Knoxville Regional Travel Model Update 2009

Model Development and Validation Report

Prepared for the
Knoxville Regional
Transportation Planning Organization
Suite 403, City-County Building
400 Main Street
Knoxville, Tennessee 37902
(865) 215-2500

September 2009

Prepared by
Bernardin, Lochmueller & Associates, Inc.
6200 Vogel Road
Evansville, IN 47715
(812) 479-6200 • (800) 423-7411 • (812) 479-6262 FAX

Contents

Overview 1
Population Synthesis 8
Vehicle Availability 16
Defining Tour and Stop Types 20
Tour and Stop Generation 25
Tour Mode Choice 31
Stop Location Choice 43
Stop Sequence Choice 60
Trip Mode Choice 63
Departure Time Choice 73
External Model 85
Truck Model 93
Toll Choice 98
Network Assignment 99

Tables

Table 1. Aggregate Ordered Response Logit Model for Household Size 10
Table 2. Aggregate Ordered Response Logit Model for Household Workers 12
Table 3. Aggregate Ordered Response Logit Model for Household Size 13
Table 4. Aggregate Ordered Response Logit Model for Household Income 14
Table 5. Ordered Response Logit and Simple Multinomial Logit Models of Vehicle Availability 18
Table 6. Tour Types 20
Table 7. Stop Types 23
Table 8. Factors Affecting Household Tour and Stop Generation 26
Table 9. Tour and Stop Generation Equations 27
Table 10. Comparison of Basic Generation Rates 29
Table 11. Factors Affecting Tour Mode Choice 32
Table 12. Disaggregate Nested Logit Model of Work Tour Mode Choice 35
Table 13. Aggregate Multinomial Logit Model of University of Tennessee Student Tour Mode Choice 36
Table 14. Disaggregate Nested Logit Model of School Tour Mode Choice 38
Table 15. Disaggregate Nested Logit Model of Other Tour Mode Choice 39
Table 16. Observed and Calibrated Mode Shares by Tour Purpose 40
Table 17. Observed vs. Modeled Transit Ridership (late January - late March) 42
Table 18. Factors Affecting Stop Location Choice 44
Table 19. Work Location Choice Model for Low Income Households 46

Table 20. Work Location Choice Model for Middle and Upper Income Households 47
Table 21. Stop Location Choice Model for non-UT College Studies.. 48
Table 22. Stop Location Choice Model for Non-work Stops on Work Tours............................. 49
Table 23. Stop Location Choice Model for Non-UT Stops on UT Student Tours 51
Table 24. School Location Choice Model 52
Table 25. Stop Location Choice Model for Non-school Stops on School Tours 53
Table 26. Stop Location Choice Model for Short (< 30 min) Maintenance Stops on Other Tours 54
Table 27. Stop Location Choice Model for Long (> 30 min) Maintenance Stops on Other Tours 55
Table 28. Stop Location Choice Model for Discretionary Stops on Other Tours 56
Table 29. Gravity Model Parameters Assumed for Visitor Stop Locations 57
Table 30. Calibration Statistics for Stop Location Choice Models 57
Table 31. Percent of Inter-county Journeys to Work.. 58
Table 32. Selected Major Inter-county Work Flows 59
Table 33. Stop Sequence Choice Model Parameters 61
Table 34. Stop Sequence Choice Model Calibration Statistics... 61
Table 35. Factors Affecting Trip Mode Choice... 64
Table 36. Work Tour Home-Based Trip Mode Choice Model... 65
Table 37. Work Tour Non-Home-Based Trip Mode Choice.. 66
Table 38. Trip Mode Choice for UT Student Tours 67
Table 39. School Tour Home-based Trip Mode Choice... 68
Table 40. School Tour Non-home-based Trip Mode Choice 69
Table 41. Other Tour Home-based Trip Mode Choice... 70
Table 42. Other Tour Non-home-based Trip Mode Choice 71
Table 43. Trip Mode Choice Calibration.. 72
Table 44. Estimated Departure Time Choice Model for Home-based Trips on Work Tours 77
Table 45. Estimated Departure Time Choice Model for Non-home-based Trips on Work Tours 78
Table 46. Estimated Departure Time Choice Model for Trips on UT Tours 79
Table 47. Estimated Departure Time Choice Model for Home-based Trips on School Tours 80
Table 48. Estimated Departure Time Choice Model for Non-home-based Trips on School Tours 81
Table 49. Estimated Departure Time Choice Model for Home-based Trips on Other Tours 82
Table 50. Estimated Departure Time Choice Model for Non-home-based Trips on Other Tours 83
Table 51. Departure Time Choice Model Shadow Prices from Calibration................................ 84
Table 52. External Station Summary.. 87
Table 53. Major External-External Auto Trip Interchanges.. 88
Table 54. Major External-External Single Unit (SU) Truck Trip Interchanges 89
Table 55. Major External-External Multiple Unite (MU) Truck Trip Interchanges.................... 90
Table 56. Daily Truck Trip Generation Rates 93
Table 57. Inter-Region and Inter-Modal Special Trip Generation 94
Table 58. Summary of 2006 Truck Trip Generation 95
Table 59. Average Truck Travel Times by Trip Type.. 96
Table 60. Truck Time of Day Factors... 96
Table 61. Default Toll Choice Model Parameters 98

Table 62. Assignment Validation Criteria ... 100
Table 63. Model Performance by Volume Group ... 102
Table 64. Model Performance by Functional Class ... 103
Table 65. Model Performance on Major Corridors ... 104
Table 66. Model Performance by Area Type ... 104
Table 67. Model Performance by County ... 104
Table 68. Model Performance on Screenlines ... 105
Table 69. Model Performance on Cutlines ... 107

Figures

Figure 1. The Knoxville Regional Travel Model Study Area ... 1
Figure 2. The Knoxville Regional Travel Model's Hybrid Model Design ... 5
Figure 3. Percent of Households by Number of Persons vs. Zonal Average Household Size (before shadow prices) ... 10
Figure 4. Percent of Households by Number of Workers vs. Zonal Average Household Workers (before shadow prices) ... 11
Figure 5. Percent of Households by Number of Students vs. Zonal Average Students per Household (w/o shadow prices) ... 12
Figure 6. Percent of Households by Income Level vs. Zonal Average Annual Household Income ... 13
Figure 7. Nesting / Choice Structure of Ordered Response Logit Model of Vehicle Availability 17
Figure 8. Mode Shares by Tour Type ... 21
Figure 9. Trip Departure Times by Tour Type ... 22
Figure 10. Average Travel Time from Home by Stop Type ... 24
Figure 11. Nesting of Travel Mode for Work and Other Tours ... 34
Figure 12. Nesting of Travel Mode for School Tours ... 37
Figure 13. Daily Distribution of Departure Times ... 74
Figure 14. Daily Distribution of Work Tour Trip Departure Times ... 75
Figure 15. Daily Distribution of UT Tour Trip Departure Times ... 75
Figure 16. Daily Distribution of School Tour Trip Departure Times ... 76
Figure 17. Daily Distribution of Other Tour Trip Departure Times ... 76
Figure 18. External Stations ... 86
Figure 19. Probability of an External Stop Location ... 92
Figure 20. Volume Delay Functions ... 99
Figure 21. Daily Traffic Count vs. Model Volume ... 103
Figure 22. New Screenlines ... 105
Figure 23. Calibration Cutlines from the Old MINUTP Model ... 106
Figure 24. Knoxville Loaded Regional Network ... 107
Figure 25. Knoxville Loaded Network (central area detail) ... 108

Overview

The Knoxville Regional Transportation Planning Organization (TPO) contracted with Bernardin, Lochmueller & Associates, Inc., (BLA) to conduct a major update of their travel demand forecasting model. The current version of the Knoxville Regional Travel Model (KRTM) is implemented in TransCAD, version 5.0, a GIS-based travel demand modeling software, using the software"s scripting language, GISDK.

