift for Departure after 9 am	0.1659 (4.34)		
Linear Shift for Duration less than 9 hours			0.0567 (2.04)
Linear Shift for Duration more than 9 hours			-0.0638 (-1.48)
High Income Group			
Linear Shift for Departure before 8 am	0.1908 (5.89)		
Linear Shift for Departure after 9 am	-0.0457 (-1.73)		
Linear Shift for Duration less than 9 hours			-0.0240 (-1.6)
Linear Shift for Duration more than 9 hours			0.1071 (4.95)
Extreme Periods - Dummy Variables			
High Income - Departure Before 5 am	0.1264 (0.44)		
High Income - Arrival after 11pm		-0.6249 (-3.75)	
NOBS	8803		
LL with Constants only	-43202.1		
LL	-41935.3727		

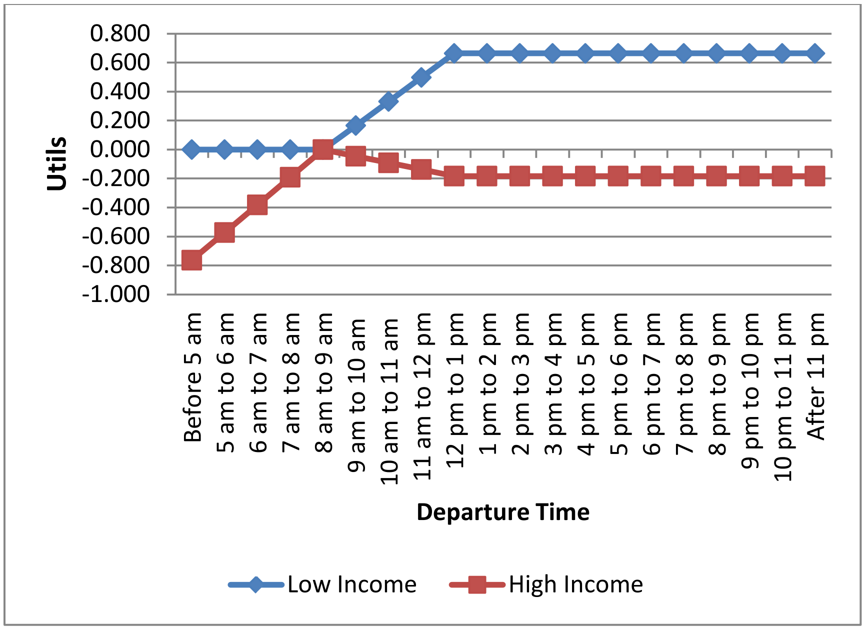


Figure 3.21. Mode and TOD choice, New York, RP, income effect on TOD.

Impacts of low income and high income are mapped using medium income commuters as the reference case with all effects equal to zero. It can be seen, that low-income commuters tend to have unconventional late schedules (departure from home after 9am) more frequently than medium and high income workers. The most prominent feature of high-income commuters is that they avoid very early starts (before 7am) compared to medium-income and low-income workers. This correlates with the nature of corresponding occupations. In particular, low-income workers may work second shifts and other late schedules associated with services and food industry. High-income workers occupy managerial positions with workplaces primarily in downtown offices that tend to start at conventional hours. They may have flexible schedules that allow for later arrivals to avoid peak hour commuting that is problematic in New York for both highway and transit modes.

Seattle Model

For the Seattle RP mode and TOD choice models, we repeated the same tests that were done for the mode choice models that are reported in Section 3.4: segmenting the cost coefficient by income and vehicle occupancy versus assuming the same power function that was adopted for the analyses on the New York data. The results shown in Table 3.54 and Figure 3.22 are virtually unchanged from what was found for the mode choice only models, with less sensitivity of the cost coefficient to income than what is represented in the assumed power functions.

Table 3.54. Mode and TOD Choice, Seattle, RP, Effect of Income and Occupancy on Cost Coefficient

Trip type:	HB Work	HB Work	HB Other	HB Other
Model – with 5 broad skim periods	**(1) motod04g**	**(2) motodw04h**	**(1) motodn04g**	**(2) motodn04h**
	Coefficient (T-Stat)	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**
Travel cost – all cases ($)	-0.334 (-14.9)		-0.240 (-4.5)	
Travel cost – income is less than $30K ($)	-0.0553 (-1.5)		0.0664 (1.1)	
Travel cost – income is $60K to $100K ($)	0.0375 (2.1)		-0.0231 (-0.5)	
Travel cost – income is more than $100K ($)	0.126 (7.0)		0.149 (2.8)	
Travel cost – 2 occupants in veh. ($)	0.121 (8.9)		0.0323 (2.5)	
Travel cost – 3+ occupants in veh. ($)	0.147 (7.0)		0.0113 (0.9)	
Travel cost (toll) divided by income to the power 0.6 and occupancy to the power 0.8, $\$/[(\$)^{0.6}(O^{0.8}]$		-198 (-17.8)		
Travel cost (toll) divided by income to the power 0.5 and occupancy to the power 0.7, $\$/[(\$)^{0.5}(O^{0.7}]$				-25.9 (-5.9)
Auto travel time (min)	-0.0269 (-9.5)	-0.0299 (-10.4)	-0.0414 (-6.3)	-0.0432 (-6.7)
Observations	11,798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.378	0.377	0.207	0.207
Final log-likelihood	-33023.3	-33043.9	-72503.1	-72517.3

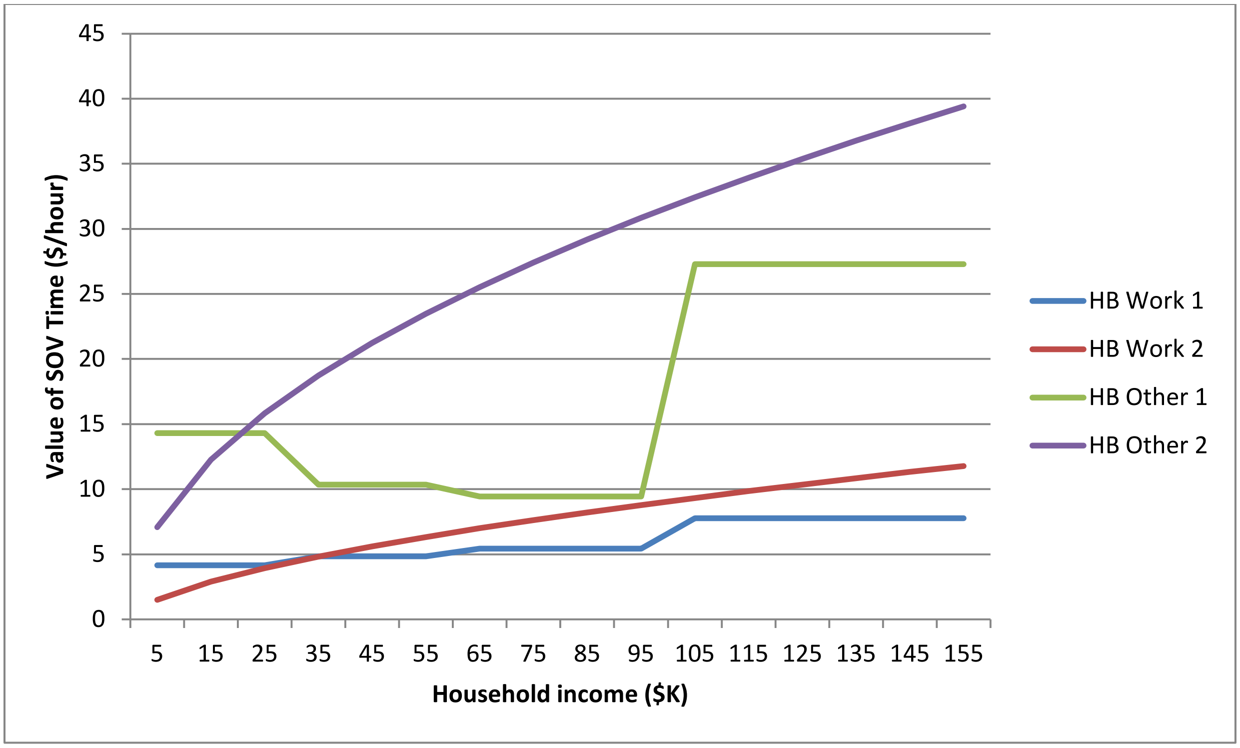


Figure 3.22. Seattle RP, trip TOD and mode choice, VOT versus household income.

Comparison and Synthesis: Seattle and New York

Income has several important impacts on joint choice of TOD & mode. The first set of impacts relates to mode preferences. With the New York model, these impacts in the joint choice framework proved to be very similar to the mode preferences discussed in Section 3.2 above for the pure mode choice model. In the same vein, for the Seattle models, we repeated the same tests that were done for the mode choice models that are reported in Section 3.4: segmenting cost coefficient by income and vehicle occupancy as opposed to assuming the same power function that was adopted for the analyses on the New York data. Similar to the tests with the New York model, the results were virtually unchanged from what was found for the mode choice only models.

The second set of income impacts tested relates to schedule preferences. For example, the New York data showed that low-income commuters tend to have later schedules (departure from home after 9am) more frequently than medium and high income workers. The most prominent feature of high-income commuters is that they avoid very early starts (before 7am) compared to medium-income and low-income workers. This correlates with the nature of corresponding occupations and schedule flexibility.

3.5.7 Impact of Joint Travel

New York Model

Similar to the income variable, joint travel variable has two intertwined effects on combined mode & TOD choice. The first effect is captured by the mode-specific utility components that enter each TOD choice alternative with the corresponding LOS variables. For example, if an HOV or HOT lane is applied in the peak period (or if toll is set in the peak period in a specific way favoring HOV) this would affect mode choice creating a shift from SOV to HOV. If this policy also makes the entire mode choice logsum in the peak period worse compared to the mode choice logsums for the other periods it will also lead to a peak spreading shift. These effects are explained by the mode choice component and they remain very similar in the joint mode & TOD choice formulation to the mode choice effects (specifically the sub-split between SOV and HOV) as was discussed above in Section 3.4 – see Table 3.37. However, in the joint mode & TOD formulation, an additional direct effect of car occupancy on TOD choice has been captured as presented in Table 3.55 (specification of the shift variables associated with HOV mode versus the rest of modes) and Figure 3.23 (mapping the composite effect in graphical form). This second effect is applied in addition to the first effect. While the first (logsum-related) effect is sensitive to LOS variables and corresponding policies like HOV/HOT lanes, the second effect is more related to carpool organization factors and associated schedule constraints of the participants.

Table 3.55. Mode and TOD Choice, New York, RP, Impact of Joint Travel on TOD

Variable	Departure	Arrival	Duration
JOINT TRAVEL (HOV)			
Linear Shift for Departure before 8 am	-0.0056 (-0.06)		
Squared Shift for Departure before 8 am	0.0896 (2.29)		
Linear Shift for Arrival before 5 pm		-0.0473 (-1.8)	
Linear Shift for Arrival after 6 pm		-0.1155 (-3.85)	
NOBS	8803		
LL with Constants only	-43202.1		
LL	-41909.9478		

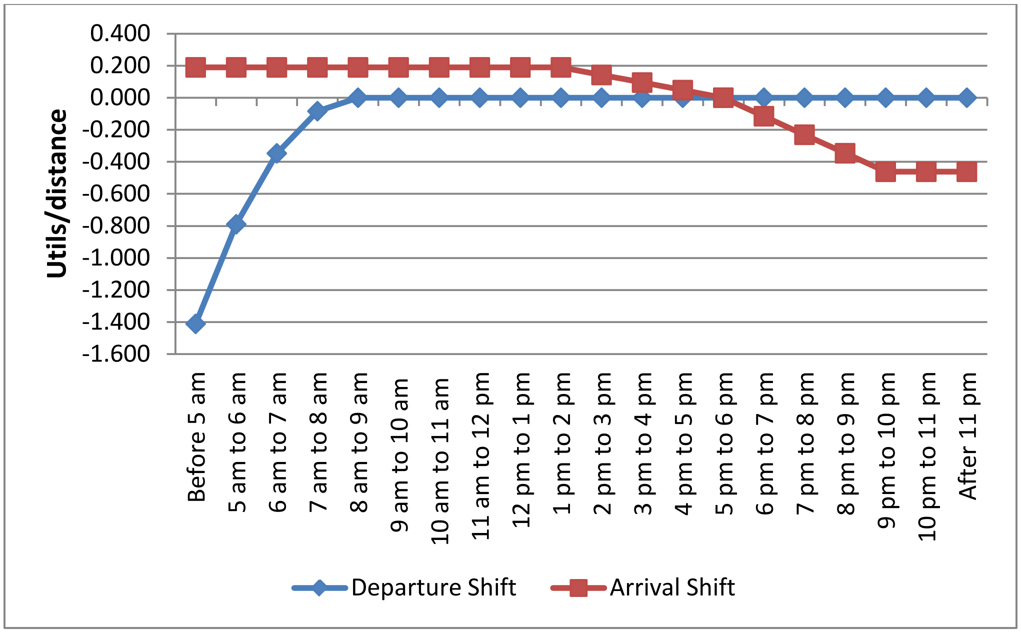


Figure 3.23. Mode and TOD choice, New York, RP, impact of joint travel on TOD.

Carpooling commuters are characterized by a later departure from home when very early hours from 5am to 7am are avoided. Taking into account that there is general sharp reduction in commuting frequency after 10am by all modes it leaves the majority of HOV commuters in a relatively narrow departure time window between 8am and 10am. This is logical since forming a carpool to work is a regular arrangement that requires schedule synchronization between several workers (most frequently not from the same household). It has a higher chance to succeed if the worker has a conventional peak-period schedule. It becomes problematic for those who have either very early or very late schedule since it would be difficult to find a partner with the same extreme schedule. In a similar vein, carpoolers avoid very late arrivals back home (after 7pm) since it might not be convenient for at least some members of the travel party.

Seattle Model

Figure 3.24 plots the results for computed VOT as a function of vehicle occupancy for the models in Table 3.54. The results are virtually unchanged from what was found for the mode choice only models and discussed in Section 3.4, with less sensitivity of the cost coefficient to vehicle occupancy than what is represented in the assumed power functions, particularly in the HB Other models. Specific impacts of car occupancy on TOD choice were not investigated.

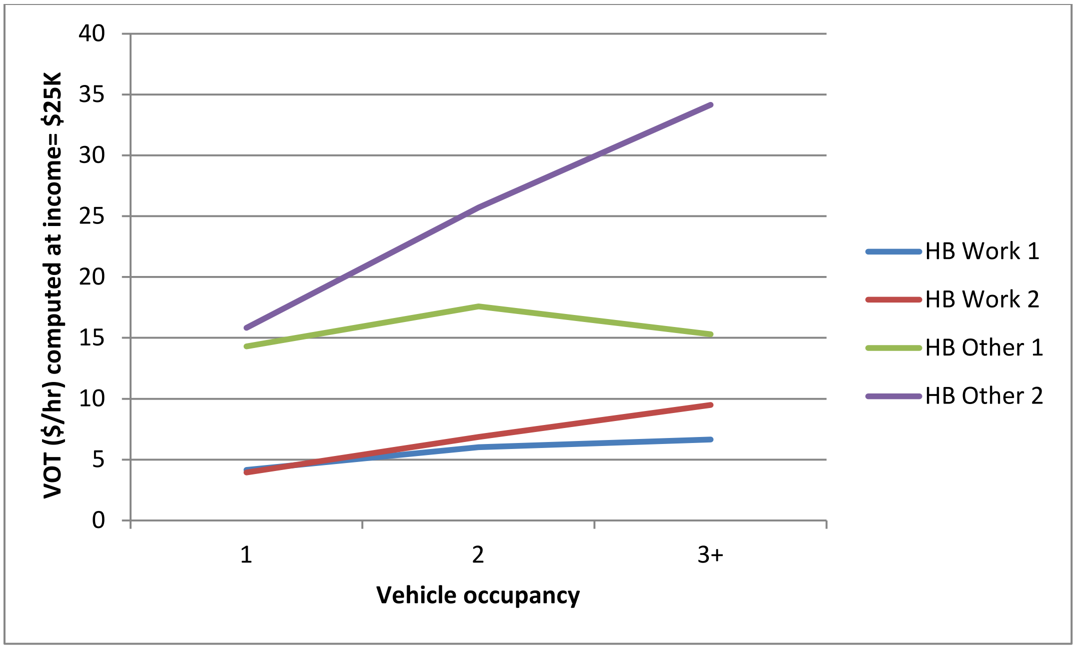


Figure 3.24. Seattle RP, trip mode and TOD choice: VOT versus vehicle occupancy.

