Innovative Methods for Pricing Studies

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Introduction

In a recent forum on road pricing,[1] attendees identified and discussed limitations with current travel demand forecasting approaches for pricing studies. In addition, CS recently completed a paper on the limitations of studies used to advance toll projects[2] and on the opinions of Washington State's community leaders.[3] Based on these sources and recent direct experience in developing forecasting models for toll projects, we have identified the following two issues of primary importance to improving existing travel models for pricing studies:

- Inaccurate values of time for specific travelers, trip purposes, modes, and time periods; and
- Lack of temporal detail and behavioral choice for time-of-day models.

The approach Cambridge Systematics has been developing to advance travel models for the purposes of pricing studies involves focusing on the first two issues (inaccurate values of time and lack of temporal detail) as the most critical to be addressed in existing models. We have been involved in the development and application of these methods for trip-based models in Minnesota and Washington, as well as for activity-based models in San Francisco. The remainder of this paper describes innovative methods to incorporate advances to address these issues. In addition, we describe strategies we have employed to optimize tolls for pricing studies. Finally, we also propose a series of additional limitations of existing models that should be addressed with additional research.

Values of Time

The estimation and application of the value of time in travel demand forecasting models is the most often cited problem for evaluating pricing projects. There are a number of issues related to the value of time that present challenges in the travel demand forecasting process:

- How to distribute values of time across individual travelers, i.e., with different income levels?
- How to distribute values of time across different trips, i.e., with different purposes and modes?
- How to distribute values of time across different destinations, i.e., trips to the airport?
- How to distribute values of time across different vehicle types, i.e., with different vehicle classes?

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[1] Expert Forum on Road Pricing, sponsored by Federal Highway Administration, Volpe Center, held on November 14-15, 2005 in Arlington, Virginia.

[2] Cambridge Systematics, *Washington State Comprehensive Toll Study Interim Report, Background Paper No. 6: Limitations of Studies used to Advance Toll Projects,* prepared for the Washington State Transportation Commission, November 2005.

[3] Cambridge Systematics, *Washington State Comprehensive Toll Study Interim Report, Background Paper No. 2: Ascertainment Interviews: Opinion of Washington's Community Leaders,* prepared for the Washington State Transportation Commission, November 2005.

- How to distribute values of time based on what type of goods are being carried for truck trips?
- How to distribute values of time for different types of congestion, i.e., recurring and nonrecurring congestion, such as accidents?

In a fully disaggregate travel demand forecasting system, these values of time could be set based on the traveler, the trip, the vehicle type and the goods being carried and could remain consistent throughout the forecasting process, eliminating the application-related issues surrounding the values of time. At this time, most travel demand forecasting models are aggregate trip-based models, which makes the distribution of values of time for individual travelers, trips, and vehicles impossible. For these models, the only solution is to identify specific categories of travelers, trips, and vehicles and apply values of time for these categories. This is an effective means of distributing values of time within the forecasting system.

However, these trip-based modeling systems do not necessarily contain the same market segmentation throughout the system (i.e., to assess values of time by income group, one must represent income group within each model component, including trip assignment). CS has completed two studies recently (in Minnesota and Washington) where model improvements were assessed and implemented specifically to address this value of time issue. For example, if one segments the market into different trip purposes and income groups throughout the system, but the modal segments are not specifically represented in trip distribution, there will be new problems for tolls that are assessed by mode (i.e., where carpools and transit go free).

The model used by CS in Washington State explicitly includes value of time in the mode choice model using time and cost coefficients for each type of traveler. In addition to income, other market segments affecting value of time, such as trip distance, time of day, gender, and age, were considered. However, their effects were difficult to incorporate into the model stream and had marginal impact on the models.

In Minnesota, in order to develop toll mode constants using other models, CS calculated the ratio of toll-alternative-specific constants to highway travel time coefficients for different market segments based on age, gender, income level, education level and trip purposes. Based on the parameters of the SR-91 and the Congestion Road Pricing models and assumptions about the Twin Cities distribution of trip and traveler characteristics by purpose (including household income, gender, educational attainment, and age), the differences between the free highway mode and toll mode constants range from a 0.88-minute penalty (non-commute trips by one-vehicle households) to a 2.89-minute advantage (home-based work trips by two-vehicle households). The average equivalent times vary by auto availability level. The variation is due to the fact that the equivalent time penalties of the toll mode constants are calculated by relating the market segments defined by the SR-91 analyses to the Metropolitan Council market segments. However, the auto availability market segmentation was intended for other model components (e.g., trip generation and distribution) and specifically for toll choice.