The KRTM predicts average weekday traffic volumes for all roadway classes of Knox and Blount counties and major arterials and collectors in Anderson, Jefferson, Sevier, Loudon, Union, Roane, and portions of Grainger County. The model"s roadway network covers over 6,600 lane miles in total over an area of 3,425 square miles represented by 1,019 traffic analysis zones. The current version of the model also predicts the Knoxville Area Transit (KAT) average weekday system ridership and the number of average weekday bicycle and pedestrian trips within the region.

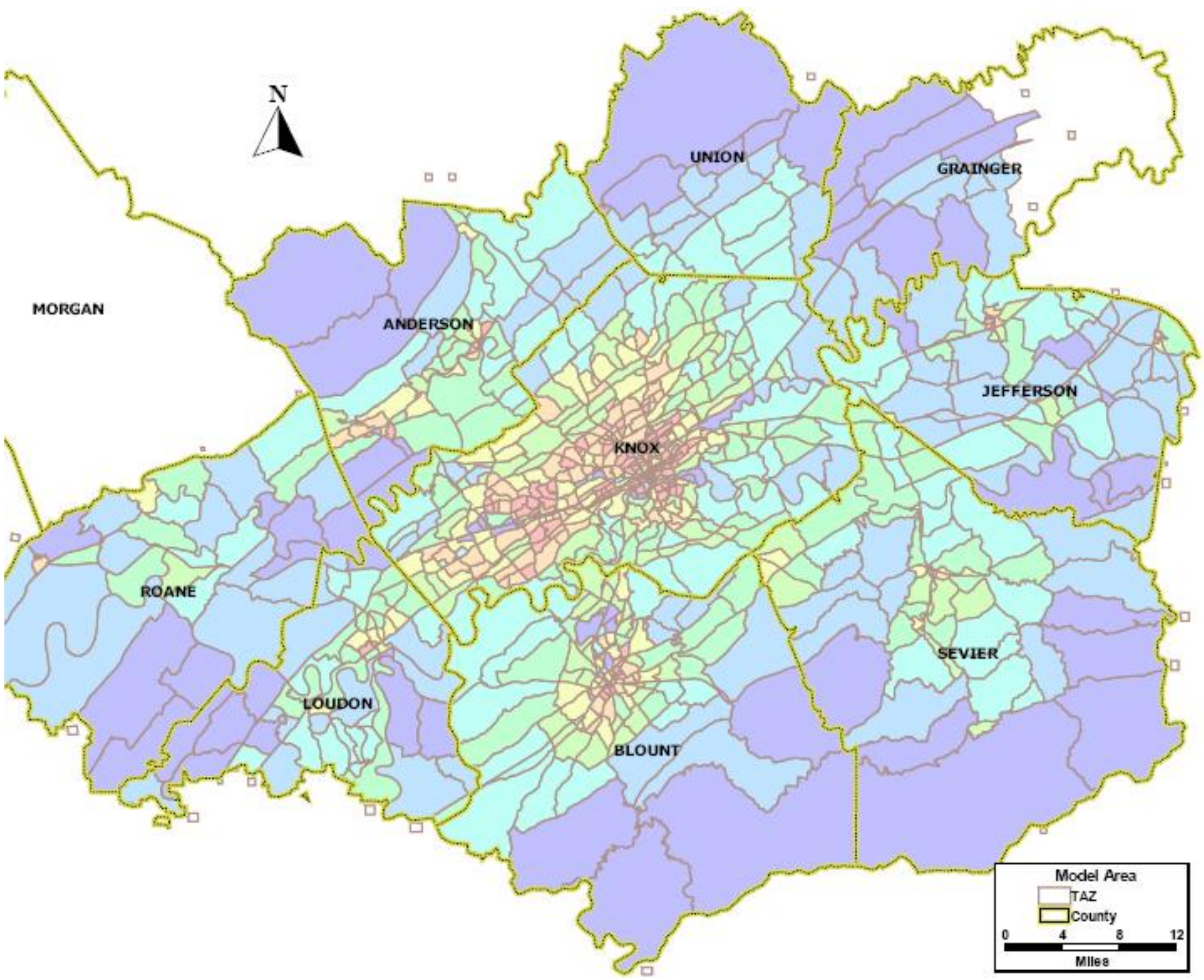

Figure 1. The Knoxville Regional Travel Model Study Area

The prediction of roadway volumes, transit ridership and bicycle and walk trips entails predicting the travel behavior of the region‟s population which was estimated at 863,000 persons in 2006. The population is diverse, distributed among several local activity centers including Knoxville, Maryville, Oak Ridge, and the Gatlinburg/Pigeon Forge/Smoky Mountains tourism area. The area incorporates varied topography and includes a large student population primarily associated with the University of Tennessee.

History

In the year 2000, the TPO commissioned the *2000 Knoxville Urban Area Household Travel Behavior Study*, a prompted recall survey of 1,538 households in Knox and Blount counties to support the development of a new TransCAD travel demand model to replace the existing travel model for Knox and Blount counties implemented in MINUTP. The TPO then contracted with BLA to develop a new model incorporating an expanded study area. The model area was expanded to incorporate neighboring counties using year 2000 census data and rich roadway attribute information from the Tennessee Roadway Information Management System. Model development began in 2003 and was completed in 2004, validated to year 2000 traffic counts.

In 2005, the TPO conducted a peer-review of their travel model. The panel included Guy Rousseau of the Atlanta Regional Commission, Leta Huntsinger of the Triangle Regional Model Service Bureau, Jerry Everett of the University of Tennessee Center for Transportation Research and Maureen Bluhm of the Federal Highway Administration, in addition to representatives of TPO and BLA staff. The peer review made several recommendations:

- Additional data collection
    - Transit on-board survey
    - External cordon line origin-destination survey
    - NHTS add-on / HH survey update including collar counties
    - Commercial vehicle survey
- Further model development/refinements
    - Develop mode choice models
    - Develop a land use model
    - Enhance network detail and zone structure
    - Make feedback loop convergence-based
    - Develop destination choice models and eliminate k-factors
    - Further freight model development

As of the delivery of this model update in 2009, all of the recommendations of the peer review have been addressed, with the single exception of the recommendation of a commercial vehicle survey.

BLA conducted an external cordon line video origin-destination study for the Tennessee Department of Transportation (TDOT) and the TPO in 2007. The results of that survey are documented in a separate report entitled *Knoxville External Cordon Line Video License Plate Survey*. The TPO commissioned the *2008 East Tennessee Household Travel Survey* covering an additional 1,400 households in Knox and Blount as well as the collar counties to supplement the original survey in 2000. KAT also had a small on-board survey conducted in September of

2008. All three of these additional data sources were incorporated in the development of the new version of the KRTM.

Prior to the update of the KRTM and per the recommendation of the peer review, the TPO also had an Urban Land Use Allocation Model (ULAM) developed to assist in the development of future land use scenarios. A short-term update of the KRTM completed for the TPO by BLA in 2008 included the following improvements:

- incorporating the new external data from the cordon line survey,
- simplifying the k-factors in the gravity models and validating the work flows against 2000 CTPP journey-to-work data,
- implementing a convergence-based version of the feedback loop,
- re-estimation of trip attraction equations using simplified employment categories consistent with the new land use model,
- and the revalidation of the model to new base year of 2006.