Comparison and Synthesis: Seattle and New York

Similar to the income variable, joint travel variable has two intertwined effects on combined mode & TOD choice. The first effect is captured by the mode-specific utility components that enter each TOD choice alternative with the corresponding LOS variables. These effects are explained by the mode choice component and, for the New York model, they remain very similar in the joint mode & TOD choice formulation to the mode choice effects (specifically the sub-split between SOV and HOV) as was discussed above in Section 3.2. In a similar way, with the Seattle model, the carpooling impacts were virtually unchanged from what was found for the mode choice only models discussed in Section 3.4, with less sensitivity of the cost coefficient to vehicle occupancy than what is represented in the assumed power functions, particularly in the HB Other models.

However, in the joint mode & TOD formulation, a second (direct) effect of car occupancy on TOD choice has been captured with the New York model. While the first (logsum-related) effect is sensitive to LOS variables and corresponding policies like HOV/HOT lanes, the second effect is more related to carpool organization factors and associated schedule constraints of the participants. Carpooling commuters are characterized by a later departure from home when very early hours from 5am to 7am are avoided. In a similar vein, carpoolers avoid very late arrivals back home (after 7pm), since it might not be convenient for at least some members of the travel party.

3.5.8 Impact of Gender, Age, and Other Person Characteristics

New York Model

The New York mode choice model for work tours does not include person variables (although it includes many household variables) and this limitation was preserved for compatibility with the previous analysis. Many person and household variables were statistically examined in the TOD utility components in terms of their impact on either departure time from home or arrival back home or work tour duration. Several most significant effects are summarized in Table 3.56 (coefficients for continuous shifts and other variables). The corresponding composite effects presented in a graphical form in Figure 3.25 (departure time related effects) and Figure 3.26 (duration related effects).

Table 3.56. Mode and TOD Choice, New York, RP, Impact of Person Characteristics on TOD

Variable	Departure	Arrival	Duration
PERSON CHARACTERISTICS			
Dummy Variables			
Full Time Worker, Duration less than 9 hrs			-1.1783 (-12.3)
Full Time Worker, Arrival before 3 pm		-0.6420 (-6.78)	
Part-Time Worker			
Linear Shift for Departure before 8 am	0.2757 (5.07)		
Linear Shift for Departure after 9 am	0.2494 (9.44)		
Linear Shift for Duration more than 9 hours			-0.1708 (-3.14)
Non-Worker			
Linear Shift for Departure before 8 am	0.1260 (1.18)		
Linear Shift for Departure after 9 am	0.2625 (4.89)		
Linear Shift for Duration less than 9 hours			-0.0954 (-3.04)
NOBS	8803		
LL with Constants only	-43202.1		
LL	-41374.6818		

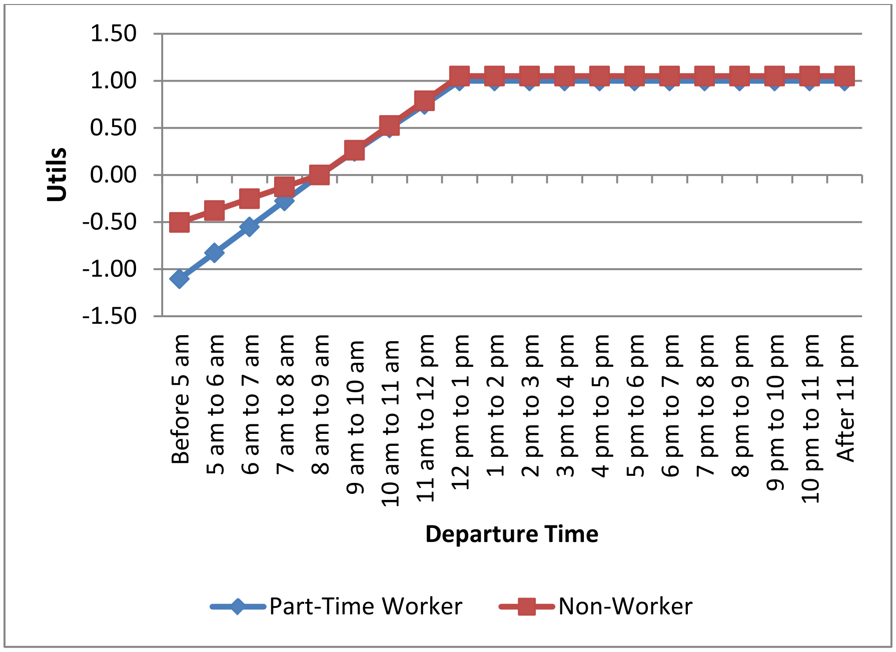


Figure 3.25. Mode and TOD choice, New York, RP, impact of person characteristics on departure time to work.

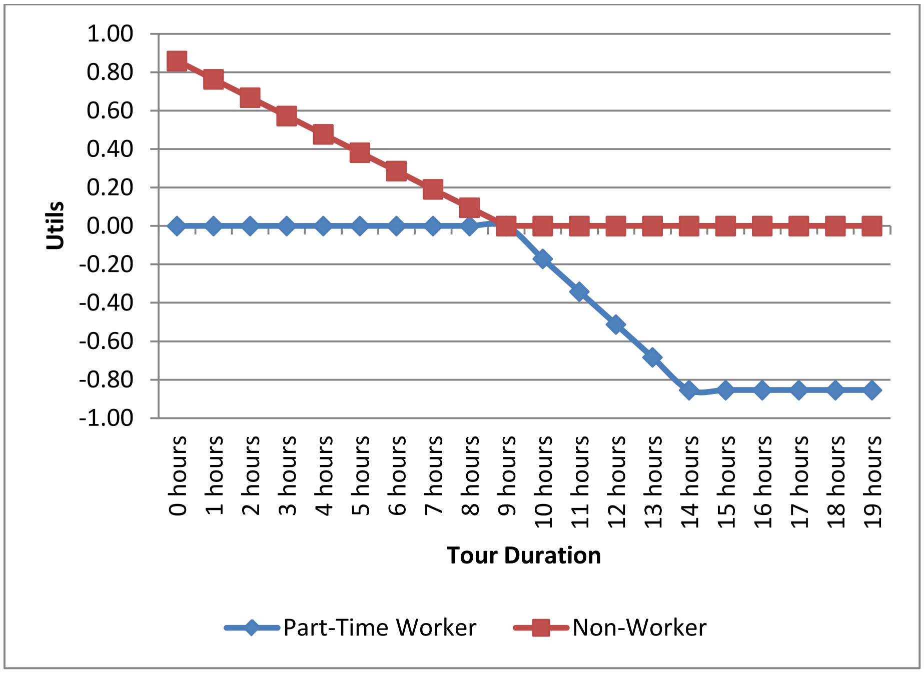


Figure 3.26. Mode and TOD choice, New York, RP, impact of person characteristics on duration of work tour.

The most important distinction that strongly affects TOD choice for commuters is worker status where three main person types are considered—full-time worker, part-time worker, and non-worker. The last category still includes some commuters for job interviews, occasional work, and volunteers. In terms of departure time effects, full-time worker is chosen as the reference case with the timing profile described by many variables presented in the full model specification in Appendix A-3. Part-time workers and non-workers are characterized by later departure-from-home time compared to full-time workers. In particular, they strongly avoid departure hours between 5am and 8am. It is logical since one of the main reasons for part-time work is to create reasonable time windows for home errands and childcare both before and after work (majority of part-time workers are female). Also, due to a shorter average duration of work activity of part time workers and shorter commuting times (part-time workers are characterized by a significantly shorter average commuting distance – see *Vovsha et al, 2012*) there is no pressing need for many of them to start early.

With respect to work tour duration, both part-time workers and non-workers are characterized by significantly shorter schedules compared to full-time workers that represent the base case. For part-time workers it is expressed in a strong negative utility component when the duration exceeds 9 hours (including work activity and commuting time). For non-workers it is expressed in a significant positive utility component for durations shorter than 8 hours. It should be noted that in the TOD choice framework like in any logit model, utilities are calculated and applied for each person in relative fashion (only the differences between alternatives matter and not the absolute values). Thus, penalizing long durations is equivalent to promoting short durations. However, the actual curvature of the utility function components for part-time workers is different from the one for non-workers. Part-time workers when compared to full-time workers, progressively avoid longer durations but do not exhibit a significant difference with respect to shorter durations (8 hours or shorter). In particular they do not prefer very short work episodes (4 hours or less including commuting time). Contrary to that, non-workers progressively prefer shorter episodes including very short durations since they include job interviews, volunteering, and other non-conventional work activities.

For arrival time back home, most of the effects will be derived as a composition of departure time and duration effects. For example, longer durations for full time workers, will naturally create later arrivals all else being equal. However, in addition to the derived effects for full-time workers, one direct arrival time related effect proved to be significant. Full-time workers rarely arrive back home before 3pm compared to part-time workers and non-workers. It is logical since for a conventional full-time workday, arrival back home before 3pm would require a very early departure from home. The observed cases of such early arrival for full-time workers correspond to special occasions and events (for example, one-time adjustment of work schedule to attend a sporting event with the family or doctor appointment, etc).

Seattle Model

Beginning with the Model 2 specification for the Seattle RP data from the previous section, with cost divided by functions of income and vehicle occupancy, we also included additive travel time variables specific to females and part-time workers, as well as an additive travel time variable multiplied by age minus 18 (set at a minimum of 0 to apply only to those over 18). This is the same analysis as reported in Section 3.4 for the mode choice only models. Here, the results shown in Table 3.57 are somewhat less significant than was found in the mode choice only models, with no significant differences in VOT related to gender, age or part-time employment status (although there are significant mode preference and TOD shift variables related to these characteristics, as reported in previous sections and shown in the full model results in the appendices).

Table 3.57. Mode and TOD Choice, Seattle, RP, Effect of Age, Gender and Employment Status on Travel Time Coefficient

Trip type:	**HB Work**	HB Work	**HB Other**	**HB Other**
Model – with 5 broad skim periods	**motodw04h**	**motodw04i**	**motodn04h**	**motodn04i**
	Coefficient (T-Stat)	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**
Travel cost (toll) divided by income to the power 0.6 and occupancy to the power 0.8, $\$/[(\$)^{0.6}(O^{0.8}]$	-198 (-17.8)	-198 (-17.7)		
Travel cost (toll) divided by income to the power 0.5 and occupancy to the power 0.7, $\$/[(\$)^{0.5}(O^{0.7}]$			-25.9 (-5.9)	-25.4 (-5.9)
Auto travel time (min)	-0.0299 (-10.4)	-0.0280 (-7.4)	-0.0432 (-6.7)	-0.0539 (-5.8)
Auto travel time - female (min)		-0.0025 (-1.3)		-0.002 (-0.3)
Auto travel time – age (min * (age-18))		-0.00005 (-0.5)		0.00028 (1.5)
Auto travel time – part time worker (min)		0.0049 (0.7)		0.0046 (0.8)
Observations	11,798	11,798	20,602	20,602
Rho-squared w.r.t. 0	0.377	0.377	0.207	0.207
Final log-likelihood	-33043.9	-33042.7	-72517.3	-72515.0

Comparison and Synthesis: Seattle and New York

First we summarize the impacts of person and household characteristics on the mode choice component comparing it to the previously estimated pure mode choice formulations in Section 3.4 above. For the Seattle model, with cost divided by functions of income and vehicle occupancy, we also included additive travel time variables specific to females and part-time workers, as well as an additive travel time variable multiplied by age minus 18 (set at a minimum of 0 to apply only to those over 18). The results were somewhat less significant than was found in the mode choice only models, with no significant differences in VOT related to gender, age or part-time employment status.

Secondly, there are significant mode preference and TOD shift variables related to these characteristics, as reported in previous sections and shown in the full Seattle model results in Appendix A-4). Similarly, with the New York model, several TOD-related effects of person characteristics have been captured in addition to person variables included in the mode choice portion of the combined utilities. The most important distinction that strongly affects TOD choice for commuters is worker status where three main person types are considered – full-time worker, part-time worker, and non-worker. The last category still includes some commuters for job interviews, occasional work, and volunteers. Part-time workers and non-workers are characterized by later departure-from-home time compared to full-time workers. With respect to work tour duration, both part-time workers and non-workers are characterized by significantly shorter schedules compared to full-time workers. For arrival time back home, most of the effects will be derived as a composition of departure time and duration effects. For example, longer durations for full time workers, will naturally create later arrivals all else being equal. However, in addition to the derived effects for full-time workers, one direct arrival time related effect proved to be significant. Full-time workers rarely arrive back home before 3pm compared to part-time workers and non-workers.

3.5.9 Incorporation of Travel Time Reliability and VOR Estimation

New York Model

Travel time reliability is a factor that was explored with respect to impacts on two travel dimensions. As was discussed earlier in Section 3.4, travel time unreliability measured as a standard deviation of travel time per unit distance, affects choice of modes as it was found statistically significant in mode choice utilities for highway modes along with the mean travel time, and this effect becomes even more statistically significant when mode choice is considered jointly with TOD choice – see Table 3.31. In general, the greater the level of unreliability of highway travel time is the lower is the share of highway modes versus transit and other modes, all else being equal. Through time-of-day-specific mode choice logsums, this impact has also effect on time-of-day choice. However, it was important to explore a possible direct impact of travel time reliability on time-of-day choice in addition to the effect incorporated in mode choice logsums. Travel time variation may have this direct effect on time-of-day choice through such behavioral mechanism as taking an extra (buffer) time, for example, depart earlier from home to ensure arrival at work on time, due to a perceived penalty associated with a late arrival.

For this purpose, travel time reliability measure was explored statistically as a shift variable in the time-of-day choice utility (departure from home and arrival back home components) in addition to inclusion of travel time reliability in the mode choice logsum. The results are summarized in Table 3.58 and presented in a graphical form in Figure 3.27.