There are, of course, a number of activity or tour-based models that disaggregate travelers and trips during the trip generation, distribution and mode choice stages of the process. But most of these activity-based modeling systems still operate on an aggregate assignment basis, which only allows for assignment of trips by category or class rather than by vehicle. This leap between disaggregate and aggregate systems sacrifices the most important step of the modeling system for pricing studies – trip assignment. Dynamic pricing especially depends on disaggregate assignment techniques as well as the assignment of trips in much smaller time slices. As we increase the number of categories needed to adequately represent the values of time within assignment, it becomes clear that disaggregate assignments would greatly improve the capability to accurately assess pricing strategies. Nonrecurring congestion also is difficult (if not impossible) to represent without a microsimulation or dynamic traffic assignment process.

Temporal Detail

Capturing the variations in travel by time of day is essential to predicting transportation system performance and air quality impacts of the transportation sector. A vast amount of transportation research has been conducted to study travel demand by time of day. Much of this research has been limited to observing trends in service usage, such as vehicular volumes and the number of person trips. While important to understanding past and present usage patterns, these types of studies are less valuable for predicting future travel by time of day given changes in transportation service availability, quality, and policy. Possibly the behavior least accounted for in travel forecasting is "peak spreading" (e.g., persons rescheduling their travel from daily periods of high demand to the portions of the day where travel takes less time and is more reliable). Travel surveys and other monitoring activities have documented the correlation between decreasing service quality (congestion) and longer peak periods. Also, many planning agencies need to test the effectiveness of policy initiatives specifically targeted at shifting travel demand to off-peak periods.

One of the most essential modeling component is the time-of-day choice model that provides sensitivity to traveler's temporal decisions with respect to sociodemographic, travel conditions, and cost of travel. This sensitivity is needed to effectively evaluate congestion pricing strategies and improve forecasting results. So in the time-of-day choice models, the inclusion of more temporal details or time periods will make the models more sensitive to congestion pricing. Most of the prior time-of-day choice modeling studies considers time as a discrete variable, that is, the various time choices are represented by several temporally contiguous discrete time periods such as a.m. peak period, off-peak period and p.m. peak period. There are several drawbacks of using such an approach to model time-of-day choice.[4] The use of discrete time periods requires a pre-determined partitioning of the day into time intervals, the characteristics of which may or may not be the same in the future. This might preclude the analyses of potential future congestion pricing strategies during time periods which are smaller than those used in the base year. Also, the discrete choice structure considers the time points near the boundaries of intervals as belonging to one or the other of the aggregate time periods. But in reality, two closely spaced time points on either side of a discrete interval boundary are likely to be perceived as being similar rather than as distinct alternatives. So either many finer discrete time intervals have to be specified to obtain a reasonable time resolution, which might not be very practical as this will involve estimating many parameters, or a distinction should be made between adjacent discrete time periods.

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[4] Bhat, C. R., and J. L. Steed, 2002, *A Continuous-time Model of Departure Time Choice for Urban Shopping Trips*, Transportation Research Part B (36), pp. 207-224.

CS recently completed an FHWA research project on time-of-day models that resulted in a methodology for time-of-day choice models that for trip-based models and another for activity-based models. These were tested and validated in case studies in Denver and San Francisco. The trip-based time-of-day modeling method was applied to a pricing scenario in the Denver region. Tolls were assumed on a (currently toll-free) 20-mile section of a circumferential freeway. Tolls were highest in the two peak periods (0.2 to 3.5 hours long), with lower tolls in shoulder periods (1 to 3.5 hours) and lowest tolls in the off-peak periods. The time-of-day choice method estimated trips by time of day for half-hour periods. The application of the model for this scenario showed a modest amount of peak spreading resulting from the implementation of the period-based tolls.

The tour-based time-of-day modeling method was applied to a pricing scenario for downtown San Francisco. The time-of-day choice method estimated trips by time of day for half-hour periods. A hypothetical $4.00 toll was applied for all auto trips entering downtown San Francisco during the a.m. peak period (6:00-9:00). Although it is impossible to separate all of the effects of the pricing, it is apparent that the largest effect appears to be on mode choice. About 20 percent of the reduction in downtown trips is due to people choosing not to travel downtown at all. About 70 percent of the total, is due to changes is mode, and about 10 percent of the reduction appears to be due to time-of-day shifts. These results seem reasonable, as many downtown travelers, such as commuters to work, may not have the flexibility to change their times of travel.