The current update of the KRTM, documented in this report, addresses the remaining recommendations of the peer review regarding model refinements. It includes the development of mode and destination choice models, various improvements to the freight model, and many other improvements documented in detail throughout this report.

The Current Model Upgrade

The model upgrade documented in this report was motivated in part by the 2005 peer review, but goes well beyond its recommendations. The move toward a new model design, incorporating experimental destination choice models was motivated by several factors.

The peer review did comment on the k-factors in the previous version of the model and, more generally, it was recognized that gravity models were not performing well in the diverse, multinucleated Knoxville region. The hope that more sophisticated models, incorporating additional variables, could do a better job of replicating and predicting travel patterns in the region was a significant motive for the model upgrade. This hope seems at least partially vindicated by the results of the new model development. A comparison of the total daily trip tables produced by the old and new versions of the KRTM reveals that the new model provides a 33% increase in explanatory power over its predecessor (see the section on stop sequence choice for details).

A seminar conducted by BLA in March of 2007 for the TPO and also attended by representatives of TDOT and the University of Tennessee identified additional planning issues of concern which would ideally be addressed in a new version of the model. In addition to the spatial distribution of trips, three broad issues received considerable attention. The first issue was the interaction of transportation with land use and the sensitivity of the travel model to different land use scenarios which might be developed with the help of the new land use model. There was some discussion of possible new land use development patterns or policies favoring more dense, mixed use development. The possible exploration of transit-oriented-development was also raised, and there was a general re-affirmation of the peer review"s recommendation of developing mode choice models to better support transit planning, although it was tempered by the recognition of the limited transit mode share and resources for transit and transit planning. Finally, the possibility of future tolling or pricing scenarios also received significant attention, although subsequent developments in Tennessee have now made those options less likely.

The new model design offers new sensitivity to alternative land use scenarios through the incorporation of additional variables such as the activity diversity within a zone, the density of intersection approaches (which is high for traditional grids and low for cul-de-sac style neighborhoods), accessibilities to complementary activities, etc. Mode choice models are included in the new KRTM, and the model produces system-level transit and regional walking/bicycle trip forecasts. The model also includes the ability to represent roadway tolls, although this feature could only be loosely calibrated for reasonableness, as there are no existing tollways in the region. However, if toll alternatives were to be seriously studied, the current model could be calibrated to stated preference or other new data.

Model Design

The new KRTM represents the next generation of travel demand models. The previous version of the model was a good traditional model. The sequential trip-based design it implemented was based on research and practice which formed in the 1970"s and served as a standard for three decades. However, within the past decade there have been major advances in the ability to model urban and regional travel which have been successfully employed in approximately a half dozen metropolitan areas across the country. Both tour- and activity-based models, as well as the hybrid trip/tour-based design implemented here offer greatly improved policy sensitivity. In particular, the new KRTM offers the following features which its predecessor lacked:

- Sensitivity to **fuel prices**
- Planning capability for **transit**, **bicycle** and **pedestrian** modes
- More realistic representation of **special populations** (seniors, low income, students)
- Sensitivity to **urban design** (mixed uses, development density, grid vs. cul-de-sac style street networks)
- Ability to represent **shifts in the timing of travel** (due to congestion, aging population, etc.)
- Consistency with **tours** and **trip-chaining** behavior
- Improved traffic impacts with **halo effects** around major developments (malls, factories, etc.)
- More accurate **commuting patterns** from destination choice models
- Improved representation of **speeds and delays** from traffic signals, stop signs, etc.
- Improved accuracy of **alternatives analysis** from new assignment algorithms
- Reduction of **aggregation bias** which can skew model results

The first tour- or activity-based models which offered these planning capabilities took considerable resources to develop and run. Most activity-based models took years to develop and run for 24-48 hours on computers with a dozen or more processors. In contrast, after several delays, primarily for the completion of data collection efforts, the new KRTM was developed by BLA in essentially eight months and runs in less than four hours on a standard dual core laptop.