Table 3.58. Mode and TOD Choice, New York, RP, Impact of Travel Time Reliability on TOD

Variable	Departure	Arrival	Duration
RELIABILITY MEASURE (STANDARD DEVIATION OF TRAVEL TIME PER MILE)			
Linear Shift for Departure before 8 am	-0.2932 (-2.32)		
Linear Shift for Departure after 9 am	0.0047 (0.04)		
Linear Shift for Arrival before 5 pm		0.1383 (0.95)	
Linear Shift for Arrival after 6 pm		0.4054 (2.65)	
NOBS	8803		
LL with Constants only	-43202.1		
LL	-41360.4143		

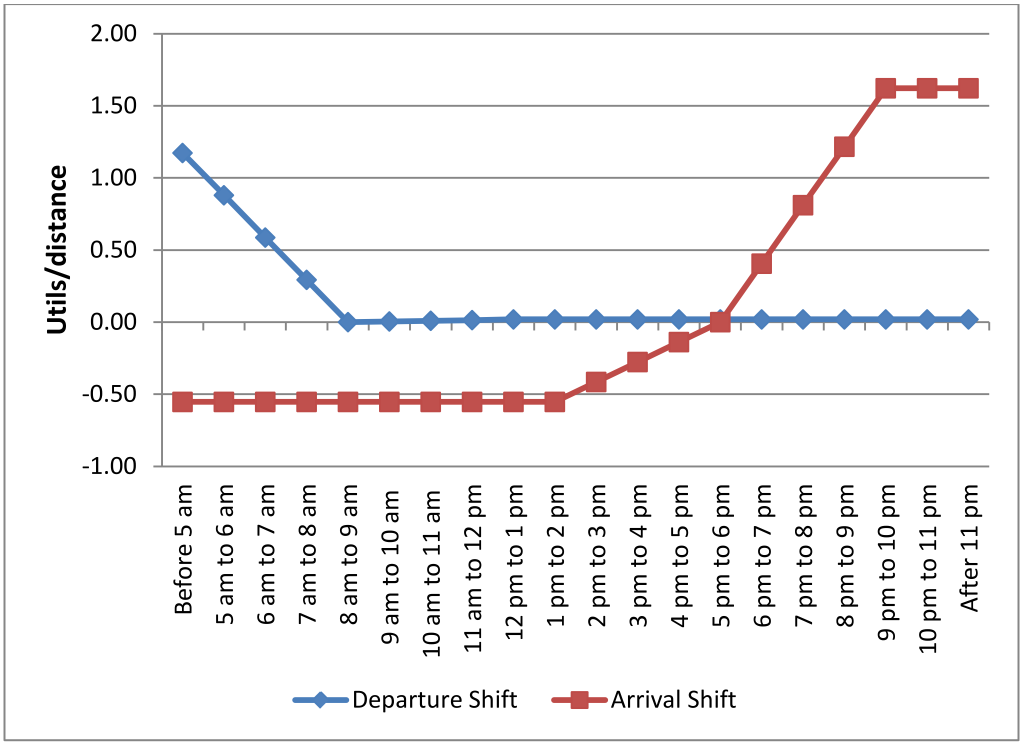


Figure 3.27. Mode and TOD choice, New York, RP, impact of reliability on TOD.

The results confirmed two logical and statistically significant effects. The first effect relates to shift of commuting departure time to hours earlier than 8AM that is progressively stronger for each earlier hour. This statistical evidence fully confirms the fact that commuters have to take into account a certain extra (buffer) time in presence of travel time unreliability. At this stage of research we do not know exactly the schedule constraints of each individual and his preferred arrival time but the aggregate buffering tendency manifested itself strongly. In future research, it would be beneficial to explore more elaborate reliability measures like schedule delay and support this by collection of additional data items on individual schedule flexibility as well as preferred arrival time (in addition to the actual arrival time).

Similar symmetric effect was found for arrival time back home after work. Travel time unreliability resulted in later arrivals with a progressive effect between 5pm and 9pm. However, the explanation of this phenomenon is different from the buffering observed in the morning commute to work since the inbound commuting does not have the same level of schedule constraints. Part of it relates to the general avoidance of congestion. It might look counterintuitive that in presence of unreliable travel times in both AM and PM periods, commuters would shift the outbound commuting to an earlier hour while simultaneously shifting the inbound commuting to a later hour. This results in a systematic bias towards longer work durations. However, it is quite plausible that many of these commuters switch to compressed work weeks (that have become a norm in the New York Metropolitan Region, especially for workers whose jobs are in Manhattan). The existing dataset did not include data on work schedule flexibility; it would be interesting to explore alternative work arrangements in future with datasets that include these variables.

Seattle Model

With the Seattle RP data, we repeated the tests of estimating with travel time reliability variables reported above in Sections 3.3 and 3.4, but this time using joint mode and TOD choice models, instead of either one separately. The results are presented below in Table 3.59. Overall, the results are quite similar to those in Table 3.32 for the mode choice models.

For the HB Work models, the reliability variables all have the incorrect sign, except when included as the buffer travel time (90th percentile minus median) divided by distance, which has a significant negative coefficient. For the HB Other models in the bottom half of Table 3.59, the buffer travel time variable is again the only reliability variable with a significant negative coefficient, but this time when <u>not</u> divided by trip distance. The coefficient on the buffer time is about 25% as high as the main travel time coefficient, meaning that the variability in terms of the buffer time would have to be quite high to reach a reliability ratio of over 1.0.

Table 3.59. Trip Mode and TOD Choice, Seattle, RP, Inclusion of Reliability Variables

Trip type:	**HB Work**	**HB Work**	**HB Work**	**HB Work**
Model – with 5 broad skim periods	**motodw04b**	**motodw04c**	**motodw04d**	**motodw04e**
	Coefficient (T-Stat)	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**
Travel cost ($)	-0.255 (-14.5)	-0.220 (-11.2)	-0.260 (-14.9)	-0.262 (-15.0)
Auto travel time (min)	-0.0396 (-10.0)	-0.0277 (-8.7)	-0.0392 (-8.6)	-0.0293 (-10.0)
Std. deviation of travel time (min)	0.118 (3.9)			
Std. dev.travel time / distance (min/mile)		0.969 (2.9)		
Buffer (90^{th} % - median) time (min)			0.0105 (2.8)	
Buffer (90^{th} % - median) / distance (min/mile)				-0.0514 (-2.6)
Trip type:	**HB Other**	**HB Other**	**HB Other**	**HB Other**
Model – with 5 broad skim periods	**motodn04b**	**motodn04c**	**motodn04d**	**motodn04e**
	Coefficient (T-Stat)	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**	**Coefficient (T-Stat)**
Travel cost ($)	-0.123 (-5.9)	-0.169 (-5.0)	-0.168 (-4.9)	-0.188 (-5.1)
Auto travel time (min)	-0.0208 (-3.7)	-0.0410 (-5.8)	-0.0346 (-5.2)	-0.0425 (-6.5)
Std. deviation of travel time (min)	-0.0397 (-1.0)			
Std. dev.travel time / distance (min/mile)		-0.292 (-0.5)		
Buffer (90^{th} % - median) time (min)			-0.0094 (-4.2)	
Buffer (90^{th} % - median) / distance (min/mile)				0.0303 (2.9)

Comparison and Synthesis: Seattle and New York

Travel time reliability was explored with respect to impacts on two travel dimensions. As was discussed earlier in Section 3.4, travel time unreliability, measured as a standard deviation of travel time per unit distance, affects choice of modes as it was found statistically significant in mode choice utilities for highway modes, along with the mean travel time. With the New York data, this effect becomes even more statistically significant when mode choice is considered jointly with TOD choice. In general, the greater the level of unreliability of highway travel time, the lower is the share of highway modes versus transit and other modes, all else being equal. Through time-of-day-specific mode choice logsums, this impact has also effect on time-of-day choice. However, the results for the Seattle Model were less successful. For the HB Work models, the reliability variables all have the incorrect sign, except when included as the buffer travel time (90^{th} percentile minus median) divided by distance, which has a significant negative coefficient. For the HB Other models, the buffer travel time variable is again the only reliability variable with a significant negative coefficient, but this time when not divided by trip distance. We may conclude that the distribution of level of congestion and associated variation in travel time reliability measures in the Seattle data was not rich enough.

It was also important to explore a possible direct impact of travel time reliability on time-of-day choice, in addition to the effect incorporated in mode choice logsums. For this purpose, with the New York model, travel time reliability measure was explored statistically as a shift variable in the time-of-day choice utility (departure from home and arrival back home components), in addition to inclusion of travel time reliability in the mode choice logsum. The results confirmed two logical and statistically significant effects. The first effect relates to the shift of commuting departure time to hours earlier than 8AM that is progressively stronger for each earlier hour. This statistical evidence fully confirms the fact that commuters take into account a certain extra (buffer) time in presence of travel time unreliability. Similar the symmetric effect that was found for arrival time back home after work. Travel time unreliability resulted in later arrivals with a progressive effect between 5pm and 9pm.

3.5.10 Impact of Urban Density and Land Use

New York Model

Several effects associated with urban density and land-use type were explored with the New York data. In general, the New York Metropolitan Region is characterized by a high diversity in terms of urban forms from the typical low-density suburban and rural areas to unique high-density conditions in Manhattan. Some of effects were already incorporated in the mode choice utilities as discussed in Section 3.4 – see Table 3.42. In addition to unique transit accessibility and walkability of Manhattan that is expressed in mode choice logsums we also explored a possible direct impact of density (and other related variables) on time-of-day choice.

The results are summarized in Table 3.60 and (in graphical from) in Figure 3.28. The most prominent effect was associated with a simple Manhattan job dummy that captures the principal difference between commuting to Manhattan and the rest of the metropolitan area. It should be noted that the Manhattan dummy was applied on top of all other variables described above including full mode choice logsusms with reliability measures and non-linear time and distance effects, as well as all person and household variables including income, work status, and gender.

Table 3.60. Mode and TOD Choice, New York, RP, Impact of Urban Density on TOD

Variable	Departure	Arrival	Duration
URBAN DENSITY			
To Manhattan			
Linear Shift for Duration less than 9 hours			0.0675 (2.21)
Linear Shift for Duration more than 9 hours			0.0694 (2.35)
NOBS	8803		
LL with Constants only	-43202.1		
LL	-41366.7813		

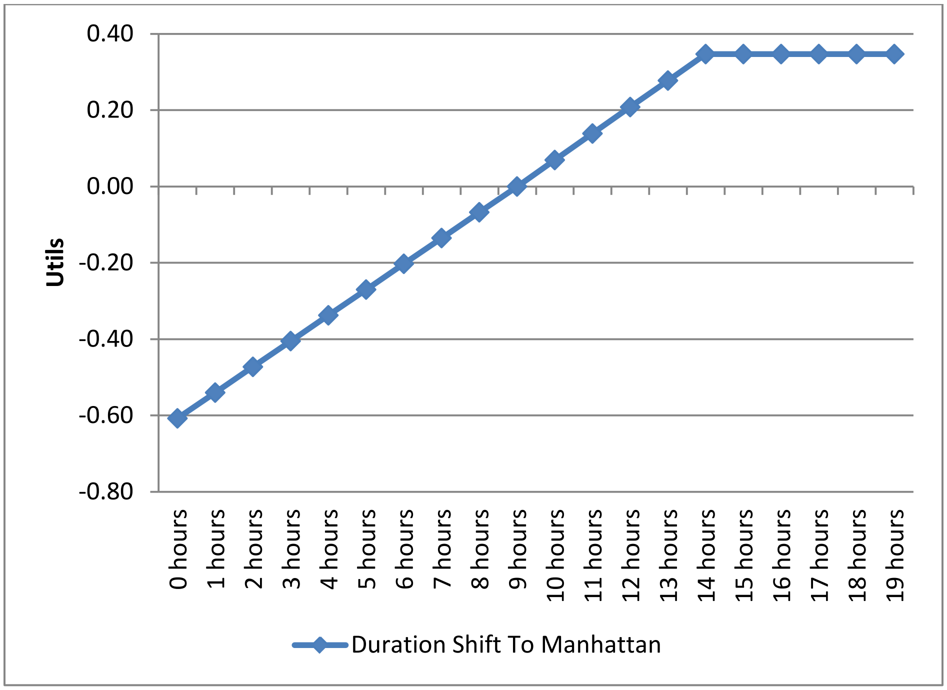


Figure 3.28. Mode and TOD Choice, New York, RP, impact of urban density on TOD.

The additional direct effect on time-of-day choice captured by the Manhattan dummy is associated with a significantly longer duration of work tours. This spans a wide range of durations from very short to 14 hours. There are two main behavioral mechanisms that can explain this phenomenon. First, Manhattan jobs are characterized by primarily office and managerial occupations that are characterized by longer durations and more flexible arrangements like a compressed work week. In absence of occupation as an explanatory variable (that is another good item for future research), the Manhattan dummy takes on itself this occupation effect. It is interesting that this effect manifests itself strongly after taking into account variables like income, commuting distance, travel time, and travel time unreliability. Secondly, in this analysis we operate with the entire-tour duration (from departure from home until arrival back home) rather than duration of the work activity itself. Thus, additional activities (stops) on the way to and from work come into play. Logically, commuting tours to Manhattan are characterized by a higher frequency of stops, primarily, in Manhattan, and because of a great variety of opportunities for shopping and discretionary activities there.

Seattle Model

No particular impact of urban density on time-of-day choice was found with the Seattle data. This means that the proposed joint time-of-day and mode choice framework with a rich set of explanatory variables incorporates the main location impacts. It can be understood that compared to New York, Seattle is characterized by more uniform urban and travel conditions in the metropolitan area.

Comparison and Synthesis: Seattle and New York

Several effects associated with urban density and land-use type were explored with the New York data. Some of effects were already incorporated in the mode choice utilities as discussed in Section 3.4. The effects remained stable after extension of the choice dimensions to include TOD in addition to mode.

The most prominent new effect on TOD choice was associated with a simple Manhattan job dummy that captures the principal difference between commuting to Manhattan and the rest of the metropolitan area. The additional direct effect on time-of-day choice captured by the Manhattan dummy is associated with a significantly longer duration of work tours. This spans a wide range of durations from very short to 14 hours. There are two main behavioral mechanisms that can explain this phenomenon. First, Manhattan jobs are characterized primarily by office and managerial occupations that are associated with longer durations and more flexible arrangements like a compressed work week. Secondly, in this analysis we operate with the entire-tour duration (from departure from home until arrival back home), rather than with duration of the work activity itself. Thus, additional activities (stops) on the way to and from work come into play. Logically, commuting tours to Manhattan are characterized by a higher frequency of stops, primarily, in Manhattan, and because of a great variety of opportunities for shopping and discretionary activities there.

3.5.11 Preferred Model Specifications with Deterministic Coefficients

New York Model

The final structure of the joint mode & time-of-day choice model for the New York Metropolitan Region that incorporates all effects described above is presented in Table 3.61 with respect to mode-related coefficients and Table 3.62 with respect to TOD-related coefficients. The mode-related part that incorporates main highway LOS variables – mean travel time, cost, distance, and reliability, is in the focus of current research. The most important question is if the general form of the generalized cost function previously substantiated for route choice (Section 3.2) and mode choice (Section 3.4) would hold in the extended choice framework that includes time-of-day choice as well. This is not a trivial question since the complexity of utility functions and corresponding behavioral mechanisms progress significantly through the choice dimensions. Thus, the fact that a route choice generalized cost function is included in the highway mode utility function and the latter is included in the joint mode & TOD utility function does not guarantee the same or similar results. Impacts of numerous other variables interact with the impact of LOS variables. Thus, we can expect a similar generalized cost function form only if the model specification captures the main stable effects associated with LOS variables and separates them from the other effects associated with a direct impact of socio-economic and other variables.