For the Washington State DOT, CS updated the time-of-day choice models by dividing the five main periods (a.m. peak, midday, p.m. peak, evening and night) into 30-minute subperiods, in order to model peak-spreading behavior. [5] In addition to auto travel time variations between periods, the model has also been structured in such a way that it will be sensitive to auto travel cost differences between periods, for instance to emulate time-of-day-specific congestion pricing. The new time-of-day choice models were estimated for eight trip purpose/direction combinations, using a new set of 32 alternatives.

These five time periods are used for transit, truck, and external trips. Auto trips are further subdivided into 32 time periods, as follows:

AM Peak	**Midday**	**PM Peak**	**Evening**	**Night**
5:00 AM-5:29 AM	10:00 AM-10:29 AM	3:00 PM-3:29 PM	8:00 PM-10:59 PM	11:00 PM-4:59 AM
5:30 AM-5:59 AM	10:30 AM-10:59 AM	3:30 PM-3:59 PM		
6:00 AM-6:29 AM	11:00 AM-11:29 AM	4:00 PM-4:29 PM		
6:30 AM-6:59 AM	11:30 AM-11:59 AM	4:30 PM-4:59 PM		
7:00 AM-7:29 AM	12:00 AM-12:29 PM	5:00 PM-5:29 PM		
7:30 AM-7:59 AM	12:30 PM-12:59 PM	5:30 PM-5:59 PM		
8:00 AM-8:29 AM	1:00 PM-1:29 PM	6:00 PM-6:29 PM		
8:30 AM-8:59 AM	1:30 PM-1:59 PM	6:30 PM-6:59 PM		

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[5] Kuppam, A. R., M. L. Outwater, M. Bradley, L. Blain, R. Tung, and S. Yan (2005) Application of Time-of-Day Choice Models Using EMME/2 – Washington State DOT Congestion Relief Analysis. Presented at 19th International EMME/2 User's Group Conference, Seattle, WA, October 19-21, 2005.

9:00 AM-9:29 AM	2:00 PM-2:29 PM	7:00 PM-7:29 PM
9:30 AM-9:59 AM	2:30 PM-2:59 PM	7:30 PM-7:59 PM

The auto time-of-day model uses highway travel times from each of the 5 time periods to predict travel for 30-minute time periods. When estimating the time-of-day models, the chosen time period for each trip will be based on the midpoint between the reported trip departure time and trip arrival time. Trip tables are developed for each time period, purpose, mode, and direction. These are applied to networks by mode and time period in the trip assignment model.

Multinomial logit choice models were estimated for 6 home-based trip purpose/direction combinations – Home to work (HW), Work to home (WH), Home to shop (HS), Shop to home (SH), Home to other (HO), and Other to home (OH).

Two main features were added to the time-of-day models to make them more sensitive to congestion pricing:

- First, the three periods where congestion occurs (a.m. peak, midday, p.m. peak) were further divided into 30-minute subperiods, in order to model peak-spreading behavior. Because it would be impractical to also perform a separate traffic assignment for each 30-minute period, the distribution of trips across the subperiods was based on travel times for the same 5 periods that are included in the current model. As the congested travel time in the "peak of the peak" increases relative to the free flow travel time, the peak tends to flatten, and a higher percentage of peak travelers will travel in the shoulders of the peak. Generally, this type of effect is not symmetric because there are different constraints for traveling earlier as opposed to traveling later. In the a.m. peak, for example, we expect more workers to shift toward the earlier shoulder of the peak rather than the later shoulder because many workers have to arrive at work before a specific time.

- Second, in addition to auto travel time variations between periods, the model is sensitive to auto travel cost differences between periods, for instance from time-of-day-specific congestion pricing. Because we have no data on such cost differences in the household survey, it is necessary to infer the sensitivity to travel cost by using the sensitivity to travel time multiplied by the appropriate value of time for each income group/travel purpose. We use the same values of time that are used in the mode choice models.

We estimated new multinomial logit models for the 6 trip purpose/direction combinations, using a set of 32 alternatives. Compared to the remainder of the modeling system, the a.m. and p.m. "peak" periods are both expanded to include wider shoulder periods. The a.m. peak, midday, and p.m. peak periods are set to be 5 hours long and contain 10 half-hour subperiods. The evening and night periods remain as single periods, spanning 3 and 6 hours, respectively.

In estimation, we use both period-specific variables, as well as "shift" variables to move trips earlier or later within each of the 3 larger periods. The shift variables are non-linear, for example, it may take more than twice as much a.m. peak congestion to get someone to shift their departure time 30 minutes earlier than it does to get the same person to shift 60 minutes earlier.

The following variables were tested in the model estimation:

- Sociodemographic – Income, and Household size.
- Land use/accessibility – Total employment accessible by auto within 6 miles, and Retail employment accessible by auto within 15 minutes.
- O-D/level of service – Auto in-vehicle generalized cost (in minutes) during each of the 5 periods, Bridge dummy variable, and Shared ride dummy variable.