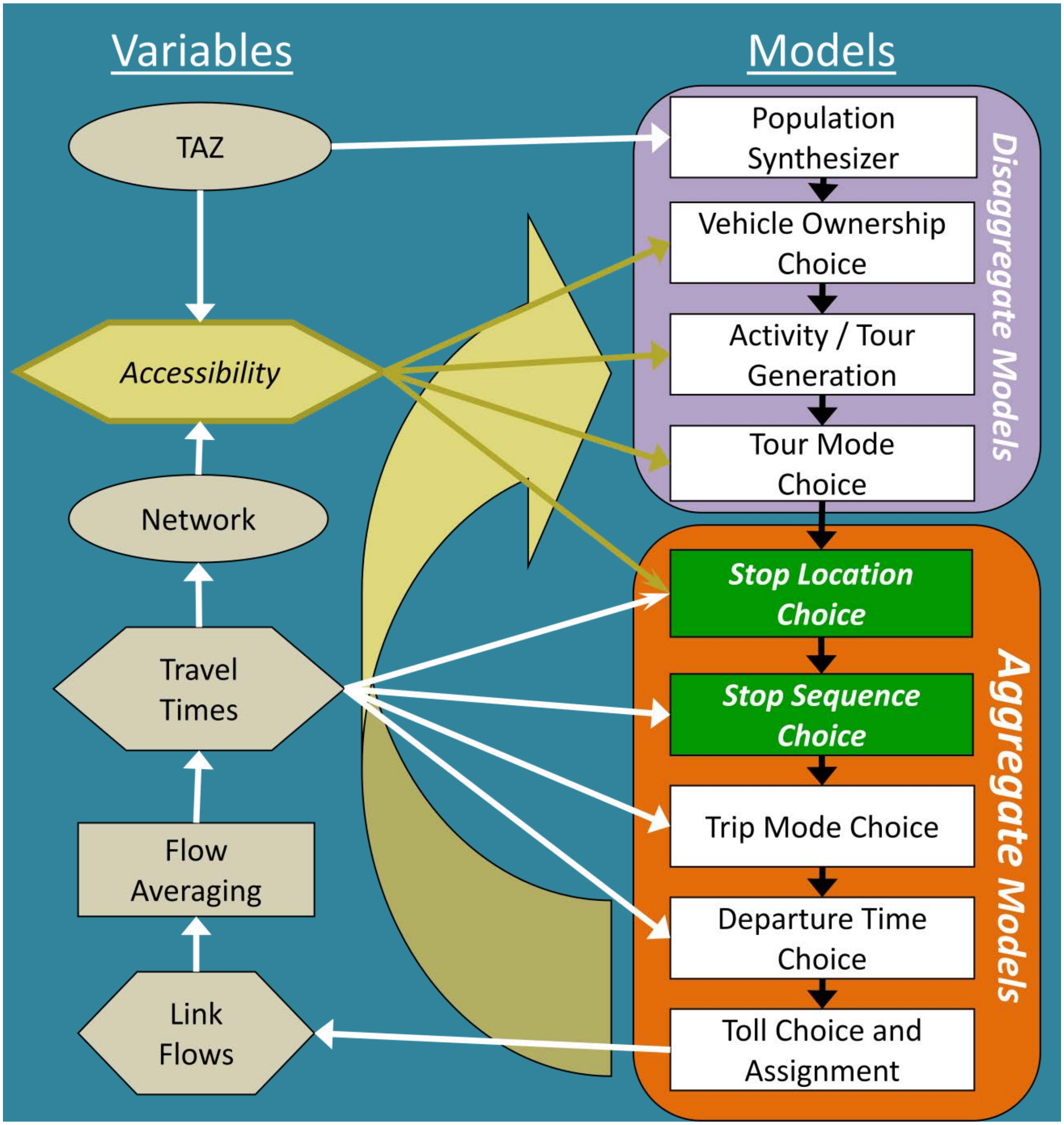

Figure 2. The Knoxville Regional Travel Model's Hybrid Model Design

The speed of the new KRTM is a result of its new, hybrid model design. This architecture is based on research conducted by Dr. Vince Bernardin, Jr., as part of his doctoral studies with Profs. Frank Koppelman and David Boyce at Northwestern University and funded in part by an Eisenhower Fellowship from the Federal Highway Administration. The hybrid model design combines some elements of traditional "four-step" and as well as several components from recent activity-based models, but is ultimately distinct, made possible by the stop location and sequence choice structure original to the hybrid design.

The KRTM modeling process, illustrated in Figure 2, begins by generating a synthetic population of individual households based on the aggregate characteristics of the population encoded in the traffic analysis zones (TAZ). Then a model predicting households‟ level of vehicle ownership is applied. The number of tours (sojourns beginning and ending at home) of various purposes (work, school, other, etc.) and the number of stops on these tours are predicted for each household. The dominant mode of travel (private automobile, school bus, public bus, walking/biking) is chosen for the household‟s tours of each purpose. Then, grouping households within the same TAZ together, probable locations of the stops on automobile tours are chosen. Next, for each probable stop location, a preceding location is chosen such that the resulting probable sequences of stops form tours which begin at home and proceed from one stop to the next until returning to home. For each trip in the resulting travel pattern, the probability of walking, driving alone or with passengers is predicted, as is the departure time (in 15 minute time periods) and toll-eligibility. Finally, the trips are assigned to the roadway network and routes are chosen such that travelers minimize their travel time and costs. The resulting travel times are used to recalculate accessibility variables, and both are then fed back and used to repeat the process, beginning from the generation of tours and stops, until the changes from one iteration to the next in the resulting roadway volumes are minimal. Each component of this process is described in detail in the following sections of this report.

The adjective “hybrid” refers to two ways in which the new model design blends aspects of four-step and activity-based models and defies traditional categorization. First, the hybrid KRTM model can be described as trip-based in so far as it essentially produces aggregate trip table matrices of trips between origins and destinations rather than disaggregate records detailing individual travelers‟ activities. However, hybrid models like the new KRTM can also be described as tour-based since the travel patterns they predict can be mathematically proven to be consistent with tours and all travel is segmented within the model by types of tours, eliminating non-home-based trips problematic in traditional models. Hence, models of this design are hybrid trip-based/tour-based models.

Second, perhaps more meaningfully, models like the KRTM are hybrid aggregate/disaggregate models. Unlike four-step models which were entirely aggregate and activity-based models which are entirely disaggregate, the KRTM and similar models include both aggregate and disaggregate component models. Yet despite its inclusion of disaggregate choice models, there are no random number draws or Monte Carlo simulation in the KRTM. As a result, the KRTM‟s model results are reproducible, unlike the results of activity-based or other simulation models. Any difference between two KRTM model runs is directly attributable to differences in their inputs as with traditional trip-based models. Whereas, in simulation models, multiple model runs are necessary when comparing alternatives to ensure that the difference between model runs results from differences in the alternative inputs rather than from differences in the random numbers drawn for each run.

The shift from the disaggregate framework of individual households to the aggregate framework of trips between zones midway through the model distinguishes the hybrid approach. The use of disaggregate components minimizes aggregation bias in the early steps of the model, including the particularly sensitive primary or tour mode choice. At the same time, the approach minimizes model run times by taking advantage of the fact that it is computationally much easier to predict a set of trips which is consistent with tours than to predict the individual tours themselves.

The hybrid approach adopted here does have limitations. It lacks the explicit representation offered by activity-based models of the interactions among household members and of constraints in the timing of travel and activities (although these phenomena are still implicit in this framework). However, given its lower development costs and run time and the reproducibility of results, the hybrid model architecture presents a practical and cost effective way of incorporating more sensitivity and realism in the KRTM to address the TPO"s current and future planning issues.

Population Synthesis

In recent years there has been a shift away from the application of demand models directly to traffic analysis zones in favor of representing individual households (and sometimes persons) and modeling travel behavior at their level. The shift is driven by the basic fact that people travel, not zones. Technically, the shift is to avoid the aggregation bias that occurs when non-linear demand models (such as logit models) are applied to aggregate or average characteristics rather than to populations with a range of attributes around their group averages. For example, a mode choice model may predict no significant transit mode share when applied to a zone with 100 households with an average of 2.2 cars per household. However, the same mode choice model, applied to the same households individually, may predict a significant number of transit trips if 5 of the households have no vehicles and 15 have only one vehicle. Examples like this illustrate that the effects of aggregation bias can be quite significant and have helped motivate the shift to modeling disaggregate synthetic populations.

Primary Inputs

- Zonal Average Household Size
- Zonal Average Workers per Household
- Zonal Average Students per Household
- Zonal Percent of Households with Senior
- Zonal Average Household Income

Secondary Inputs

- Population Density
- Percent of Zone within .5 mi of Bus Route
- Urban Design Factor

Output

Synthetic households for each TAZ with

- Number of persons
- Number of workers
- Number of students
- Presence of seniors
- Income Group (low, mid, high)

The Knoxville Regional Travel Demand Model generates a disaggregate synthetic population of households based on the demographic information associated with the traffic analysis zones. For each zone, individual households are created. Each household has a total number of persons, a number of workers and of students, a binary variable indicating whether or not any of the household members is over the age of 65 and an income variable that indicates whether the household belongs to the lower (under $25,000/year), middle ($25,000 - $50,000/year) or upper (over $50,000/year) income category, each of which comprises approximately a third of the households in the region. The number of vehicles available to each household is modeled separately, after the population synthesis, based on these variables and other variables describing the zone in which the household is located.

The synthetic population is developed in two steps. First, a set of ordered response logit models predict for each variable (such as household size, number of workers, etc.) the number of households which have each level of that variable (one person, two persons, etc., zero workers, one worker, two workers, etc.). Second, iterative proportional fitting is used to develop the synthetic population based on a seed population of households from the household travel surveys and the marginal distributions for each variable provided by the logit models. Unlike the procedures used to develop synthetic populations in many activity-based models, this procedure is entirely deterministic and does not introduce randomness or simulation error into the model through the use of any random draws. This is possible since it is allowed to produce more or less individual households than exist in the real population, creating consistency instead by weighting the households so that their weighted sum is the total actual number of households in each zone.