Table 3.61. Mode and TOD Choice, New York, RP, Final Structure, Mode-Related Coefficients

Variable	Mode								
	SOV	HOV2	HOV3	HOV4+	WCR	DCR	WT	DT	TX
IVT	-0.0058 (-7.35)								
COST [Inc$^{0.6}$,Occ$^{0.8}$]	-806.1826 (-17.81)								
TIME×DIST	-0.00036 (-6.52)								
TIME×DIST^2	0.00000167 (4.56)								
STD/D	-0.4923 (-3.29)								
WAIT					-0.0116				
WALK					-0.0087				
DIST					0.0085 (6.68)				
DACC						-0.0058		-0.0058	
LOW/A=0	-99.000		-1.0522 (-2.98)	-1.0522 (-2.98)	5.6427 (5.87)	1.9154 (2.9)	3.8945 (17.88)	1.4045 (1.27)	
LOW/A<W	0.8878 (9.66)		-1.6767 (-19.46)	-1.6767 (-19.46)	1.000	0.6347 (0.96)	1.0008 (3.53)	-2.126 (0)	-3.7498 (-14.67)
LOW/A=W	2.251 (12.01)		-1.6767 (-19.46)	-1.6767 (-19.46)	0.500	0.6347 (0.96)	1.0008 (3.53)	-2.126 (0)	-3.7498 (-14.67)
LOW/A>W	2.3666 (32.17)		-1.6767 (-19.46)	-1.6767 (-19.46)	0.200	0.6347 (0.96)	-0.195	-2.126 (0)	-4.5994 (-6.36)
MED/A=0	-99.000		-1.0522 (-2.98)	-1.0522 (-2.98)	4.5717 (8.03)	1.9154 (2.9)	3.8945 (17.88)	1.1935 (1.54)	
MED/A<W	0.8878 (9.66)		-1.6767 (-19.46)	-1.6767 (-19.46)	0.6641 (1.59)	-0.7122 (-1.99)	0.7729 (4.81)	-1.4656 (-2.62)	-3.7498 (-14.67)
MED/A=W	2.0059 (34.35)		-1.6767 (-19.46)	-1.6767 (-19.46)	0.0933 (0.27)	-0.0767 (-0.33)	0.2356 (1.47)	-0.8158 (-2.39)	-3.7498 (-14.67)
MED/A>W	2.3666 (32.17)		-1.6767 (-19.46)	-1.6767 (-19.46)	-0.0279 (-0.07)	-0.0767 (-0.33)	-0.1954 (-0.8)	-0.8158 (-2.39)	-4.5994 (-6.36)
HIGH/A=0	-99.000		-1.0522 (-2.98)	-1.0522 (-2.98)	4.5717 (8.03)	-0.8869 (0)	2.9936 (8.88)	2.0013 (1.61)	
HIGH/A<W	0.8952 (4.81)		-1.6767 (-19.46)	-1.6767 (-19.46)	-0.4909 (-0.79)	-0.7122 (-1.99)	0.1051 (0.4)	-2.2979 (-2.02)	-2.0188 (-5.67)
HIGH/A=W	2.0059 (34.35)		-1.6767 (-19.46)	-1.6767 (-19.46)	-0.0118 (-0.03)	-0.0767 (-0.33)	-0.2406 (-1.02)	-0.8491 (-1.88)	-3.0458 (-7.77)
HIGHA>W	2.3666 (32.17)		-1.6767 (-19.46)	-1.6767 (-19.46)	-0.0279 (-0.07)	-0.0767 (-0.33)	-0.332 (-1.01)	-0.8491 (-1.88)	-3.6607 (-5.05)
INMANH		0.2238 (0.53)	0.6731 (1.22)	0.6731 (1.22)			3.5445 (12.73)		4.078 (12.58)
TOMANH		0.1677 (1.06)	-0.2699 (-0.96)	-0.2699 (-0.96)	3.1571 (9.82)	3.7841 (15.46)	1.9132 (12.64)	2.4935 (6.52)	0.3575 (0.69)
TOLLB	0.0465 (0.48)	-0.5747 (-4.88)	-0.6785 (-3.62)	-1.1066 (-8.02)					
NOBS	8803								
LL with Constants only	-43202.1								
LL	-41360.4143								
VOT (62.5K, 10 mile)	4.7								

It can be seen that the main form of the generalized cost function for highway modes that was discussed above for the route type choice models (Section 3.2) and mode choice models (Section 3.4) manifests itself in the more general choice framework when time-of-day choice dimension is added. Thus, we can recommend this general form for practical use in different types of models. This form can be written in the following way that is essentially equivalent to (Equation 3.38):

$$U = \Delta + a_1 \times T + a_2 \times T \times D + a_3 \times T \times D^2 + b \times \left[C / \left(I^{0.6} \times O^{0.8} \right) \right] + c \times R \tag{3.59}$$

where:

U	=	generalized cost,
T	=	travel time,
C	=	travel cost,
D	=	travel distance,
R	=	travel time reliability measure (standard deviation of time per unit distance),
I	=	household income of the driver,
O	=	car occupancy,
$a_1 < 0$	=	coefficient for travel time,
$a_2 < 0$	=	coefficient for travel time multiplied by distance,
$a_3 > 0$	=	coefficient for travel time multiplied by squared distance,
$b < 0$	=	coefficient for travel cost,
$c < 0$	=	coefficient for travel time reliability measure.

Table 3.62. Mode and TOD Choice, New York, RP, Final Structure, TOD-Related Coefficients and Constants

Variable	Departure	Arrival	Duration
CONSTANTS			
Before 5 am	-2.9232 (-15.32)	-9.0000	
5 am to 6 am	-2.0143 (-18.42)	-0.8000 (-0.74)	
6 am to 7 am	-0.7006 (-12.99)	-0.2448 (-0.46)	
7 am to 8 am	0.0000	-0.9182 (-1.92)	
8 am to 9 am	0.1328 (2.41)	-0.5293 (-1.39)	
9 am to 10 am	-0.7717 (-8.9)	-0.2016 (-0.62)	
10 am to 11 am	-1.7369 (-7.63)	-0.6364 (-2.14)	
11 am to 12 pm	-1.9274 (-7.51)	-0.0883 (-0.36)	
12 pm to 1 pm	-2.2463 (-7.58)	0.3933 (1.91)	
1 pm to 2 pm	-2.2217 (-6.95)	0.2315 (1.31)	
2 pm to 3 pm	-1.7086 (-5.05)	0.4012 (2.78)	
3 pm to 4 pm	-1.5165 (-4.13)	0.2127 (2.35)	
4 pm to 5 pm	-1.2538 (-3.18)	0.0186 (0.32)	
5 pm to 6 pm	-1.3450 (-3.15)	0.0000	
6 pm to 7 pm	-1.5495 (-3.38)	-0.3910 (-7.36)	
7 pm to 8 pm	-1.6506 (-3.22)	-0.8863 (-9.91)	
8 pm to 9 pm	-1.9958 (-3.53)	-1.2694 (-10.15)	
9 pm to 10 pm	-2.6334 (-3.35)	-1.4183 (-8.91)	
10 pm to 11 pm	-2.2516 (-2.83)	-1.6836 (-8.61)	
After 11 pm	-2.9079 (-2.54)	-0.9569 (-4.44)	
0 to 2 hours			-1.7787 (-6.07)
3 to 4 hours			-0.7760 (-3.66)
5 to 6 hours			-0.3854 (-2.53)
7 hours			-0.2608 (-2.19)
8 hours			0.2307 (2.35)
9 hours			0.0000
10 hours			-0.1479 (-3)
11 hours			-0.5581 (-6.7)
12 to 13 hours			-1.1261 (-8.59)
14 to 19 hours			-2.5918 (-11.41)
TRAVEL TIME			
Linear Shift for Departure before 8 am	-0.0048 (-4.23)		
Squared Shift for Departure before 8 am	0.0009 (2.29)		
Linear Shift for Departure after 9 am	-0.0051 (-10)		
Linear Shift for Arrival before 5 pm		0.0075 (6.47)	
Squared Shift for Arrival before 5 pm		-0.0001 (-0.21)	
Linear Shift for Arrival after 6 pm		0.0005 (1.33)	
INCOME			
Low Income Group			
Linear Shift for Departure after 9 am	0.1326 (3.43)		
Linear Shift for Duration less than 9 hours			0.0949 (3.25)
Linear Shift for Duration more than 9 hours			-0.0460 (-1.07)
High Income Group			
Linear Shift for Departure before 8 am	0.1955 (6.02)		
Linear Shift for Departure after 9 am	-0.0468 (-1.77)		
Linear Shift for Duration less than 9 hours			-0.0253 (-1.64)
Linear Shift for Duration more than 9 hours			0.1045 (4.81)
Extreme Periods - Dummy Variables			
High Income - Departure Before 5 am	0.1189 (0.42)		
High Income - Arrival after 11pm		-0.6220 (-3.74)	

JOINT TRAVEL (HOV)			
Linear Shift for Departure before 8 am	-0.0750 (-0.77)		
Squared Shift for Departure before 8 am	0.1006 (2.56)		
Linear Shift for Arrival before 5 pm		-0.0134 (-0.5)	
Linear Shift for Arrival after 6 pm		-0.1185 (-3.95)	
PERSON CHARACTERISTICS			
Dummy Variables			
Full Time Worker, Duration less than 9 hrs			-1.1749 (-12.26)
Full Time Worker, Arrival before 3 pm		-0.6453 (-6.81)	
Part-Time Worker			
Linear Shift for Departure before 8 am	0.2706 (4.97)		
Linear Shift for Departure after 9 am	0.3191 (5.04)		
Linear Shift for Duration more than 9 hours			-0.1677 (-3.09)
Non-Worker			
Linear Shift for Departure before 8 am	0.1215 (1.14)		
Linear Shift for Departure after 9 am	0.3322 (4.22)		
Linear Shift for Duration less than 9 hours			-0.0936 (-2.98)
URBAN DENSITY			
To Manhattan			
Linear Shift for Duration less than 9 hours			0.0667 (2.18)
Linear Shift for Duration more than 9 hours			0.0684 (2.32)
RELIABILITY MEASURE (STANDARD DEVIATION OF TRAVEL TIME PER MILE)			
Linear Shift for Departure before 8 am	-0.2932 (-2.32)		
Linear Shift for Departure after 9 am	0.0047 (0.04)		
Linear Shift for Arrival before 5 pm		0.1383 (0.95)	
Linear Shift for Arrival after 6 pm		0.4054 (2.65)	

Seattle Model

The final joint mode & TOD choice model estimated for Seattle is included in Appendix A-4. This model comprises all effects discussed above.

3.6 Route Type, TOD, and Mode Choice – Stated Preference (SP) Framework

This section summarizes the findings from models estimated on data from the Seattle Puget Sound Regional Council (PSRC) Mode Choice SP experiment, the San Francisco (SFCTA) Cordon Pricing Study SP and the Los Angeles HOT Lane SP. The three stated preference (SP) experiments were described previously in Section 3.3. Table 3.63 provides a summary overview of the design characteristics of the three SP experiments that are analyzed. Some key differences between the experiments are as follows:

- The Seattle and Los Angeles experiments recruited people who had actually made recent trips in relevant highway corridors in the region, and then presented experiments (sent via a survey form customized to their actual trip) that offered hypothetical tolled options in that corridor. For the Los Angeles experiment, the tolled option was offered as a HOT lane or Express lane alongside free general purpose lanes. In the Seattle experiment, the free option could be on a different route, requiring a different travel distance.
- The San Francisco experiment recruited people who made recent auto trips and parked downtown, and then presented hypothetical options with a cordon toll charged to enter the downtown area. The experiment was customized to the actual trips and presented via computer-based interview screens, either in-person on laptops or via the internet. There was no free auto alternative offered.
- All three experiments offered different prices in the peak and off-peak periods, but the San Francisco and Los Angeles experiments also customized and randomly varied the definition of the peak period across the sample in order to better estimate TOD switching preferences.
- The San Francisco and Los Angeles experiments offered a transit alternative, while no transit option was included in the Seattle experiment.
- The Seattle and San Francisco experiments included a travel time variability/reliability attribute, while the Los Angeles experiment (by design) did not. For the Seattle SP, the duration of extra delay was fixed at 15 minutes and the frequency was varied, while for the San Francisco SP, the frequency of extra delay was randomly set at either 1 in 5 trips or 1 in 10 trips for each respondent, and then the duration of the extra delay was varied within respondents.

Table 3.63. SP Experiments, Summary of Design Characteristics

Characteristic	Seattle SP	Los Angeles SP	San Francisco SP
SP choice context	Introduction of tolls on route (general)	Introduction of HOT or Express lanes	Introduction of toll to enter downtown area
Recruitment method	Recent trips on relevant highways, from HH travel survey sample	Recent trips on relevant highways, from telephone recruit survey	Recent trips to downtown SF, recruited at parking locations
Offered non-tolled auto alternative?	Yes – could be on a different highway	Yes – free general lanes on same highway	No – all auto trips to downtown pay toll
Offered different prices in the off-peak?	Yes, same peak periods for all respondents	Yes, varied peak toll periods across sample	Yes, varied peak toll periods across sample
Offered transit mode alternative?	No	Yes	Yes
Included a travel time reliability variable?	Yes, varied frequency of extra delay, fixed at 15+ minutes duration	No	Yes, varied duration of delay, presented as “1 in 5” or “1 in 10” trips

3.6.1 Basic Specification, Segmentation, and Associated VOT

We have attempted to make the framework for estimation of the SP data sets somewhat consistent with the framework used in the preceding chapters for the RP-based analyses. We started with basic models and then incrementally added detail about specific SP attributes and segmentation variables. In contrast to RP data, however, the models estimated for SP data are largely determined by the design of the SP experiment—one can include only those choice alternatives and level of service attributes that were portrayed in the choice scenarios. For example, we can only include a variable for travel time reliability/variability only if that attribute was explicitly included in the SP design. Furthermore, we must include all of the variables that were included in the SP experimental design; otherwise their omission may bias the estimates of the include attributes.

Table 3.64 shows summary results for the Seattle, San Francisco and Los Angeles SP experiments, for a basic model specification including only the basic SP attributes, along with appropriate alternative-specific constants and nesting logsum parameters. For each experiment, two models are shown, one for work trips and another for non-work trips. In this model specification, there is no segmentation by income or auto occupancy, and all relationships are assumed to be linear. For purposes of comparison, the table generally shows only results in the form of ratios of the coefficients. Unless otherwise stated, the coefficient estimates were significantly different from 0 (although we did not account for repeated measurements within respondents in estimation, so the standard errors will be somewhat underestimated). The values of all estimated coefficients and t-statistics can be found in the appendices.

All SP models were estimated as nested models. For the experiments which offered both tolled and non-tolled auto alternatives (Seattle and Los Angeles), the tolled and non-tolled route options were nested under each time of day period, and the logsum parameters were all significantly less than 1.0, generally around 0.4. Although one would not necessarily expect to estimate the same nesting coefficients for RP and SP data (due to differences in the way the choice sets are specified), it is interesting that this same nesting of route type under time period was also found for the New York RP and Traffic Choices data sets.

For the experiments which offered a transit alternative (San Francisco and Los Angeles), it was also found best to nest the auto alternatives across time periods, and put the auto versus transit choice at the highest level. The logsum parameters were estimated at around 0.6 for the HB Work models, while for HB Other, there was some instability in estimating logsum coefficients, but coefficients constrained to 0.5 gave a better fit than a non-nested model. Note that this nesting of TOD under mode is different than the results obtained for the Seattle and New York RP data. The SP experiments, however, were offered only to auto users in the context of actual trips they had made by auto, so there will naturally be less tendency to choose transit than one would find in a representative RP sample.

A key finding of the SP experiments is the overall willingness to pay for auto travel time savings in the form of the ratio of the auto in-vehicle and cost coefficients. Table 3.64 shows very similar estimates for the Seattle and Los Angeles data sets—both in the range of 11 to 12 $/hour for HB Work trips and 9 to 10 $/hour for HB Other trips. These values are in a range typically estimated for highway users in the context of a toll project. For the San Francisco SP, however, we estimate values that are about 50% higher than for the other experiments (in the range of 15 to 18 $/hour). This result could be due to higher incomes, on average, for those who travel to downtown San Francisco, a possibility which we will test explicitly in the next section. It could also be due, however, to the different context of cordon pricing—there is no non-tolled option except for switching mode (or destination), so auto users may be more willing to pay a toll, particularly in the case of downtown San Francisco, where the cost of parking is already quite high by comparison.

It is worth noting that all three SP experiments show very similar overall VOT for those making work trips versus non-work trips, with VOT for work trips 10-20% higher in each case. This is in contrast to our findings for the New York RP, with higher VOT for work trips, and the findings for the Seattle RP, with higher VOT for non-work trips. Standard practice is to use much higher VOT for work trips than for non-work trips, but such a result is rarely found in SP-based studies. According to household welfare economics, one would expect VOT for any personal trip, commuting or otherwise, to be proportional to the value of spending time in the leisure activity that the saved time would be devoted to—i.e., the value of leisure time at the margin—relative to the value of spending time driving a vehicle. This, however, assumes that travelers can schedule their travel and activities predictably, and that time is fully substitutable between activities. In reality, there are a number of reasons why those conditions may not always hold:

- There may be unexpected delays or conditions which mean that time is taken from more valuable activities, such as work or more highly valued leisure activities.
- In response to unreliability, travelers may leave more of a buffer time between activities—particularly those with a high penalty or disutility for arriving late. Adding

buffer time to travel times results in a sub-optimal scheduling of activities and, possibly, a lower-valued use of time savings.