All the variables that were tested and either retained or excluded in the utility equation for the logit choice models was based on their significance, whether the sign of the coefficient was logical and whether the data can be forecasted by the MPO or the DOT. Variables that were tested but not included in the final models are the employment accessibility variables. A description of the variables retained in the final models and the impact of these variables on the temporal choice behavior of travelers are as follows:

- **Household income –** The dummy variable that indicates high income group (>$75K) has a significant coefficient specific to p.m. peak period in the 'Work to Home' model whereas in the 'Home to Work' model, the coefficient is significant in the a.m. peak period. This indicates that commuters from higher income households are more likely to travel to work during the a.m. peak period and less likely to travel during the p.m. peak period than other time periods. This result is further corroborated in the 'Work to Home' model where the income coefficient for the a.m. period was insignificant (and not included) suggesting that commute trips from higher income households are not as likely to be destined to home during the morning peak period. The income coefficients for the p.m. time period are greater than for other time periods in the 'Work to Home' model, indicating that higher income commuters are more likely to return home during the p.m. peak period. The lower income variable (<$45K) has a negative coefficient in the a.m. peak period of the 'Home to Work' model, probably because the lower income jobs have more irregular hours than high income jobs and are more likely to occur in off-peak time periods.

- **Household size –** Larger households are less likely to travel to work in a.m. peak than smaller households, as indicated by the negative and significant household size coefficient in the 'Home to Work' model. It may be that larger household sizes indicate the presence of children or more complicated household structures, which, combined with multiple workers in the household, lead to flexible or extended work schedules resulting in more reverse direction work trips. By contrast, smaller households are more likely to return home from work in the p.m. peak period, as indicated by the negative and significant coefficient in the 'Work to Home' model. It is possible that smaller households have fewer outside constraints on work hours and schedules, and work trips can occur in more traditional work hours.

- **Carpool dummy –** If a work to home trip is made using the carpool mode of travel, then this variable is equal to one; otherwise, it equals zero. The coefficient of this variable is very significant and positive in the 'Home to Work' model, and very significant and negative in 'Work to Home' model. This coefficient is negative in the 'Work to Home' model, indicating that carpool trips from work to home are less likely to occur, and it is hypothesized that there are fewer opportunities for casual carpooling from work to home than there are from home to work. For non-work trips, this variable is significant and positive in both directions of the trip except for trips returning home during a.m. peak period where it is negative owing to the fact that carpooling is usually not an option from a non-home non-work location.

- **Bridge dummy –** If a trip is made using one of three bridges in the Puget Sound region (namely Tacoma Narrows, I-90, and SR 520), then this variable is equal to one; and, if not, it is zero. In the 'Home to Work' model, this coefficient was significant and positive in the a.m. peak period, indicating that there is a higher likelihood that trips across the bridge will be made during morning peak hours solely for work-related purposes. These coefficients were more significant in the mid-day and p.m. peak periods of the 'Work to Home' model indicating a higher likelihood of trips across bridges in the reverse work commute direction. This variable was found to be significant and positive in the non-work models during the mid-day period indicating the propensity of non-work travelers to opt for uncongested periods to perform non-work activities.

- **Congestion level –** The level of congestion or delay is measured by the difference in generalized cost (in minutes) for a.m., mid-day, p.m., and evening time periods and the generalized cost for night time period. This variable is found to be negative and significant in all the models, indicating that delay affects travel decisions by time-of-day choice significantly. The size of the coefficient in the 'Home to Work' model is less negative than in the 'Work to Home' model, indicating a stronger negative effect on travel decisions for trips from work to home during the congested periods.

- **Shift variables –** Two kinds of 'Shift' variables are computed, namely, 'Shift Early' and 'Shift Later', which measure the difference between the time period indicator (on a scale from 1 through 24 with 0.5 increments) and the mid-point of the first three time periods (a.m., mid-day and p.m. peak periods). 'Shift Early' is used when the time period indicator is less than the mid-point whereas 'Shift Later' is used when it is greater. The square of these variables is also used in the models to see the impact of very short and very long delays on temporal choice behavior. During model estimation, these 'Shift' variables are multiplied by the delay variable as well as other variables to see the combined effect on time-of-day choice. The coefficients for the delay variables multiplied by 'Shift Early' and 'Shift Later' are significant and positive while on the other hand these are negative when multiplied by the square of 'Shift Early' and 'Shift Later'. This indicates that there is more likelihood of travelers switching their time choice when undertaking trips that might generate either very short or very long delays.