Ordered Response Logit Models of Marginal Distributions

Aggregate ordered response logit (ORL) models were developed to model the discrete distributions of each household characteristic variable noted above. These models essentially replace the stratification curves used in many traditional travel models to cross-classify households for trip generation. The models are fairly simple, largely driven by the aggregate zonal average variable describing the distribution which they represent (e.g., the model which determines the number of households with zero, one, two or three or more workers is driven largely by the zonal average number of workers per household).

Ordered response logit models are a special form of nested logit models designed to accommodate the correlation pattern typical of ordinal data, such as the number of persons, workers, etc., in a household. They were tested against simpler multinomial logit models which assume independence across alternative categories, and in each case, the ordered response model provided better goodness-of-fit to the observed data. ELM software (www.elm-works.com) was used for all logit model estimation.

To insure consistency with the zonal averages, the models also include "shadow prices" which guarantee the average characteristics of the synthetic population will agree with averages for each zone. The concept of shadow prices is taken from economics and optimization science. Technically, they are simply lagrangian multipliers associated with constraints in an optimization problem, in this case, constraints that the observed zonal averages be reproduced.

Conceptually, consider the situation in which the basic relationship between the demand for some good and its price is known (from various observations), and yet, for some (other) observation or observations, the observed demand is lower than what is predicted based on the known relationship with its price. One way this situation can be addressed, if there is confidence in the basic demand function and the contrary observations, is that an additional, unobserved "shadow price" in addition to the observed price can be postulated to account for the observed demand. This shadow price becomes an additive correction term in the demand function.

In these models, the formula for the shadow prices added to the utility function of alternatives less than the true zonal average is given:

$$s_i = s_{i-1} + (TrueAvg - AltAvg)\ln\,(EstAvg_{i-1}/TrueAvg)$$

or for alternatives greater than the true zonal average:

$$s_i = s_{i-1} + (TrueAvg - AltAvg)\ln\,(TrueAvg/EstAvg_{i-1})$$

where *TrueAvg* is the zonal average from the TAZ geographic layer, $EstAvg_{i-1}$ is the resulting zonal average in iteration *i-1*, and *AltAvg* is the average for that alternative (generally equal to the alternative number, except for the last category, e.g., 5+ persons, 3+ workers, etc.).

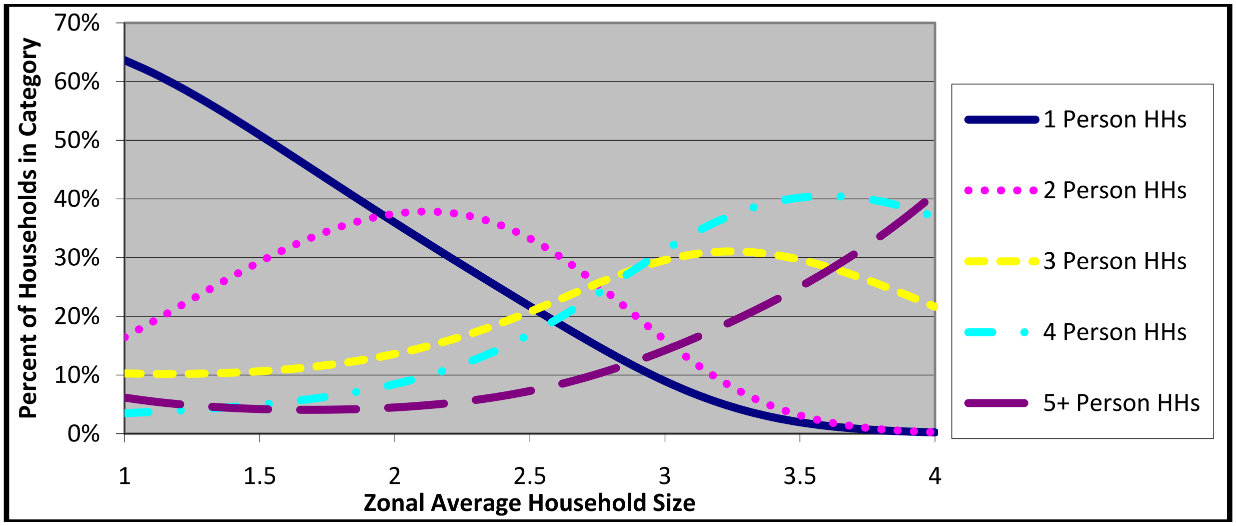

Figure 3. Percent of Households by Number of Persons vs. Zonal Average Household Size (before shadow prices)

Table 1. Aggregate Ordered Response Logit Model for Household Size

Household Size	Alternative	Parameter	t-statistic
-- Logsum Parameters			
Nest_1	alt_2, Nest_2	0.9	Constrained
Nest_2	alt_3, Nest_3	0.8	Constrained
Nest_3	alt_4, alt_5	0.7	Constrained
-- Alternative Specific Parameters			
CONSTANT	alt_1	1.4991	1.15
CONSTANT	alt_2	-4.2750	-2.18
CONSTANT	alt_3	-0.4124	-0.29
CONSTANT	alt_4	-1.9605	-1.35
Zonal Average Household Size	alt_1	2.5378	2.05
Zonal Average Household Size	alt_2	4.9789	2.96
Zonal Average Household Size	alt_3	1.5143	1.26
Zonal Average Household Size	alt_4	1.9344	1.58
Zonal Average Household Size, Squared	alt_1	-0.9999	-3.55
Zonal Average Household Size, Squared	alt_2	-1.3571	-3.70
Zonal Average Household Size, Squared	alt_3	-0.3655	-1.39
Zonal Average Household Size, Squared	alt_4	-0.3655	Constrained
Population Density	alt_1	0.0581	2.07
Log of Zonal Average HH Income	alt_1	-0.3076	-2.41
Log of Zonal Average HH Income	alt_2	0.3827	3.43
Percent of Households with Senior	alt_3	-1.5443	-2.62
-- Model Statistics	statistic		
Log Likelihood at Zero	-4730.5		
Log Likelihood at Constants	-4363.7		
Log Likelihood at Convergence	-4229.1		
Rho Squared w.r.t. Zero	0.106		
Rho Squared w.r.t Constants	0.031		

The models also include some other, secondary demographic variables which are related to the distributions of the primary variable as well. For instance, even for a given average number of students per household for a zone, the number of zero student households is generally greater in zones with more households with seniors (age 65 and older); whereas, in contrast, the zero student households tend to decrease with the zone"s average income, all other things being equal.

The model parameters, t-statistics and goodness-of-fit measures are shown in Table 1 through Table 4. The goodness-of-fit of these models is generally quite low, which is not unusual or unexpected for models of disaggregate phenomena based on aggregate variables. However, a reasonable level of confidence can still be had in the synthetic populations which they produce since they are both constrained to agree with zonal average characteristics (through the use of shadow prices) and only applied to factor the observed seed distribution in the subsequent round of iterative proportional fitting. The implied distribution of households (assuming regional average secondary zonal demographic characteristics) before the application of shadow prices are shown in Figure 3 through Figure 6. While the need for the shadow prices is evident for extreme zonal averages, the distributions are clearly reasonable.