- All alternative uses of time are not available at all times of day. For example, many leisure activities may not be possible during the early AM hours, and it may not be possible to shift work schedules to allow travel time saved in the AM to be used later in the day. Leisure activities often need to be scheduled in coordination with others, which further limits the possibility to schedule them at any given time of day.

Table 3.64. SP Experiments, Basic Specification

SP Experiment	Seattle	Los Ang.	San Fran	Seattle	Los Ang.	San Fran
Summary of results	**HB Work**	**HB Work**	**HB Work**	**HBOther**	**HBOther**	**HBOther**
	psspw1	**laspw1**	**sfspw1**	**psspn1**	**laspn1**	**sfspn1**
VOT, auto in-vehicle time ($/hour)	12.0	11.2	17.7	9.9	9.4	15.8
Values in equivalent minutes auto in-vehicle time						
Toll route constant (min)	7.0	13.5		8.8	14.5	
Distance to avoid toll (min/mile)	0.47			1.02		
Average extra delay (min/min)	2.42		0.42	2.65		2.91
Shift earlier in AM (min/min)	0.17	0.40	0.21	0.05	0.62	0.29
Shift later in AM (min/min)	0.28	0.91	0.66	0.25	0.97	0.09
Shift earlier in PM (min/min)	0.20	0.36	0.09	0.03	0.39	0.27
Shift later in PM (min/min)	0.10	0.79	1.71	0.00	0.72	0.24
Transit total travel time (min/min)		1.36			0.99	
Transit in-vehicle time (min/min)			0.72			1.10
Transit out-of-vehicle time (min/min)			1.09			0.97
Transit service frequency (min/min)		0.43			0.73	
Transit transfers (min/transfer)		15.7	9.7		15.9	15.9
Transit mode constant (min)		57.4	28.0		193.1	35.6
Nesting logsum parameters						
Toll / non-toll nested under TOD (t-statistic vs. 1.0)	0.402 (-4.4)	0.387 (-15.2)		0.463 (-6.2)	0.264 (-17.8)	
TOD periods nested under modes (t-statistic vs. 1.0)		0.581 (-3.5)	0.669 (-3.8)		0.50 (constr)	0.50 (constr)
Summary statistics						
Observations	1355	2976	2357	1507	2932	2722
Rho-squared w.r.t. 0	0.247	0.297	0.166	0.247	0.276	0.109
Final log-likelihood	-1414.4	-3907.5	-2723.7	-1574.0	-3961.5	-3360.4

These various conditions may differ for work travel relative to non-work travel. In particular, the effects of reliability and unexpected delays will, on average, tend to be stronger for work trips than for leisure trips (although they may also be quite strong for specific types of non-work trips). This means that the more that reliability can be explicitly accounted for in models, the more we would expect to see that the net value of travel time is similar between work and non-work travel.

Toll route constant: Returning to the results of Table 3.64, the remaining estimates are reported as ratios relative to the auto in-vehicle time coefficient, normalized to equivalent minutes of travel time. The first row is for the toll route constant, which was significant and negative for both travel purposes in the Seattle and Los Angeles experiments. (All auto alternatives were priced in the San Francisco case, so no constant was estimated.) Negative toll route constants are typically found in SP studies, and often in RP studies as well (including the RP studies on New York and Seattle data described above). All else equal, the constant on the tolled route is equivalent to about 8 minutes of extra in-vehicle time for the Seattle SP, and about 14 minutes in the Los Angeles SP.

Detour distance to avoid tolls: In the Seattle SP, the non-tolled path was not always on the same facility, and could involve driving additional distance. Each mile of extra distance was valued negatively, above and beyond the time required to drive it. The value is twice as high for non-work as for work trips, suggesting that work trips are more willing to search for alternative paths to avoid tolls (perhaps due to more familiarity with alternative routes). The value for work trips is equivalent to about 0.5 minutes per mile. If the average speed on the extra distance were 30 MPH, then it would take 2 minutes to drive each extra mile, so this extra term would increase the disutility by 25% in that case.

Extra delay/reliability: As mentioned above, the Seattle and San Francisco SP experiments both included attributes related to the frequency and duration of extra delays above the "usual" travel time. Ideally, we would present respondents with a distribution of day-to-day travel times to obtain estimates comparable to the RP-based results in the previous sections. Some recent SP studies have done this by presenting respondents with a series of 5 or 10 possible travel times for each alternative instead of a single time. Both the Seattle and San Francisco experiments opted for simpler approaches. The Seattle SP obtained more significant estimates, suggesting that people find it easier to understand the approach with fixed duration of extra delay and comparing different frequencies (e.g., 1 in 10 trips versus 1 in 20 trips), rather than vice-versa. In either case, it is possible to multiply the frequency and duration to obtain the expected minutes of extra delay, which is somewhat comparable to a standard deviation measure (if travel times were never shorter than the typical time). Apart from the work trip result for the San Francisco SP, which was not statistically significant, the other three estimates indicate that each expected minute of extra delay is equivalent to about 2 to 3 minutes of "expected" travel time. If the expected extra delay is comparable to standard deviation, this result suggests a reliability ratio (RR) between 2 and 3, which does not seem out of the question. In general, it is expected that an extra delay minute would be valued more than a minute of the mean travel time [Li et all, 2010; CUTR, 2009]. Standard deviation is a symmetric measure that reflects both cases of being earlier and late. The relationship between standard deviation and expected lateness depends on the distribution of travel time. For symmetric distributions around the mean, the expected lateness is equal to $1/\sqrt{2}$ of the standard deviation.

Shifting out of the peak pricing period: In addition to various period-specific constants that are reported in the appendices, all of the SP models include shift variables for people who actually traveled in the peak pricing period and who could shift out of it to pay a lower toll. In contrast to RP-based TOD "shift" variables that are cross-sectional in nature, the SP-based variables are pseudo-longitudinal, measuring before and after response to hypothetical system changes. In general, the Seattle measures are lower in magnitude and less statistically significant than from the other studies. The main reason for that is that just one definition of the peak pricing period was used for the entire sample in the Seattle experiment, which does not provide as much variation to identify shifting preferences as in the other experiments where the peak period definitions were semi-randomly customized to respondents' trips.

In general, the largest resistance to shifting trip time is to shift later in the AM peak, particularly for work trips. As many individuals have to be at work by a specific time, this results makes some sense. For the Los Angeles and San Francisco experiments, the disutility of each minute of shifting later in the AM is almost as large as the disutility of a minute of travel time, which is quite a high result. In the PM, there seems to be somewhat more resistance to shifting later than shifting earlier. These results will tend to also vary depending on the current departure time—e.g., someone already traveling at 7 am may be less willing to shift earlier than someone traveling at 8 am. They may also be non-linear, with some travelers having thresholds where the shift becomes more difficult to schedule. These aspects of behavior are investigated in section 4.6.4.

Shifting to transit: A number of different variables were used to represent the transit alternative, as is necessary to give respondents some clear idea of how attractive the transit alternatives would be for their particular trips. This includes travel time broken down into components, as well as transfers, frequency, and fare. Because the SP samples only included actual auto users and transit was offered as an alternative to paying tolls, we would not expect these experiments to provide the most accurate or representative measures of the value of various transit service levels—RP and SP data from representative samples is better for that. Nevertheless, we do see that each minute of travel by transit has estimated values fairly similar to the value of auto time. Each transit transfer has a disutility equal to about 15 minutes of extra travel time, which is in a range typically estimated. The most interesting result is perhaps for the residual mode constant for transit. As one might expect, the resistance to switching to transit, all else equal, is higher for the Los Angeles experiment than for the downtown San Francisco experiment, equivalent to about 60 minutes and 30 minutes auto travel time, respectively, for work trips. There is a wide selection of transit options into downtown S.F., whereas many of the highway corridors studied in the L.A. experiment currently have very little transit service, and many of the L.A. respondents may have never used transit for those trips. The resistance to shifting to transit is particularly high for the Los Angeles non-work trips.

3.6.2 Impact of Household or Person Income

For discussion in this and the following sections, a second set of models was estimated, including the following additional variables:

- Segmentation of the travel cost coefficient by income quartile
- Segmentation of the auto in-vehicle time coefficient by occupancy (SOV versus HOV)
- Segmentation of the TOD shift variables by actual time of day, plus estimation of non-linear functions rather than simple linear effects.

The income effects on the cost coefficient and value of time are shown in detail in the appendices, and summarized in Table 3.65 and Figure 3.29. The differences between income groups are generally significant and in the expected direction, with cost having a more negative coefficient (lower VOT ratio) for lower income groups. When plotted in the graph, all of the experiments and purpose show a fairly similar trend of increasing VOT across quartiles. (Roughly, the lowest quartile is below $30K, the second is $30-60K, the third is $60-100K, and the highest is over $100K, though this varies somewhat by sample.) Curiously, after the change of model specification, the San Francisco sample now shows somewhat lower VOT than the other regions, except in the highest income quartile. The graph also uses dotted lines to show approximately what the curve would look like if the VOT trend conformed to a power function of 0.4, 0.5, 0.6 or 0.7. In general, the curves of 0.4 and 0.5 seem closest in slope to the estimated trends, slightly lower than the exponents of 0.5 and 0.6 that were assumed in the RP analyses for this project.

Table 3.65. SP Experiments, Cost Coefficients and VOT Segmented by Income

SP Experiment	Seattle	Los Ang.	San Fran	Seattle	Los Ang.	San Fran
Summary of results	HB Work	HB Work	HB Work	HBOther	HBOther	HBOther
	psspw2	laspw2	sfspw2	psspn2	laspn2	sfspn2
VOT, auto in-vehicle time ($/hour)						
Lowest income quartile	8.6	7.6	6.0	6.7	6.9	4.4
Second income quartile	10.2	8.3	7.5	7.9	7.2	6.7
Third income quartile	13.2	10.5	9.2	9.1	8.5	7.1
Highest income quartile	17.7	16.2	11.6	12.7	10.3	16.6

[Originally Table B23.]

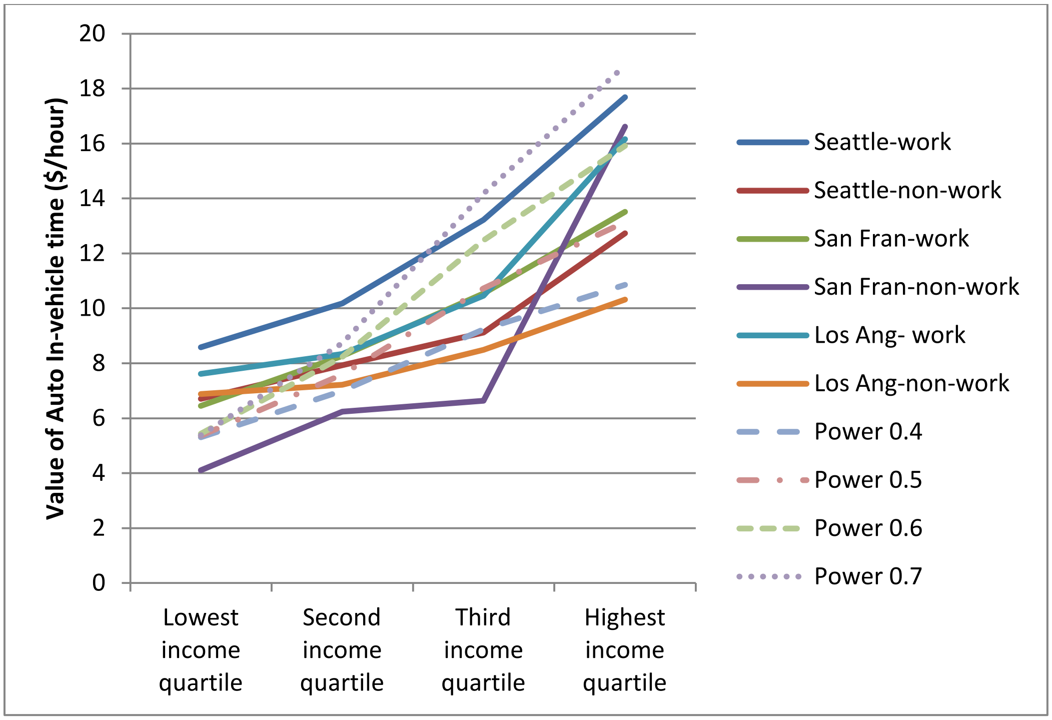


Figure 3.29. Summary of Estimated Value of Time by Income Group

3.6.3 Impact of Joint Travel

For the SP experiments, after various specification tests, the effect of vehicle occupancy (SOV vs. HOV) on willingness to pay was captured better by segmenting the travel time coefficient rather than the cost coefficient. As summarized in Table 3.66 (the detailed estimation results are given in appendices), willingness to pay is higher for HOV than for SOV in all models, particularly for non-work trips. In general, though, the effect is less than linear with vehicle occupancy, and less than the power function exponents assumed in the RP analysis. Typically, SP samples only include the vehicle driver and not the other vehicle occupants, and it is not always clear to what extent respondents are answering only on their own behalf and to what extent they are answering for the entire traveling party, particularly with regard to sharing payment of tolls or other travel costs. As a result, SP results may be more accurate and representative for SOV trips than for HOV trips.

Table 3.66. SP Experiments, Time Coefficients and VOT Segmented by Occupancy

SP Experiment	**Seattle**	**Los Ang.**	**San Fran**	**Seattle**	**Los Ang.**	**San Fran**
Summary of results	**HB Work**	**HB Work**	**HB Work**	**HBOther**	**HBOther**	**HBOther**
	psspw2	**laspw2**	**sfspw2**	**psspn2**	**laspn2**	**sfspn2**
Ratio of shared ride (HOV) VOT to drive alone (SOV) VOT	1.03	1.28	1.12	1.39	1.34	1.90

3.6.4 Incorporation of Departure Time Shift Effects

The San Francisco and Los Angeles SP data sets allowed detailed analysis on the willingness to shift out of peak pricing periods as a function of the toll level, the amount of time shift necessary, and the current time of travel. The exact coefficients are given in the appendix, and the functions plotted below. As an example, the two graphs below in Figure 3.30 show the disutility of shifting departure time either earlier or later to avoid the AM peak pricing period for trips to work. The results indicate a stronger resistance to moving work departure time later versus moving it earlier, at least for smaller shifts. In the range of 0 to 45 minutes or so, the second chart has a slope of more than one minute versus SOV travel time—each minute of moving departure time earlier has a disutility worth more than one minute of in-vehicle time. At higher levels, however, the slope flattens out. Presumably, once one is very late for work, additional shifts do not make as much difference.

The shifts in the curves for different actual departure times indicate that those who actually go to work very early in the morning are more resistant to changing departure time in either direction, earlier or later. It is understandable that these people would be more averse to shifting earlier, since they would need to start their day very early to do so. The fact that “early risers” are also more averse to moving later may be due to the fact that they have less flexible work schedules. The fact that the same trend is found for both experiments provides evidence that it is not an anomaly.

For non-work trips in the AM peak, the picture is not as clear. For the San Francisco experiment, we again find more resistance to moving later than moving earlier, but with a different picture by time of day. Now, it is those who are already traveling later in the AM that are most resistant to moving even later. For moving earlier, there is very little difference related to the actual time of day. For Los Angeles, the pattern for non-work trips in the AM looks more similar to the pattern for work trips. The resistance to moving later levels off after about 45 minutes (the bend in the curve is an artifact of the cubic function adopted).

For non-work trips in the PM, both San Francisco and Los Angeles show similar sensitivities, generally somewhat less resistance to shifting times than in the AM peak. For San Francisco, we once again see that those who travel earlier in the day are somewhat more resistant to changing times. The trips made earlier in the afternoon may be more likely to be for fixed appointments than for trips made after usual office hours. For Los Angeles, we see that those traveling earlier are more averse to shifting earlier, while those traveling later in the afternoon are more averse to shifting later.