The model statistics demonstrate that the rho-squared with respect to zero is reasonable (0.191 for 'Work to Home' and 0.188 for 'Home to Work'), but the rho-squared with respect to the constants (0.003 for 'Work to Home' and 0.014 'Home to Work') shows that the constants account for nearly all the variation in time-of-day choices. While it may be desirable for the variables in the models to account for more of the time-of-day choices, the primary objective of the model is to provide sensitivity to trip characteristics, which is achieved by these models.

A number of additional steps are carried out for the time-of-day models:

- The models were estimated using the full set of variables listed above, and with additional testing for the best specification of the shift variables. The estimation results by trip purpose are shown in Tables 1, 2, and 3.

- Travel cost differences by time of day are added separately into the models, but as part of the generalized cost impedance used in trip distribution. This comes from the assignment procedure as a separate price/toll skim by time of day. Unlike travel time, however, the user is able to specify this cost to remain constant over a specific period (e.g., a congestion pricing policy operating only between 6:00 a.m. and 9:00 a.m.).

- The models are applied in iteration with traffic assignment, as the time-of-day models use the auto travel times from assignment, but in turn provide a different peaking "factor" (peak hour demand) to use in the one-hour assignment. So, the assignment process constrains the amount of peak spreading predicted by the time-of-day models.

In the application of the time-of-day model, we assign the peak 60-minute time period for the a.m. peak and midday time periods as input to the feedback process of travel times for trip distribution and mode choice. After the final iteration, the trips in each 30-minute time period are aggregated back to the 5 time periods (a.m. peak, midday, p.m. peak, evening and night) for evaluation of performance on the system.

Table 1. Home-Based Work Time-of-Day Choice Model

			Home to Work		Work to Home	
	Observations		**6931**		**6076**	
	Final log L		**-19500.8**		**-17032.7**	
	Rho-sq.(0)		**0.188**		**0.191**	
	Rho-sq(const)		**0.014**		**0.003**	
Alternatives	**Variable**	**Definition**	**Coefficient**	**T-Stat**	**Coefficient**	**T-Stat**
AM1-AM10	AM Delay	max(0, AM GC – NI GC)	-0.06172	-4.7	-0.4277	-3.2
MD1-MD10	MD Delay	max(0, MD GC – NI GC)	-0.2834	-6.0	-0.3935	-9.9
PM1-PM10	PM Delay	max(0, PM GC – NI GC)	-0.1747	-4.2	-0.100	const
EV	EV Delay	max(0, EV GC – NI GC)			-0.1714	-5.7
AM1-AM5	AM Shift Early	AM Delay x (7.5-T)	0.1121	7.7		
AM1-AM5	AM Shift Early2	AM Delay x (7.5-T)^2	-0.01914	-3.4		
AM6-AM10	AM Shift Later	AM Delay x (T-7.5)	0.01842	2.3		
AM6-AM10	AM Shift Later2	AM Delay x (T-7.5)^2				
MD1-MD5	MD Shift Early	MD Delay x (12.5-T)	0.1063	4.4		
MD1-MD5	MD Shift Later	MD Delay x (T-12.5)	0.09548	2.8	0.1144	4.6
PM1-PM5	PM Shift Early	PM Delay x (17.0-T)	0.0766	2.8	0.09523	7.0
PM1-PM5	PM Shift Early2	PM Delay x (17.0-T)^2	0		-0.03593	-4.8
PM6-PM10	PM Shift Later	PM Delay x (T-17.0)	0.05933	1.8	0.1056	9.4
PM6-PM10	PM Shift Later2	PM Delay x (T-17.0)^2	0		-0.03027	-6.0
AM1-AM10	AM HH size	min(HH size,4)	-0.3419	-7.6		
AM1-AM10	AM Low Inc	HH income<$45K	-0.5176	-5.9		
AM1-AM10	AM High Inc	HH income>$75K	0.515	4.3		
AM1-AM10	AM Crossing	dummy(Bridge_N > 0)	0.3545	2.3		
MD1-MD10	MD HH size	min(HH size,4)	-0.3427	-6.6		
MD1-MD10	MD High Inc	HH income>$75K	0.461	3.4	0.6694	3.7
MD1-MD10	MD Shared ride	dummy(car occ.>1)	0.479	3.8	-0.5917	-3.5
MD1-MD10	MD Crossing	dummy(Bridge_N > 0)			0.618	2.6
PM1-PM10	PM HH size	min(HH size,4)			-0.05966	-2.1
PM1-PM10	PM High Inc	HH income>$75K			0.9454	5.6
PM1-PM10	PM Shared ride	dummy(car occ.>1)	0.6686	4.2	-0.5694	-4.6
PM1-PM10	PM Crossing	dummy(Bridge_N > 0)			0.6383	3.7
EV	EV High Inc	HH income>$75K			0.5285	2.7
AM1-AM5	AM HS Shift Early	AM HH Size x (7.5-T)	0.0722	4.0		
AM1-AM5	AM HI Shift Early	AM Low Inc x (7.5-T)	0.1194	2.3		
AM1-AM5	AM HI Shift Early	AM High Inc x (7.5-T)	-0.1216	-2.8		
AM1-AM5	AM BR Shift Early	AM Crossing x (7.5-T)	-0.4295	-5.8		
AM6-AM10	AM LI Shift Late	AM Low Inc x (T-7.5)	0.2483	3.8		
PM1-PM5	PM HI Shift Early	PM High Inc x (17.0-T)			-0.2217	-4.1