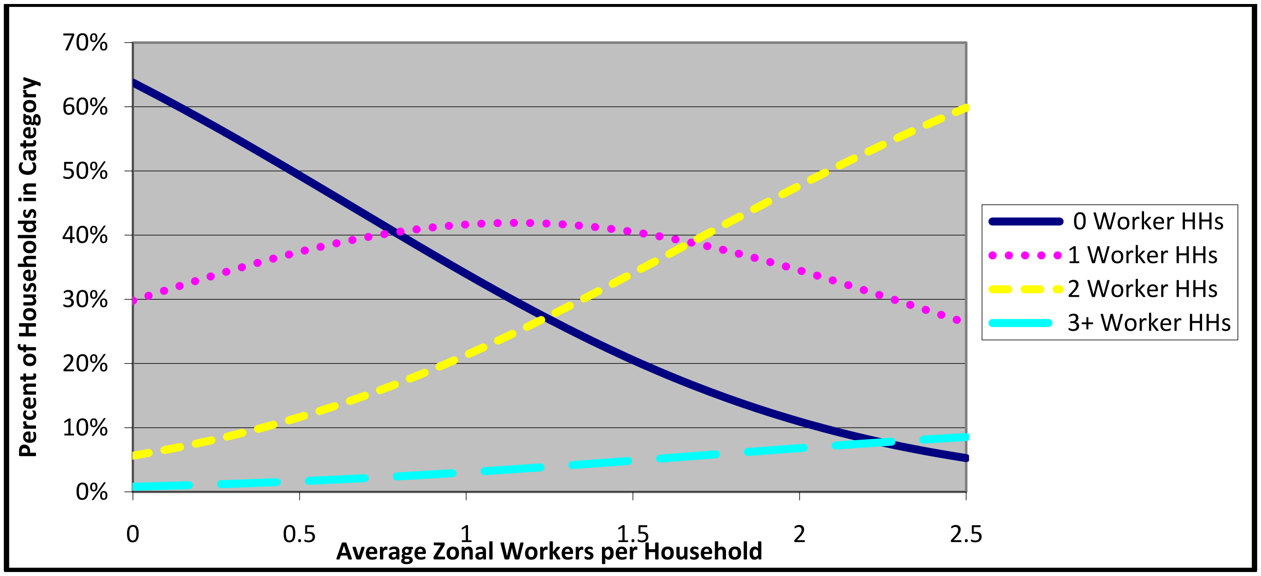

Figure 4. Percent of Households by Number of Workers vs. Zonal Average Household Workers (before shadow prices)

Table 2. Aggregate Ordered Response Logit Model for Household Workers

Household Workers	Alternative	Parameter	t-statistic
-- Logsum Parameters			
Nest_1	alt_1, Nest_2	0.9	Constrained
Nest_2	alt_2 and alt_3	0.8	Constrained
-- Alternative Specific Parameters			
CONSTANT	alt_0	7.6405	18.50
CONSTANT	alt_1	4.3154	13.78
CONSTANT	alt_3	-2.8834	-4.31
Zonal Average Workers per Household	alt_0	-1.7514	-7.13
Zonal Average Workers per Household	alt_1	-0.8903	-4.54
Zonal Average Household Size	alt_3	0.6177	2.27
Percent of Households with Senior	alt_0	1.4036	2.43
Percent of Zone within .5 mi of Bus Route	alt_0	-0.4966	-4.09
Log of Zonal Average HH Income	alt_0	-1.6299	-24.33
Log of Zonal Average HH Income	alt_1	-0.7897	-14.25
-- Model Statistics	Statistic		
Log Likelihood at Zero	-4888.2		
Log Likelihood at Constants	-4356.4		
Log Likelihood at Convergence	-3869.1		
Rho Squared w.r.t. Zero	0.209		
Rho Squared w.r.t Constants	0.112		

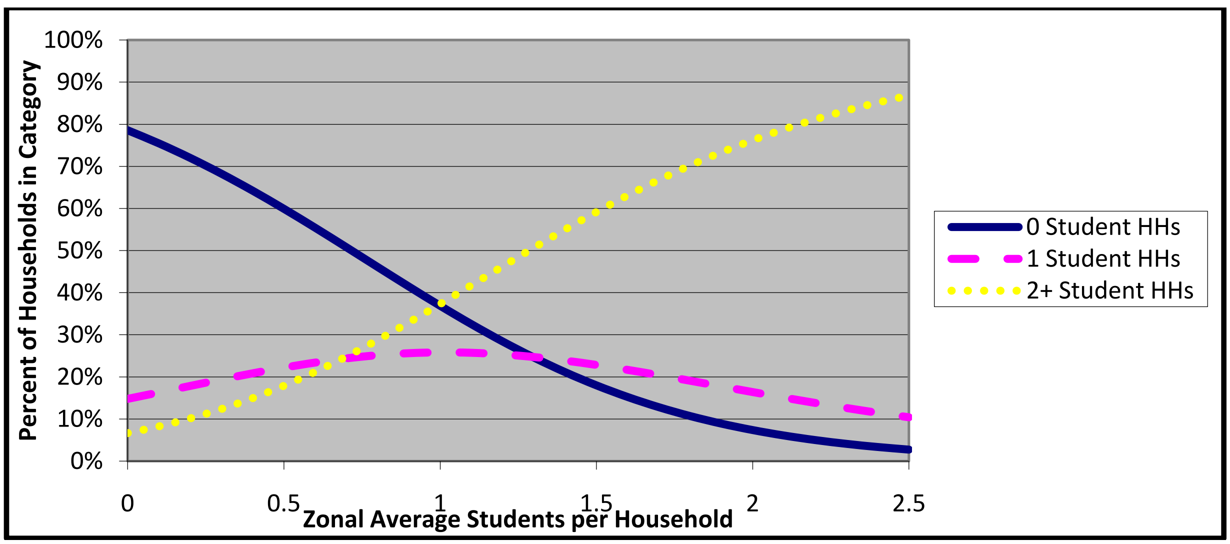

Figure 5. Percent of Households by Number of Students vs. Zonal Average Students per Household (w/o shadow prices)

Table 3. Aggregate Ordered Response Logit Model for Household Size

Household Students	Alternatives	Parameter	t-statistic
-- Logsum Parameters			
Nest_1	alt_1, alt_2	0.5	Constrained
-- Alternative Specific Parameters			
CONSTANT	alt_0	1.2587	9.46
CONSTANT	alt_2	-0.1672	-1.85
Zonal Average Students per Household	alt_0	-1.5742	-5.09
Zonal Average Students per Household	alt_2	0.5839	2.75
Percent of Households with Senior	alt_0	1.6364	14.73
Percent of Households with Senior	alt_2	-0.9695	-7.07
Zonal Average Household Income	alt_0	-0.0046	-4.88
-- Model Statistics	Statistic		
Log Likelihood at Zero	-3873.8		
Log Likelihood at Constants	-3307.8		
Log Likelihood at Convergence	-2992.5		
Rho Squared w.r.t. Zero	0.228		
Rho Squared w.r.t Constants	0.095		