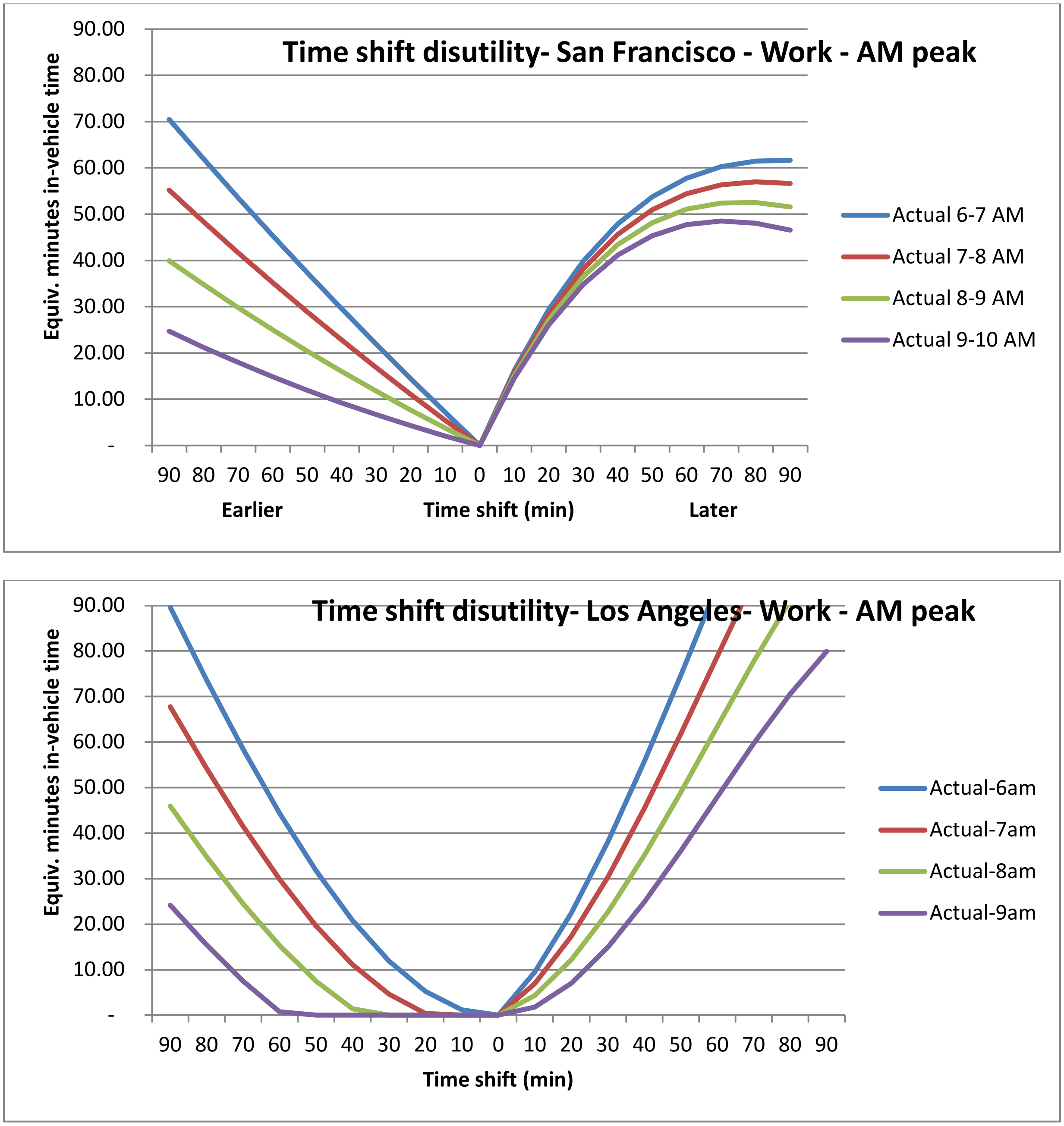
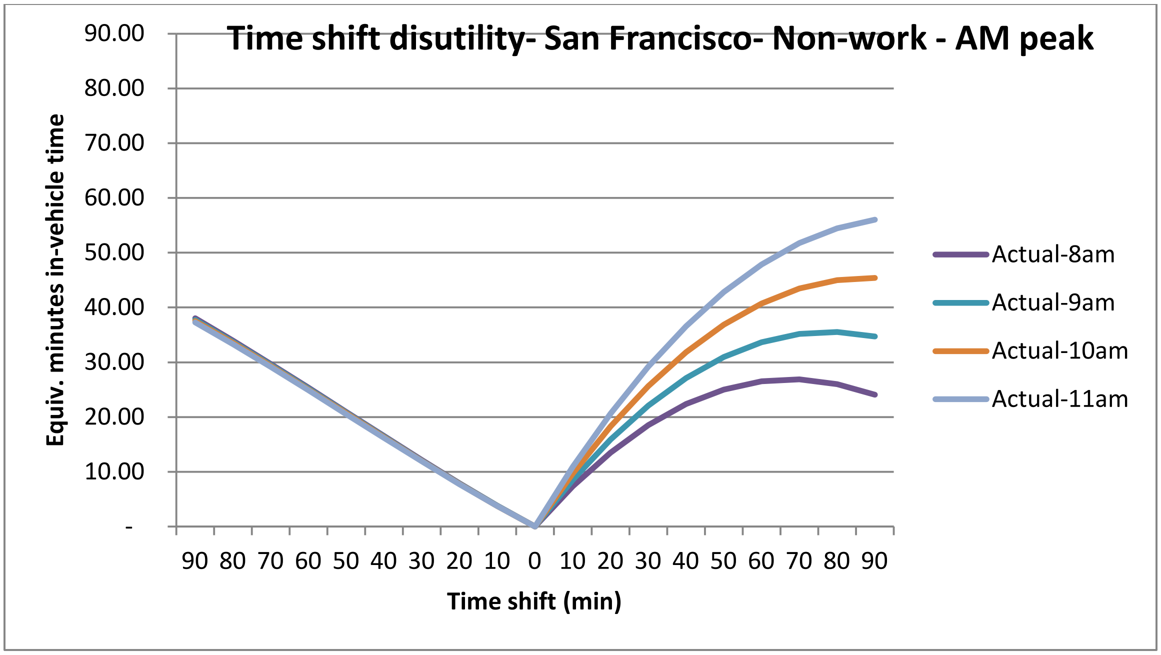


Figure 3.30. Resistance to shifting time to respond to time-of-day – AM peak work trips.



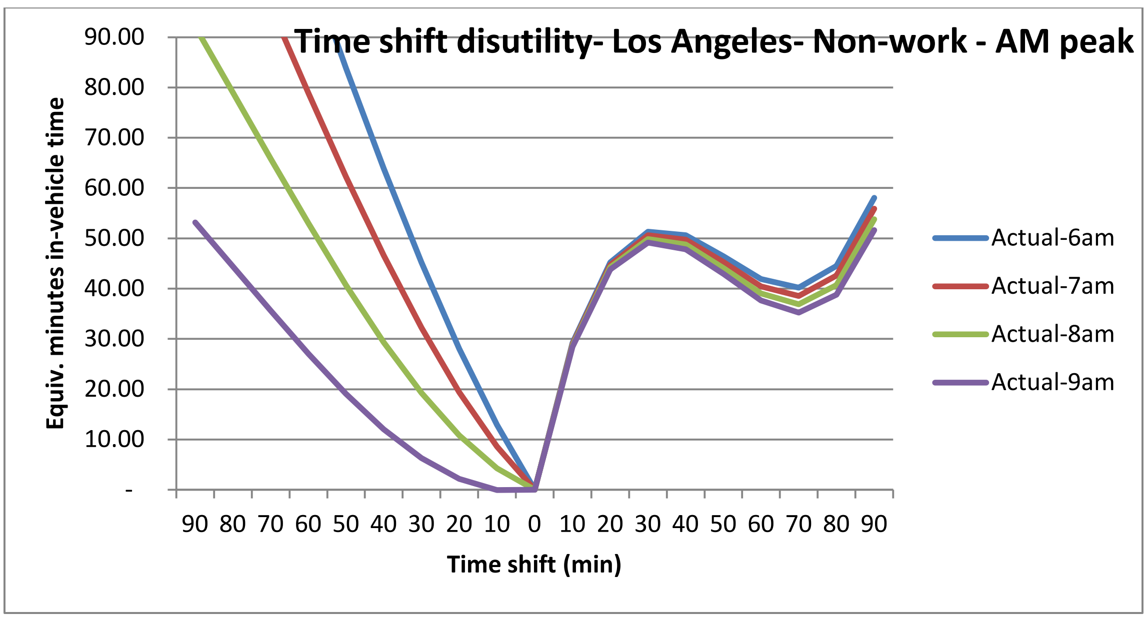
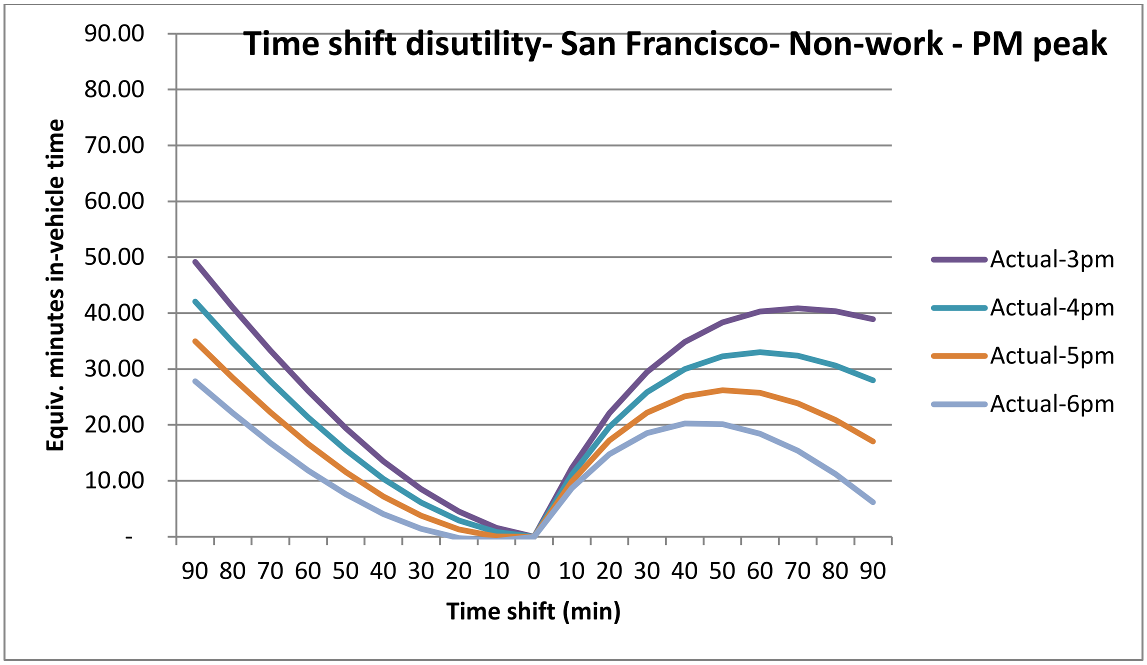


Figure 3.31. Resistance to shifting time to respond to time-of-day – AM peak non-work trips.



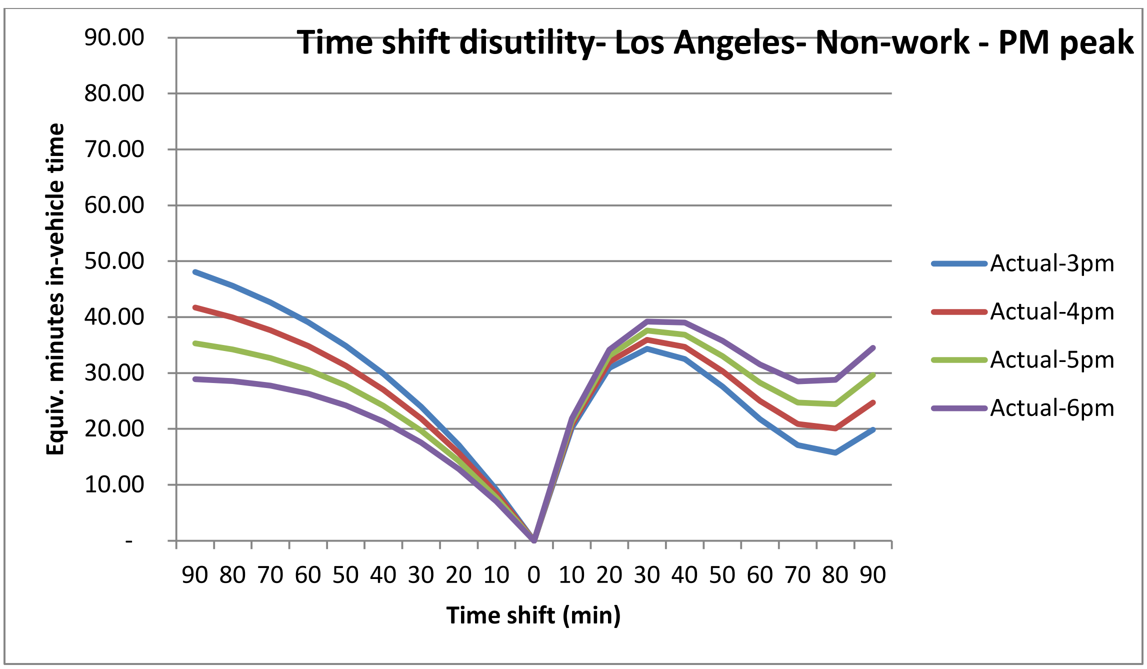


Figure 3.32. Resistance to shifting time to respond to time-of-day – PM peak non-work trips.

3.6.5 Incorporating Unobserved Heterogeneity

To investigate unobserved heterogeneity in route type choice and time of day, data from the Seattle SP toll choice experiment was used. Four alternatives were available to individuals:

- Peak-Period + Free
- Peak-Period + Toll
- Non-Peak-Period + Free
- Non-Peak-Period + Toll

with the peak period being between 6AM–9AM or 3PM–7PM. Due to overlapping of the alternative, the following nesting structure was assumed for modeling, shown in Figure 3.33.

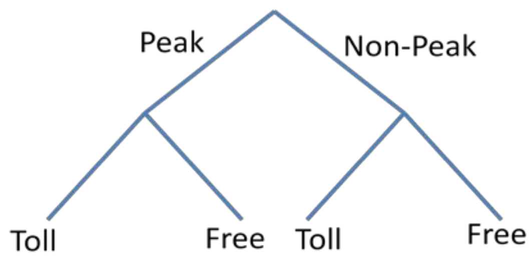


Figure 3.33. Nesting structure for Seattle SP TOD + route type choice.

The estimation results are shown in Table 3.67. The results illustrate some important insights that can be gained by accounting for unobserved heterogeneity in travel time response. By capturing the distribution of individuals' value of time, the proportion of the population with a specific value of time can be determined. In contrast with assuming all individuals have the same value of time represented by the average, the Figure 3.34 shows that individuals vary greatly in their value of time.

By examining the estimation results in Table 3.67, the impact of accounting for unobserved heterogeneity in choice models is realized. First, notice that as more unobserved heterogeneity is captured, the log-likelihood in general decreases. For a mixed logit model that captures serial correlation in addition to unobserved heterogeneity in the travel time coefficient, the log-likelihood improves from -3095.5678 to -2789.5533. Although the log-likelihood did not improve when just adding a random coefficient for travel time, this may be attributed to fixing the nesting parameter. Second, depending on the type of correlation and heterogeneity captured, for example randomness in the travel time coefficient or both random coefficient and serial correlation across observations, the value of time varies over the population differently. Initially, by only capturing variation or heterogeneity in the travel time coefficient, the variance of the value of time is larger, relative to if both serial correlation and random travel time perception is captured. One possible explanation is that more of the variance is captured by serial correlation. By not accounting for this serial correlation, the value of time exhibits greater variance.