Table 2. Home-Based Shop Time-of-Day Choice Model

			Home to Shop		Shop to Home	
	Observations		**3590**		**5616**	
	Final log L		**-11852.9**		**-17311.8**	
	Rho-sq.(0)		**0.047**		**0.111**	
	Rho-sq(const)		**0.011**		**0.004**	
Alternatives	**Variable**	**Definition**	**Coefficient**	**T-Stat**	**Coefficient**	**T-Stat**
AM1-AM10	AM Delay	max(0, AM GC – NI GC)	-0.06	const	-0.3201	-2.4
MD1-MD10	MD Delay	max(0, MD GC – NI GC)	-0.06	const	-0.06	const
PM1-PM10	PM Delay	max(0, PM GC – NI GC)	-0.08281	-2.1	-0.06	const
EV	EV Delay	max(0, EV GC – NI GC)	0		0	
AM1-AM5	AM Shift Early	AM Delay x (7.5-T)	0.4556	5.5		
AM1-AM5	AM Shift Early2	AM Delay x (7.5-T)^2	-0.1914	-3.7		
AM6-AM10	AM Shift Later	AM Delay x (T-7.5)	0.07396	4.0		
AM6-AM10	AM Shift Later2	AM Delay x (T-7.5)^2				
MD1-MD5	MD Shift Early	MD Delay x (12.5-T)	0.1124	5.0		
MD1-MD5	MD Shift Later	MD Delay x (T-12.5)	0.03864	0.8		
PM1-PM5	PM Shift Early	PM Delay x (17.0-T)	0.05506	2.0	0.1413	4.5
PM1-PM5	PM Shift Early2	PM Delay x (17.0-T)^2			-0.0597	-3.2
PM6-PM10	PM Shift Later	PM Delay x (T-17.0)	0.02994	1.3	0.01379	1.7
PM6-PM10	PM Shift Later2	PM Delay x (T-17.0)^2				
AM1-AM10	AM Shared ride	dummy(car occ.>1)			-1.896	-4.4
MD1-MD10	MD Shared ride	dummy(car occ.>1)	0.5574	5.6		
PM1-PM10	PM Shared ride	dummy(car occ.>1)	0.9826	9.3		
EV	EV Shared ride	dummy(car occ.>1)			0.4935	5.7
AM1-AM5	AM SR Shift Early	AM Shared Ride x (7.5-T)	-1.255	-4.9		
AM6-AM10	AM SR Shift Late	AM Shared Ride x (T-7.5)			0.7076	2.6
MD1-MD5	MD HS Shift Early	MD HH Size x (12.5-T)	-0.09479	-4.2		
MD1-MD5	MD SR Shift Early	MD Shared Ride x (12.5-T)			-0.2199	-4.0
MD6-MD10	MD HS Shift Late	MD HH Size x (T-12.5)	-0.2284	-5.9		
PM1-PM5	PM HS Shift Early	PM HH Size x (17.0-T)	-0.09581	-2.6	-0.09922	-4.3
PM1-PM5	PM SR Shift Early	PM Shared Ride x (17.0-T)	-0.237	-2.8		
PM6-PM10	PM SR Shift Late	PM Shared Ride x (T-17.0)			0.1159	2.8