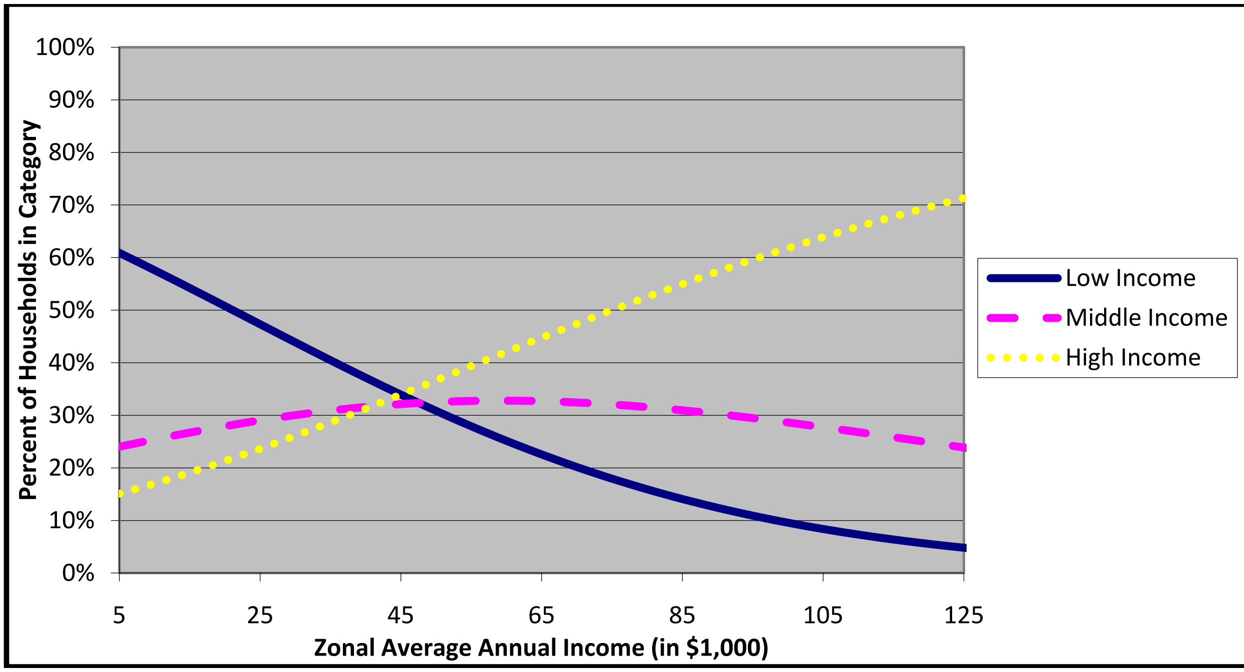

Figure 6. Percent of Households by Income Level vs. Zonal Average Annual Household Income

Table 4. Aggregate Ordered Response Logit Model for Household Income

Household Income	Alternatives	Parameter	t-statistic
-- Logsum Parameters			
Nest_1	alt_2, alt_3	0.5	Constrained
-- Alternative Specific Parameters			
CONSTANT	alt_1	0.3624	2.55
CONSTANT	alt_3	-0.7902	-3.51
Zonal Average Household Income	alt_1	-0.0248	-8.41
Zonal Average Household Income	alt_3	0.0065	4.88
Zonal Average Household Size	alt_3	0.2832	3.07
Urban Design Factor	alt_1	0.0016	7.79
Urban Design Factor	alt_3	-0.0003	-2.05
-- Model Statistics	Statistic		
Log Likelihood at Zero	-3873.8		
Log Likelihood at Constants	-3852.2		
Log Likelihood at Convergence	-3621.7		
Rho Squared w.r.t. Zero	0.065		
Rho Squared w.r.t Constants	0.060		

The ordered response logit models are applied in TransCAD using its Nested Logit Application module. This produces a table with probabilities for each alternative category. A simple GISDK script converts these probabilities into the marginal distribution of households by zone needed for input for iterative proportional fitting.

Iterative Proportional Fitting

The synthesis of the population is completed using traditional iterative proportional fitting in multiple dimensions, making use of TransCAD"s functionality. TransCAD includes a module for developing synthetic populations with iterative proportional fitting. TransCAD provides basic documentation of this procedure.

The Knoxville model actually only uses the TransCAD module to produce a cross-classification table. A simple procedure then enumerates the non-empty cells of the cross-classification table as individual households, weighting them by the cell value, to produce the disaggregate synthetic population. This method is preferred to TransCAD"s built-in functionality to generate a table of individual households because it relies on random draws and would introduce simulation error into the model. The method implemented here, instead, is deterministic.

The inputs to the iterative proportional fitting procedure are the marginal distributions produced by the ordered response logit models and a seed or sample population of households and persons. The combined sample from the 2000 and 2008 household surveys, properly weighted, is used for this purpose. The use of the household survey sample as a seed distribution for iterative proportional fitting offers consistency with the models of the marginal distributions which were estimated from the same data and helps ensure convergence.

The use of shadow prices in the generation of the marginal distributions guarantees that the synthetic population created by iterative proportional fitting will agree with the TAZ layer not only on the number of households, but also the number of persons, workers, students and households with seniors in each zone.

Vehicle Availability

The final characteristic of each household in the synthetic population is the number of vehicles available to it (whether they are owned, leased or „company cars" garaged at home). Because of the importance of vehicle availability in travel demand and the sensitivity of vehicle availability to transportation policies and investments, vehicle availability is not modeled simply as a demographic variable, essentially input to the travel model. Rather, vehicle availability is modeled behaviorally with each household choosing the number of vehicles it will own, lease, etc., based on its demographic characteristics (household size, income, number of workers and students), urban design (grid vs. cul-de-sacs) of its neighborhood, regional gas prices and its access to transit.

Input Variables

- Individual Household Size
- Individual Household Workers
- Individual Household Students
- Individual Household Income
- Percent of Zone within .5 mi of Bus Route
- Urban Design Factor
- Gas Price

Output

Household vehicle availability

- Zero vehicles
- One vehicle
- Two vehicles
- Three vehicles
- Four or more vehicles

Methodology

The estimation of vehicle availability is accomplished by a disaggregate ordered response logit choice model. Unlike the aggregate ordered response logit models used in the population synthesizer, this model does not include average zonal vehicle availability as an input/control variable or shadow prices to ensure consistency with an input variable. Whereas those aggregate models are applied to each zone to generate a distribution of households within each zone (and thus have only statistical and no behavioral interpretation), this disaggregate model, applied to the individual households generated by the population synthesizer, can be interpreted as modeling each household"s choice of how many vehicles to have in its fleet. In this context, the ordered response nesting structure is consistent with (but does not necessarily imply) the plausible hypothesis that the number of vehicles available to a household is ultimately the product of a series of choices of whether or not to own, lease, etc., one more vehicle. Figure 7 illustrates the nesting structure of the ordered response logit model with the corresponding series of choices.

The model parameters were estimated using ELM software (www.elm-works.com), and the ordered response logit (ORL) model was tested against a simpler multinomial logit (MNL) model which would correspond to a single, simple choice of the number of vehicles (assumption of no correlation across alternatives). The chi-squared test shows that the ordered response logit model rejects the null hypothesis that the multinomial logit model is the true model at a high level of confidence (0.02 significance). The parameter estimates and associated t-statistics, together with model goodness-of-fit statistics for both the ORL and MNL models are displayed in Table 5.