Table 3.67. Estimation Results for RP Route Type Choice

Model	Nested Logit		Mixed Logit		Mixed Logit	
Distribution	---		Log-Normal		Log-Normal	
Observations	2862		2862		2862	
Final Log-Likelihood	-3041.6584		-3095.5678		-2789.55	
Rho-squared (const)	0.234		0.234		0.234	
Rho-squared (zero)	0.214		0.214		0.214	
Variable	**Coefficient**	**T-statistic**	**Coefficient**	**T-statistic**	**Coefficient**	**T-statistic**
Toll Cost ($)	-0.5580	-7.91	-0.5766	-6.54	-1.0110	-8.59
Toll Cost/Income ($/K$)	-6.9949	-2.65	-9.6423	-2.78	-9.6595	-2.10
Toll Cost*#Passengers ($)	0.0660	2.03	0.0219	0.47	-0.2077	-3.29
Travel Time (min)	-0.1252	-13.36	-0.1821	---	-0.3558	---
Travel Distance (miles)	-0.0928	-3.53	-0.0887	-3.08	0.0263	0.55
Fraction of Times Late	-8.2644	-5.55	-8.8527	-10.16	-10.4306	-7.94
Fraction of Times Late Squared	6.5640	2.52	7.0237	4.58	6.2875	2.32
Off-Peak*actual minutes after 6AM	-0.0152	-5.22	-0.0157	-5.21	-0.0202	-5.45
Off-Peak*actual minutes before 9AM	-0.0363	-12.08	-0.0372	-10.90	-0.0407	-10.35
Off-Peak*actual minutes after 3PM	-0.0083	-4.83	-0.0084	-4.79	-0.0106	-4.47
Off-Peak*actual mintues before 7PM	-0.0056	-3.34	-0.0060	-3.46	-0.0051	-2.11
Off-Peak*actual off-peak	3.1297	43.41	3.1482	17.00	3.3892	13.99
Toll route constant	-1.0408	-11.85	-1.0755	-10.24	-1.4469	-8.76
Toll Nesting Parameter	0.3862	19.65	0.3862	---	0.3862	---
Error Term Parameters						
Variance of Beta-Travel Time	---	---	0.0835	---	0.0792	---
Variance Alternative 1	---	---	---	---	2.7751	1.98
Variance Alternative 2	---	---	---	---	3.7015	5.82
Variance Alternative 3	---	---	---	---	9.0000	---
Variance Alternative 4	---	---	---	---	2.2841	94.16
Covariance Alternative 1 Time Lag	---	---	---	---	1.1139	1.51
Covariance Alternative 2 Time Lag	---	---	---	---	1.9792	1.15
Covariance Alternative 3 Time Lag	---	---	---	---	2.7712	2.20
Covariance Alternative 4 Time Lag	---	---	---	---	2.2793	5.00
Mean Value of Time ($/hour)	11.22		15.49		18.7291	
Std. Deviation Value of Time ($/hour)	---		24.59		14.8155	

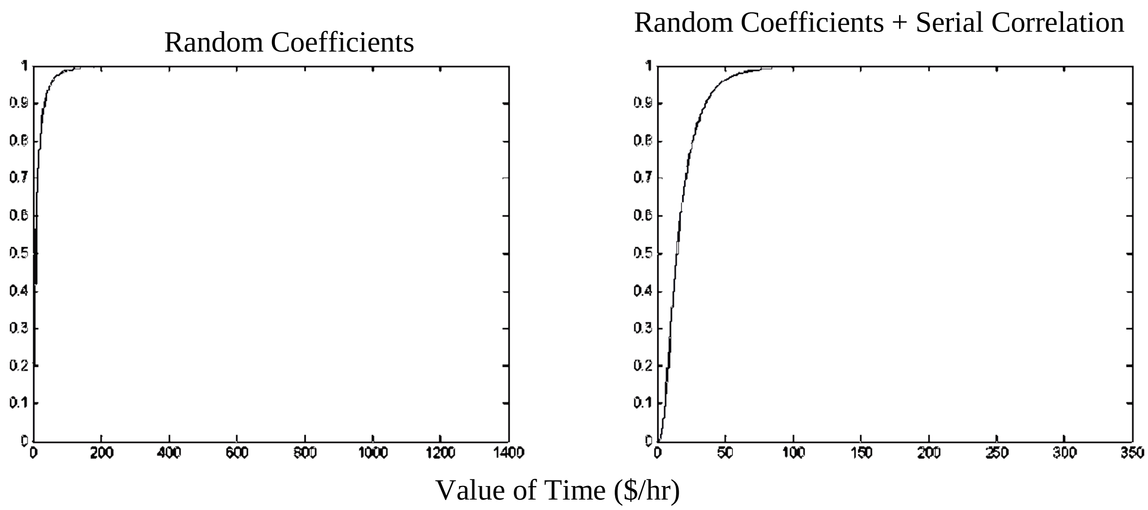


Figure 3.34. Cumulative distribution functions for VOT for the case of i) random coefficients and ii) random coefficients + serial correlation.

Examining the cumulative distribution functions of the value-of-time under different assumed correlations shows that assuming only a random coefficient for travel time gives a steeper initial cumulative distribution relative to the case with both serial correlation and random coefficients.

An interesting result is that similar to the mode choice model, as more correlations are captured in the model, the variance of the VOT decreases, relative to the case where no correlations are captured. This is similar to the comparison between the VOT for route type choice only and the nested model which captured both mode and route type choice. This suggests that much of the variance associated with the VOT across a population may be due to not capturing other choice dimensions in addition to inherent taste variation across users.

3.7 Other Choice Dimensions

The choice framework describe above that includes such dimensions as time-of-day, mode, car occupancy, and route type can also be effectively employed to incorporate congestion and pricing effects on all other choice dimensions including destination choice, tour and trip frequency, daily activity patterns, car ownership, etc. This technique that is based on various derived accessibility measures has been already successfully employed in many Activity-Based Models in practice. The advantage of using accessibility measures is that all LOS variables, including travel time reliability measures included in the route, mode, or time-of-day utility components will be automatically incorporated in all upper-level choice models that include these accessibility measures as explanatory variables. This technique however does not preclude from using some relevant congestion, pricing, and reliability effects in the upper level choice model directly. This direction, however, has been less explored and represents one of the possible good topics for future research. In the current report, we further describe the approach based on accessibility measures derived from the lower-level tour and trip models that is immediately "implementable" with the highway utility (generalized cost) functions described above.

3.7.1 General Forms of Accessibility Measures

There are multiple accessibility measures applied in the recently developed ABMs for such metropolitan regions as Sacramento, CA, San-Diego, CA, and Phoenix, AZ. Most of the applied accessibility measures represent simplified destination choice logsums, which is the composite utility of travel across all modes to all potential destinations from an origin zone to all destination zones in different time-of-day periods. This way the accessibility measure is essentially a zonal characteristic that can be stored as a vector indexed by TAZ. Another type of accessibility measure that is calculated in the process of calculations for the zonal measure is the measure of impedance between the zones. Accessibilities of this type have to be stored as TAZ-to TAZ matrices.

These accessibility measures are primarily needed to ensure that the upper-level models in the ABM hierarchy such as car ownership, daily activity pattern (DAP), and (non-mandatory) tour frequency are sensitive to improvements of transportation level-of-service across all modes, as well as changes in land use. Accessibility measures are similar in nature to density measures and can be thought of as continuously buffered "fuzzy" densities.

Accessibility measures are needed since it is infeasible to link all choices by full logsums due to the number of potential alternatives across all dimensions (activities, modes, time periods, tour patterns, and daily activity patterns). Accessibility measures reflect the opportunities to implement a travel tour for a certain purpose from a certain origin (residential or workplace). They are used as explanatory variables in the upper level models (daily activity pattern type and tour frequency) and the corresponding coefficients are estimated along with the coefficients for person and household variables.

The Sacramento, Phoenix, and San-Diego ABMs are among the first advanced travel models that completely avoid "flat" are-type dummies like CBD, urban, suburban, and rural dummies frequently used in other models to explain such choice as car ownership, tour/trip frequency, and mode choice. These qualitative "labels" have been completely replaced by the physical measures of accessibility sensitive to travel time, cost, (and potentially) reliability.

The applied *zonal accessibility measures* have the following general form:

$$A_i = \ln\left[\sum_{j=1}^{I} S_j \times \exp\left(TMLS_{ij}\right)\right] \tag{3.60}$$

where:

$i, j \in I$	=	origin and destination zones,
A_i	=	accessibility measure calculated for each origin zone,
S_j	=	attraction size variable for each potential destination zone,
$TMLS_{ij}$	=	time-of-day and mode choice logsum as the measure of impedance.

The composite travel impedance between zones that can be referred to as *origin-destination (OD) accessibility measure* is calculated as a two-level logsum taken over the time-of-day periods and modes:

$$TMLS_{ij} = \mu \ln\left[\sum_{t=1}^{2} \exp\left(MLS_{tij} + \alpha_t\right)\right] \tag{3.61}$$

where:

$t = 1,2$	=	time-of-day periods (currently peak and off-peak are used),
MLS_{ij}	=	mode choice logsum for a particular time-of-day period,
α_t	=	time-of-day-specific constant,
μ	=	nesting coefficient for mode choice under time-of-day choice.

In this form, the destination choice accessibility measure is essentially a sum of all attractions in the region discounted by the travel impedance. Note, that this measure is sensitive to travel improvements in both peak and off-peak periods. The relative impact of each period is regulated by the time-of-day-specific constant that is estimated for each travel segment (or activity type).

Accessibility measures are linearly included in a utility function of an upper-level model. To preserve consistency with the random-utility choice theory, the coefficient for any accessibility measure should be between 0 and 1; though it is not as restrictive as in a case of a proper nested logit model.

The general logic of inclusion of accessibility measures in travel models is as follows. For models that generate activity patterns, tours, and trips where specific destinations are not known yet, zonal accessibility measures should be applied that describe how dense is the supply of potential activity locations. For models where accessibility to an already known location (modeled prior in the model chain) is evaluated, OD measures should be used. In this case, there is no need in a size variable.

3.7.2 Size Variables by Activity Type

Size variables are prepared for each TAZ and segmented by activity type (trip purpose). The zonal size variables are calculated as linear combinations of the relevant land-use variables. The corresponding coefficients can be pre-estimated by means of regressions of the expanded observed trip ends on the available land-use variable, primarily employment types. In this sense, the size variables are similar to conventional trip attraction models.

A more theoretically consistent but also more complicated procedure would involve a simultaneous estimation of the size terms and impedance functions in the destination choice context by Equation 3.60. The estimation results for all activity types with the Phoenix data are presented in Table 3.68 for non-work purposes (numbered from 4 through 9) with an addition of a special purpose reserved at-work sub-tours (10) and combined non-work attraction measure for all home-based non-work (non-mandatory) purposes (11). The explanatory variables in the rows are referred to by their tokens used in the model application where “nxx” implies employment for NAICS code “xx”. The resulted size variables in the columns are referred by the purpose number “px” and short token indicated the purpose.

Table 3.68. Zonal Size Variables for Accessibility Measures by Activity Type

Explanatory variables		Size variables by activity type							
Variable	**Description**	**4=escort**	**5=shop**	**6=maint**	**7=eating**	**8=visit**	**9=discr**	**10=at work**	**p11=all**
total_HH	Total number of households	1.0000				0.1421	0.3595		0.5016
retail	Retail employment (n44+n45)		4.2810	1.4185	1.2908		0.4387	0.5403	7.4291
n51	Information			0.7091					0.7091
n52	Finance & Insurance							0.1265	
n53	Real Estate Rental Leasing			2.4753					2.4753
n55	Management of Companies & Enterprises							1.3759	
n56	Administrative & Support							0.2357	
n62	Health Care, Social Assistance			1.0618		0.2349			1.2968

Explanatory variables		Size variables by activity type							
Variable	**Description**	**4=escort**	**5=shop**	**6=maint**	**7=eating**	**8=visit**	**9=discr**	**10=at work**	**p11=all**
n71	Arts, Entertainment, Recreation				0.3224		0.9049		1.2273
n72	Accommodation, Food Services		1.1224		1.0458		0.4422	0.2809	2.6104
n92	Public Administration			0.5356				0.2265	0.5356
total_emp	Total employment							0.1578	

For escorting purpose (purpose=4) the size variable is set to the total population. This is a special purpose where accessibility to potential destination does not directly relate to the household decision to escort one of the household members (most frequently a child). Also, despite that fact that escorting most frequently associated with the school purpose for the escorted person (child), density of schools around the residential place does not mean that escorting would occur more frequently. On the contrary, if a child can walk to the nearby school escorting will not be needed. Population density (accessibility to population can be viewed as continuously buffered population density) is somewhat the most reasonable zonal size variable that affects probability of escorting (all else being equal, meaning the household composition and necessity of escorting). Population density is the only accessibility measure for which both negative and positive signs can be accepted in the tour/activity frequency model. All other accessibility measures are accepted only if they have a logical positive sign.

For shopping purpose (purpose=5) the main attractions are logically associated with retail employment and food services. Food services are frequently intertwined with shopping and it is difficult to completely separate these two land-use types. It is equally true for both major shopping malls and small street shops or restaurants. It is recommended in future to enrich shopping size variables with such explanatory variables as floor area to better distinguish between large shopping malls and small street shops. The (household) maintenance purpose (purpose=6) that includes a wide range of activities such as personal business, banking, visiting post office, visiting doctor or dentist or lawyer, etc, is scattered over a wide range of related employment types including retail, information, real estate, rental, leasing, health care, social assistance, and public administration.

Eating out (purpose=7) and discretionary (purpose=9) are closely intertwined and frequently combined in the same tour. They share the same attraction variables that relate to retail employment, recreation & entertainment, and food services although the coefficients are logically different. In addition to that, discretionary purpose includes population as an additional attraction factor that serves as a proxy for such factors as sport facilities and playing grounds. In this regard it is recommended in future to add nom-employment variables like land or floor areas for public parks and sport facilities that would enrich the attraction model for discretionary activities.

Visiting relatives and friends (purpose=8) is a special purpose where the major attraction factor is population (number of households). In addition to that, visiting also frequently occurs at a hospital that is measured by employment in health. Attraction factors for trips originated from the workplace (purpose=10) includes many variables that is a reflection on the fact that there are three main purposes of which at-work travel is comprised. First, it includes eating out during the lunch break that is reflected in such attractions as retail employment and food services. Secondly, it may include business trips for a meeting that is reflected in such employment categories as management of companies and administration (most probable places for business meetings) and some proportion of total employment. Thirdly, workers might use the lunch break for personal business and shopping that is reflected in such employment categories as finance, insurance, and public administration. Finally, a size variable that expresses total attractions for all non-mandatory home-based purposes 4-9, includes a mix of all corresponding employment types and population. Logically, retail employment plays a major role in this mix.

In addition to the complex size variables for non-mandatory activities, an ABM requires several size variables for zonal accessibility measures to mandatory activities. They are primarily used in the choice models for work from home and schooling from home. These size variables are simpler since they include all relevant variables with coefficient 1.0. For work from home, it is employment for the relevant occupation (broken into five categories in the NHTS 2008 used to estimate the Phoenix ABM). These five categories are related to employment by NAICS codes used as the source of explanatory variables. For schooling from home, it is enrollment in the corresponding school type broken into three categories: K-8 (elementary or mid school), 9-12 (high school), university or college. The corresponding size variables are summarized in Table 3.69.