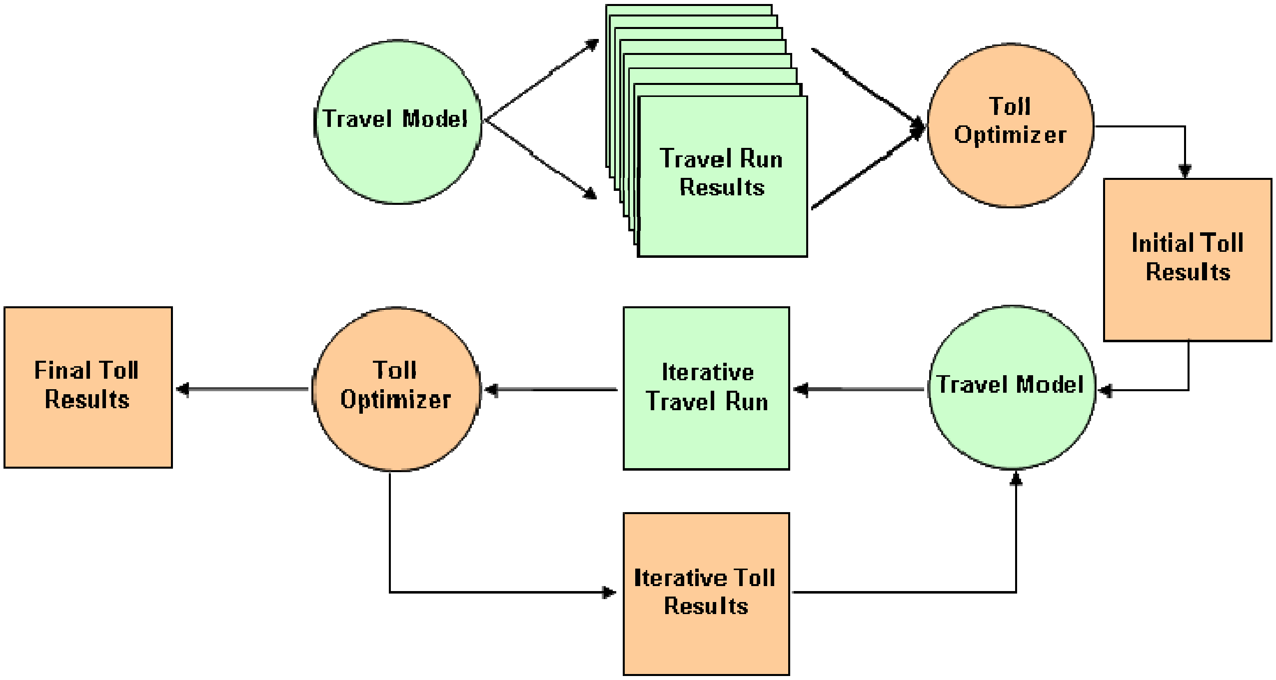
Table 3. Home-Based Other Time-of-Day Choice Model

			Home to Other		Other to Home	
	Observations		**12816**		**12277**	
	Final log L		**-42890.3**		**-36732.7**	
	Rho-sq.(0)		**0.034**		**0.137**	
	Rho-sq(const)		**0.007**		**0.014**	
Alternatives	**Variable**	**Definition**	**Coefficient**	**T-Stat**	**Coefficient**	**T-Stat**
AM1-AM10	AM Delay	max(0, AM GC – NI GC)	-0.06	const	-0.3936	-5.9
MD1-MD10	MD Delay	max(0, MD GC – NI GC)	-0.06	const	-0.2209	-8.6
PM1-PM10	PM Delay	max(0, PM GC – NI GC)	0.94	const	-0.10	const
EV	EV Delay	max(0, EV GC – NI GC)	0		0	
AM1-AM5	AM Shift Early	AM Delay x (7.5-T)	0.0705	7.9		
AM1-AM5	AM Shift Early2	AM Delay x (7.5-T)^2				
AM6-AM10	AM Shift Later	AM Delay x (T-7.5)	0.0533	6.6	0.0659	1.3
AM6-AM10	AM Shift Later2	AM Delay x (T-7.5)^2				
MD1-MD5	MD Shift Early	MD Delay x (12.5-T)	0.06646	6.9		
MD1-MD5	MD Shift Later	MD Delay x (T-12.5)			0.07048	3.5
PM1-PM5	PM Shift Early	PM Delay x (17.0-T)	0.02375	2.9	0.1184	5.6
PM1-PM5	PM Shift Early2	PM Delay x (17.0-T)^2			-0.05623	-4.5
PM6-PM10	PM Shift Later	PM Delay x (T-17.0)	0.04191	8.9	0.02461	6.1
PM6-PM10	PM Shift Later2	PM Delay x (T-17.0)^2				
AM1-AM10	AM HH size	min(HH size,4)			0.5104	9.8
AM1-AM10	AM Shared ride	dummy(car occ.>1)	1.181	10.2	-2.04	-14.7
MD1-MD10	MD HH size	min(HH size,4)	-0.2226	-9.1		
MD1-MD10	MD Shared ride	dummy(car occ.>1)	0.3611	3.4		
MD1-MD10	MD Crossing	dummy(Bridge_N > 0)	0.2625	1.8		
PM1-PM10	PM Shared ride	dummy(car occ.>1)	1.032	9.0	0.3235	4.7
EV	EV Shared ride	dummy(car occ.>1)			0.5723	9.8
AM1-AM5	AM SR Shift Early	AM Shared Ride x (7.5-T)	-0.5179	-8.2		
AM6-AM10	AM HS Shift Late	AM HH Size x (T-7.5)	-0.0513	-2.7	-0.2111	-4.9
AM6-AM10	AM SR Shift Late	AM Shared Ride x (T-7.5)	-0.5855	-10.5	0.7224	6.9
MD1-MD5	MD SR Shift Early	MD Shared Ride x (12.5-T)			-0.1739	-3.8
MD6-MD10	MD HS Shift Late	MD HH Size x (T-12.5)	0.182	7.7		
MD6-MD10	MD SR Shift Late	MD Shared Ride x (T-12.5)	-0.262	-5.2		
PM1-PM5	PM HS Shift Early	PM HH Size x (17.0-T)	0.1518	6.7	-0.09922	-4.3
PM1-PM5	PM SR Shift Early	PM Shared Ride x (17.0-T)	-0.5215	-8.9	0.1104	2.2
PM6-PM10	PM SR Shift Late	PM Shared Ride x (T-17.0)	-0.1959	-4.3	0.1915	4.8