Table 3.69. Zonal Size Variables for Mandatory Activities

Explanatory variables		Size variables	
Variable	**Description**	**Variable**	**Description**
n42	Wholesale Trade	p12_whom1	Sales or marketing
n52	Finance and Insurance		
n44	Retail Trade	p13_whom2	Clerical administrative or retail
n45	Retail Trade		
n53	Real Estate and Rental and Leasing		
n71	Arts, Entertainment, and Recreation		
n72	Accommodation and Food Services		
n92	Public Administration		
n11	Agriculture, Forestry, Fishing, Hunting	p14_whom3	Production, construction, manufacturing, or transport
n21	Mining, Quarrying, Oil & Gas Extraction		
n22	Utilities		
n23	Construction		
n31	Manufacturing		
n32	Manufacturing		
n33	Manufacturing		
n48	Transportation and Warehousing		
n49	Transportation and Warehousing		
n51	Information	p15_whom4	Professional, managerial, or technical
n54	Professional, Scientific, and Technical Services		
n55	Management of Companies and Enterprises		

Explanatory variables		Size variables	
Variable	**Description**	**Variable**	**Description**
n56	Administrative and Support and Waste Management and Remediation Services		
n61	Educational Services		
n62	Health Care and Social Assistance		
n81	Other Services (except Public Administration)	p16_whom5	Person care and services
Enroll1	Enrollment K-8	p17_shom1	Enrollment primary & mid
Enroll2	Enrollment 9-12	p18_shom2	Enrollment high school
Enroll3	Enrollment university & college	p19_shom3	Enrollment university & college

3.7.3 Impedance Functions by Person, Household, and Activity Type

Impedance functions are calculated as OD matrices of logsums over modes and time-of-day periods (peak and off-peak) according to Equation 3.61. The calculation is based on *mode choice utilities* that have to be calculated for all modes and time-of-day periods as the first step. Then, these utilities are combined in the *composite logsum* at the second step. Both steps are described below in the subsequent sub-sections.

Mode Utilities

For calculation of accessibility measures, the set of modes is simplified and includes five main modes: 1=SOV, 2=HOV, 3=Walk to Transit, 4=Drive to Transit, 5=Non-Motorized. Walk to Transit (WT) and Drive to Transit (DT) utilities are based on the best transit skims implemented for the entire transit network including all modes. Mode utilities also calculated separately for each of the four aggregate travel purposes: 1=Work, 2=University, 3=School, 4=Other. Segmentation by travel purpose is essential since each travel purpose is characterized by a different set of mode preferences. For example, DT is frequently chosen for Work purpose but it is practically not observed for School trips or Other trips. All non-work purposes are aggregated for calculation of impedances although they are separated with respect to size variables. Additional important segmentation relates to household car sufficiency. We distinguish at this stage between three household groups: 1=household without cars, 2=household with cars fewer than workers, 3=households with cars greater than or equal to workers. This is also important because car sufficiency strongly affect mode availability and preferences.

Overall, by combining 5 aggregate modes with 4 travel purposes, 3 car sufficiency groups and 2 time-of-day periods a set of 5×4×3×2=120 mode utilities was pre-calculated for all OD pairs. The components of the mode utility functions and corresponding coefficients are summarized in Table 3.70. The coefficients shown were adopted for the San-Diego and Phoenix ABMs. All coefficients are generic across time-of-day periods. The distinction between peak and off peak utilities is due to different LOS variables. Mode utilities can incorporate STD, perceived highway time, or any other measure of travel time reliability if is supported by the network simulation and skimming procedures. That is not currently the case with the ABMs in practice and primarily because of the lack of effective network procedures that could generate reliability measures. This issue is in the focus of such SHRP 2 projects and L04 and C10 that are currently underway. However, the current research lays down a complete methodology for incorporating reliability in travel demand models that is fully compatible with the potential network procedures.

Table 3.70. Components and Coefficients of Mode Utilities

Variable	SOV	HOV	WT	DT	NM
Work travel purpose:					
SOV time, min	-0.03				
HOV time, min		-0.03			
Highway distance, miles	-0.015	-0.01			-1.5
Highway distance greater than 3 miles, dummy					-999
WT weighted time, min			-0.03		
WT fare, cents			-0.002		
WT in-vehicle time less than 1 min, dummy			-999		
DT weighted time, min				-0.03	
DT fare, cents				-0.002	
DT in-vehicle time less than 1 min, dummy				-999	
Zero car household	-999	-3.0			
Cars fewer than workers	-1.5	-2.0			
Cars greater than or equal to workers		-2.5			
University travel purpose:					
SOV time, min	-0.03				
HOV time, min		-0.03			
Highway distance, miles	-0.03	-0.02			-1.5
Highway distance greater than 3 miles, dummy					-999
WT weighted time, min*			-0.03		
WT fare, cents			-0.004		
WT in-vehicle time less than 1 min, dummy			-999		
DT weighted time, min**				-0.03	
DT fare, cents				-0.004	
DT in-vehicle time less than 1 min, dummy				-999	
Zero car household	-999	-2.0			
Cars fewer than workers	-1.5	-1.0			
Cars greater than or equal to workers	0	-1.5			
School travel purpose:					
SOV time, min	-0.05				
HOV time, min		-0.05			
Highway distance, miles	-0.06	-0.04			-1.5
Highway distance greater than 3 miles, dummy					-999
WT weighted time, min*			-0.03		
WT fare, cents			-0.006		
WT in-vehicle time less than 1 min, dummy			-999		
DT weighted time, min**				-0.03	
DT fare, cents				-0.004	
DT in-vehicle time less than 1 min, dummy				-999	
Zero car household	-999	-1.0		-5.0	2.0
Cars fewer than workers	-1.5	0		-5.0	2.0
Cars greater than or equal to workers	0	-0.5		-5.0	2.0
Other travel purpose					
SOV time, min	-0.03				
HOV time, min		-0.03			
Highway distance, miles	-0.03	-0.02			-1.5

Variable	SOV	HOV	WT	DT	NM
Highway distance greater than 3 miles, dummy					-999
WT weighted time, min*			-0.03		
WT fare, cents			-0.004		
WT in-vehicle time less than 1 min, dummy			-999		
DT weighted time, min**				-0.03	
DT fare, cents				-0.004	
DT in-vehicle time less than 1 min, dummy				-999	
Zero car household	-999	-3.0		-5.0	
Cars fewer than workers	-1.5	-2.0		-5.0	
Cars greater than or equal to workers	0	-2.5		-5.0	

*WT weighted time includes in-vehicle time and out-of-vehicle time with weight equal to 2.5. Out-of-vehicle time includes initial wait, transfer wait, access walk, transfer walk, egress walk, and 4 min penalty for each transfer.
**DT weighted time additionally includes access drive in out-of-vehicle time.

Mode & Time-of-Day Choice Logsums

After mode utilities have been calculated for each mode, purpose, car-sufficiency group, and time-of-day period they are combined into composite *OD accessibility measures*, i.e., mode & time-of-day choice logsums by Equation 3.61. The list of logsum measures that have to be prepared to support various accessibility measures is summarized in Table 3.71.

Table 3.71. List of Mode and Time-of-Day Choice Logsums

Impedance	Accessibility from the given (residential) zone to:	Token
1	Workplace by all modes for all car-sufficiency groups	Work
2	University by all modes for all car-sufficiency groups	Univ
3	School by all modes for all car-sufficiency groups	Scho
4	Non-mandatory activity location by auto	Auto
5	Non-mandatory activity location by WT	Tran
6	Non-mandatory activity location by NM (walk)	Nonm
7	Non-mandatory activity by all modes, individual travel, zero-car household	Indi_0
8	Non-mandatory activity by all modes, individual travel, cars<workers	Indi_1
9	Non-mandatory activity by all modes, individual travel, cars≥workers	Indi_2
10	Non-mandatory activity by all modes, joint travel, zero-car household	Join_0
11	Non-mandatory activity by all modes, joint travel, cars<workers	Join_1
12	Non-mandatory activity by all modes, joint travel, cars≥workers	Join_2
13	Escort accessibility, joint travel, zero-car household	Esco_0
14	Escort accessibility, joint travel, cars<workers	Esco_1
15	Escort accessibility, joint travel, cars≥workers	Esco_2
16	Workplace by auto modes for all car-sufficiency groups (auto dependency)	Wrkad
17	University by auto modes for all car-sufficiency groups (auto dependency)	Unvad
18	School by auto modes for all car-sufficiency groups (auto dependency)	Schad
19	Workplace by non-auto modes (non-auto dependency)	Wrknad
20	University by non-auto modes (non-auto dependency)	Unvnad
21	School by non-auto modes (non-auto dependency)	Schnad

Overall, 21 different OD accessibility measures are prepared to support various zonal accessibility measures needed for different sub-models of the MAG ABM. Structure of each logsum and associated parameters are summarized in Table 3.72. This table essentially represents a control file for the impedance (OD) part of the program that calculates accessibility measures.

Table 3.72. Structure of Mode and Time-of-Day Choice Logsums

		Car sufficiency			Modes included					
Token	**Purpose**	**Zero cars**	**Cars fewer than workers**	**Cars equal to or greater than workers**	**SOV**	**HOV**	**WT**	**DT**	**NM**	**Off-peak constant**
Work	1=Work	0.05	0.35	0.6	1	1	1	1	1	-0.9
Univ	2=Univ	0.05	0.35	0.6	1	1	1		1	-0.5
Scho	3=Scho	0.05	0.35	0.6	1	1	1		1	-1.2
Auto	4=Other	0.05	0.35	0.6	1					0.5
Tran	4=Other	0.05	0.35	0.6			1			0.5
Nonm	4=Other	0.05	0.35	0.6					1	0.5
Indi_0	4=Other	1			1		1		1	0.5
Indi_1	4=Other		1		1		1		1	0.5
Indi_2	4=Other			1	1		1		1	0.5
Join_0	4=Other	1				1	1		1	0.5
Join_1	4=Other		1			1	1		1	0.5
Join_2	4=Other			1		1	1		1	0.5
Esco_0	4=Other	1				1			1	-0.5
Esco_1	4=Other		1			1			1	-0.5
Esco_2	4=Other			1		1			1	-0.5
Wrkad	1=Work	0.05	0.35	0.6	1	1		1		-0.9
Unvad	2=Univ	0.05	0.35	0.6	1	1		1		-0.5
Schad	3=Scho	0.05	0.35	0.6	1	1		1		-1.2
Wrknad	1=Work	0.05	0.35	0.6			1		1	-0.9
Unvnad	2=Univ	0.05	0.35	0.6			1		1	-0.5
Schnad	3=Scho	0.05	0.35	0.6			1		1	-1.2

Each impedance measure is associated with a certain aggregate travel purpose (1-4) for which the mode utilities are calculated according to the coefficients in Table 3.70. Then, depending on the type of accessibility measure, car sufficiency is taken into account. If a general accessibility measure is calculated that is going to be applied in the model system before the car-ownership model, the mode utilities are averaged across all car-sufficiency groups with the weight that reflect the observed proportion between different car-sufficiency groups in the region. If an accessibility measure is calculated for a specific car-sufficiency group (that means that it is going to be applied after the car-ownership model) the mode utilities for this specific group are used.

Not every mode is included in each logsum. The set of modes is restricted for two reasons. The first reason is that some modes are not observed for some of the trip purposes. For example, Drive to Transit (DT) is relevant for work trips only. The second reason is that certain modes are made unavailable in order to calculate a specific (mode-restricted) type of accessibility needed for a particular behavioral model. For example, mode-specific accessibilities that are used in the car-ownership model are based on a single representative mode each. Accessibilities that describe individual activities should logically exclude HOV. Accessibilities that describe joint activities naturally exclude SOV. Accessibilities that describe auto dependency include only modes that need an auto (SOV, HOV, and DT). Accessibilities that describe auto non-dependency include only modes that do not need an auto (WT and NM).

Finally, to complete the logsum calculation across time-of-day periods, a bias constant for off-peak period is specified (the peak period is used as the reference alternative with zero bias). This constant is set to replicate the observed proportion of trips in the peak period vs. off-peak.

3.7.4 List of Zonal Accessibility Measures Adopted for Advanced ABM

The set of *zonal accessibility measures* incorporated in the Sacramento, San-Diego and Phoenix ABMs (with some simplifications to create a common denominator across different models) is summarized in Table 3.73. The variety of measures stems from the combination of different size variables segmented by the underlying activity type with different impedance measures segmented by trip purpose and person/household type. Such models as car ownership (mobility attributes), work and schooling from home, and coordinated daily activity-travel pattern are very good illustrations for zonal accessibility measures with some components that relate to OD accessibility measures. Such models as usual workplace and school location are based on OD accessibility measures.

The 52 zonal accessibility measures are combined of 19 size variables (numbered and tokenized in Table 3.68 and Table 3.69 above) and 15 impedance measures (numbered and tokenized in Table 3.71 and Table 3.72 above). There are 6 impedance measures (16-21) that are used only as OD accessibilities. Multiple examples of impacts of the accessibility measures on different aspects of travel behavior can be found in model estimation reports for the Sacramento, San-Diego, and Phoenix ABMs.

Table 3.73. Zonal Accessibility Measures

Measure	Size variable		Impedance measure		Model in which applied
	No	Token	No	Token	
1	12	Whom1	1	Work	Work from home
2	13	Whom2	1	Work	Work from home
3	14	Whom3	1	Work	Work from home
4	15	Whom4	1	Work	Work from home
5	16	Whom5	1	Work	Work from home
6	17	Shom1	3	Scho	Schooling from home
7	18	Shom2	3	Scho	Schooling from home
8	19	Shom3	2	Univ	Schooling from home
9	11	AllNM	4	Auto	Car ownership
10	11	AllNM	5	Tran	Car ownership
11	11	AllNM	6	Nonm	Car ownership
12	11	AllNM	7	Indi_0	Coordinated Daily Activity-Travel Pattern

Measure	Size variable		Impedance measure		Model in which applied
	No	Token	No	Token	
13	11	AllNM	8	Indi_1	Coordinated Daily Activity-Travel Pattern
14	11	AllNM	9	Indi_2	Coordinated Daily Activity-Travel Pattern
15	11	AllNM	10	Join_0	Coordinated Daily Activity-Travel Pattern
16	11	AllNM	11	Join_1	Coordinated Daily Activity-Travel Pattern
17	11	AllNM	12	Join_2	Coordinated Daily Activity-Travel Pattern
18	5	Shop	10	Join_0	Joint tour frequency
19	5	Shop	11	Join_1	Joint tour frequency
20	5	Shop	12	Join_2	Joint tour frequency
21	6	Main	10	Join_0	Joint tour frequency
22	6	Main	11	Join_1	Joint tour frequency
23	6	Main	12	Join_2	Joint tour frequency
24	7	Eati	10	Join_0	Joint tour frequency
25	7	Eati	11	Join_1	Joint tour frequency
26	7	Eati	12	Join_2	Joint tour frequency
27	8	Visi	10	Join_0	Joint tour frequency
28	8	Visi	11	Join_1	Joint tour frequency
29	8	Visi	12	Join_2	Joint tour frequency
30	9	Disc	10	Join_0	Joint tour frequency
31	9	Disc	11	Join_1	Joint tour frequency
32	9	Disc	12	Join_2	Joint tour frequency
33	4	Esco	13	Esco_0	Allocated tour frequency
34	4	Esco	14	Esco_1	Allocated tour frequency
35	4	Esco	15	Esco_2	Allocated tour frequency
36	5	Shop	7	Indi_0	Allocated tour frequency
37	5	Shop	8	Indi_1	Allocated tour frequency
38	5	Shop	9	Indi_2	Allocated tour frequency
39	6	Main	7	Indi_0	Allocated tour frequency
40	6	Main	8	Indi_1	Allocated tour frequency
41	6	Main	9	Indi_2	Allocated tour frequency
42	7	Eati	7	Indi_0	Individual tour frequency
43	7	Eati	8	Indi_1	Individual tour frequency
44	7	Eati	9	Indi_2	Individual tour frequency
45	8	Visi	7	Indi_0	Individual tour frequency
46	8	Visi	8	Indi_1	Individual tour frequency
47	8	Visi	9	Indi_2	Individual tour frequency
48	9	Disc	7	Indi_0	Individual tour frequency
49	9	Disc	8	Indi_1	Individual tour frequency
50	9	Disc	9	Indi_2	Individual tour frequency
51	10	Atwo	7	Indi_0	Individual sub-tour frequency
52	10	Atwo	9	Indi_2	Individual sub-tour frequency