These models have been integrated within the four-step trip-based modeling system and are being used currently to optimize throughput in select corridors by applying as many as 15 sets of toll rates that vary by direction and facility.

Toll Optimization Strategies

In order to set rational toll policies that meet operational and revenue goals, the data from the travel model requires a post-processing methodology. This methodology is required in part to perform simple accounting functions not available in normal travel models (such as revenue calculations), as well as the need to perform more complex toll optimization procedures, taking operation constraints into account. This post-processing methodology adopts the language of optimization as its core approach. Policy goals that do not have a specific numerical target, such as throughput or revenue maximization, are expressed as an objective function. Goals that have a specific target – such as maintaining a specific level of service in a HOT lane – are expressed as constraints on the objective.



Toll optimization occurs in two phases, as illustrated in the figure. First, the travel model is run for a set of toll rates that remain constant throughout the day. Then, these flat toll rates are fed into the toll optimizer, which uses them to select an initial estimate of a set of tolls that meet the constraints, while also optimizing the policy goals. The toll levels from these estimates are then fed back into the travel model; the outputs from this run are then examined by the toll optimizer and given a score, based on how well they meet objectives and constraints. The toll optimizer uses these results to create a new estimate of optimal tolls, which are fed back into the travel model. This process continues as the scores of the resultant toll scenarios increase by a threshold amount. Once the deltas between scores drop below this threshold amount, the tolls are considered optimized.

Additional Areas of Research

There are additional limitations of existing models that should be addressed with additional research on forecasting for pricing studies, as follows:

- Lack of representation of modal options in distribution models;
- Lack of representation of reliability in evaluating travel choices;
- Inability of static demand models to represent dynamic pricing options;
- Need to evaluate fairness as important in implementation;
- Need to represent overall societal benefits for road pricing strategies;
- Need to represent safety as a performance measure; and
- Need to better understand and communicate risk and uncertainty.

We believe that innovative approaches can be developed and integrated with existing models to address these issues and that this will significantly improve our ability to forecast the impacts of pricing strategies. For example, the lack of representation of modal options in trip distribution models means that for pricing strategies that allow carpools or transit users to travel toll-free, the impact of tolls on trip distribution patterns needs to be performed for toll users and toll-free users separately. Simultaneous trip distribution and mode choice models would address this particular issue, but there are very few of these available and have not been used in pricing studies (to the knowledge of the authors).

Another example of a modeling issue is the lack of representation of reliability in evaluating pricing strategies. There are indications from previous research that travel time reliability is as important as value of time and may be valued significantly higher. At the same time, there has been less research on how reliability affects traveler's route choice. Although great strides have been made in measuring reliability, there is less progress in considering reliability in forecasting models.

Another important consideration for any pricing study is the fact that one of the most important drivers of travel demand is growth in household and employment growth and income levels. It is common to use the socioeconomic data approved by the planning agencies within a region, and while these forecasts may be developed with care for the purpose for which they were intended, they have not been evaluated for their suitability for use in traffic forecasts intended to provide conservative assumptions for purpose of revenue estimates. Indeed, planning forecasts for typical projects may be "conservative" in the other direction, trying to anticipate the worst-case situation for future highway needs.