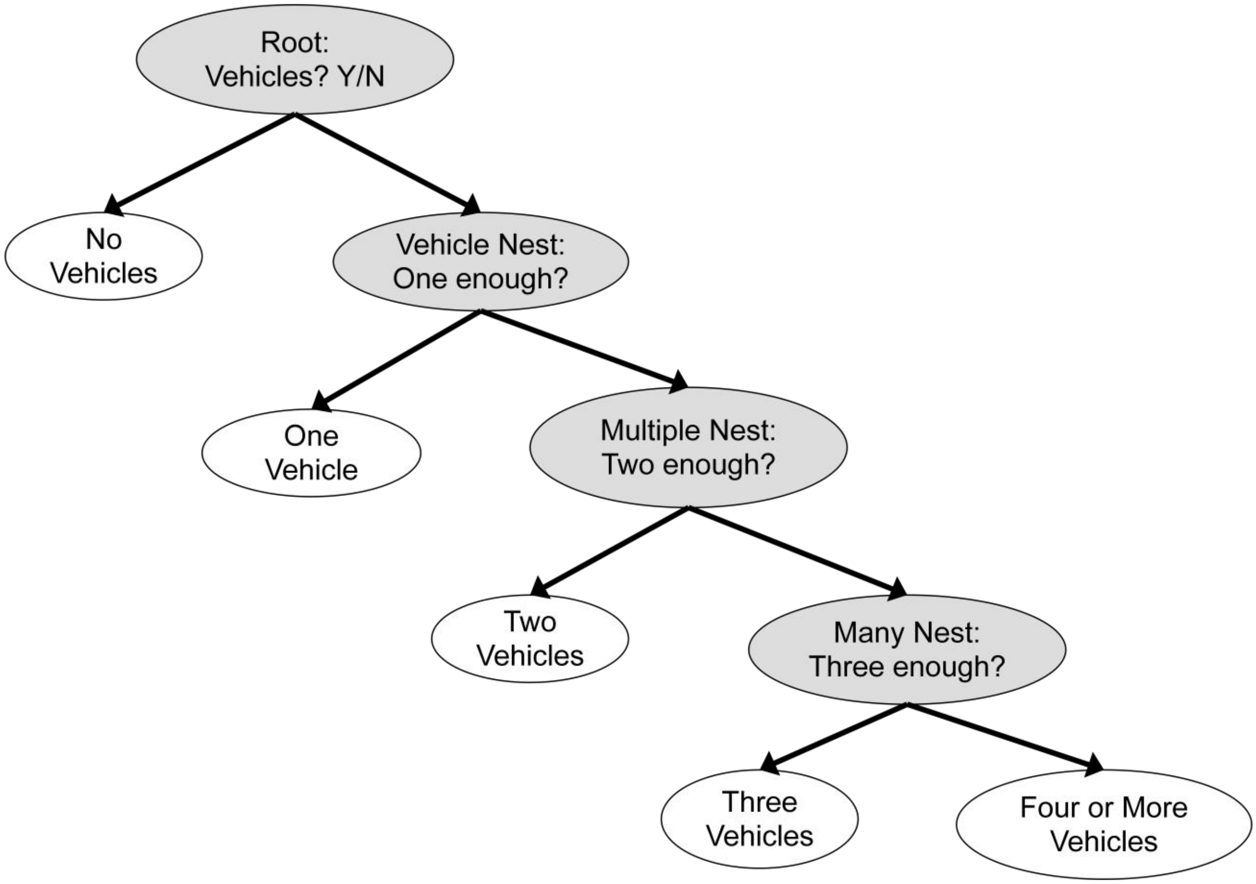

Figure 7. Nesting / Choice Structure of Ordered Response Logit Model of Vehicle Availability

The model estimation results show that the number of vehicles increases with household size, workers and income and decreases with the number of students (for a constant household size). As would be expected, these demographic variables are highly significant and largely dominate a household‟s choice of how many vehicles to procure/maintain. However, model estimation results also found that the urban design of the neighborhood (grid vs. cul-de-sac design, as measured by the number of intersection approaches per square mile) was highly significant and denser grid designs correlated with lower vehicle availability. Since income is controlled for as a separate variable, this is likely attributable to the ease of walking and biking in these neighborhoods. Access to transit service (as measured by the percent of the household‟s zone within half a mile of a KAT bus route) was also statistically significant and decreased the probable number of vehicles per household. Finally, gas prices were also found to be significant and negatively correlated with the number of household vehicles available. Given the nature of the dataset, partly collected during the gas price spike in early 2008, and the lag in households‟ response by changing vehicle ownership, the sensitivity to gas prices observed in the model is likely actually due to the more slowly increasing gas price levels in the previous several years. The model therefore likely reflects a fairly conservative assumption regarding the elasticity of vehicle ownership with response to fuel prices.

Table 5. Ordered Response Logit and Simple Multinomial Logit Models of Vehicle Availability

Variables	Alternatives	ORL			MNL	
-- Logsum Parameters		Calibrated	Parameter	t-statistic	Parameter	t-statistic
Nest_1	alt_1, Nest_2		0.30	*	1.00	*
Nest_2	alt_2, Nest_3		0.25	*	1.00	*
Nest_3	alt_3, alt_4		0.20	*	1.00	*
-- Alternative Specific Parameters		Calibrated	Parameter	t-statistic	Parameter	t-statistic
CONSTANT	alt_0	1.5997	1.5479	6.59	3.7645	12.13
CONSTANT	alt_1	1.0586	1.0346	15.24	3.4202	15.12
CONSTANT	alt_3	-0.6959	-0.6645	-9.91	-2.5797	-9.43
CONSTANT	alt_4	-1.4177	-1.3412	-13.48	-6.0144	-13.19
Gas Price	alt_0		0.0663	3.75	0.1936	3.31
Gas Price	alt_1		0.0663	*	0.1936	*
Gas Price	alt_4		-0.0161	-0.85	-0.0739	-0.81
Household Size	alt_0		-0.6488	-9.26	-1.1161	-12.60
Household Size	alt_1		-0.2605	-12.96	-0.7967	-12.49
Household Size	alt_3		0.0753	4.17	0.2777	3.78
Household Size	alt_4		0.1556	7.02	0.6766	6.93
Number of Workers	alt_0		-2.2813	-12.68	-2.8449	-14.89
Number of Workers	alt_1		-0.3532	-15.91	-1.1524	-15.57
Number of Workers	alt_3		0.1539	8.46	0.5810	7.79
Number of Workers	alt_4		0.2612	11.13	1.1294	10.76
Number of Students	alt_0		0.2283	8.66	0.6715	8.02
Number of Students	alt_1		0.2283	*	0.6715	*
Number of Students	alt_3		-0.0487	-2.34	-0.1770	-2.07
Number of Students	alt_4		-0.1044	-4.25	-0.4567	-4.22
Income Group (1-3)	alt_0		-1.3580	-10.33	-1.7912	-12.53
Income Group (1-3)	alt_1		-0.2617	-12.78	-0.8671	-12.74
Income Group (1-3)	alt_3		0.0249	1.33	0.0901	1.17
Income Group (1-3)	alt_4		0.0846	3.00	0.3959	3.05
Urban Design Factor	alt_0		0.0024	10.79	0.0023	10.21
Urban Design Factor	alt_3		-0.0002	-1.74	-0.0008	-2.01
Urban Design Factor	alt_4		-0.0002	*	-0.0008	*
Percent of Zone Near Bus	alt_0		0.1864	4.62	0.6735	5.05
Percent of Zone Near Bus	alt_1		0.1864	*	0.6735	*
Percent of Zone Near Bus	alt_3		-0.0796	-1.47	-0.2856	-1.33
Percent of Zone Near Bus	alt_4		-0.0796	*	-0.2856	*
-- Model Statistics						
Log Likelihood at Zero			-5675.0		-5675.0	
Log Likelihood at Constants			-4943.0		-4943.0	
Log Likelihood at Convergence			-3609.4		-3614.4	
Rho Squared w.r.t. Zero			0.364		0.363	
Rho Squared w.r.t Constants			0.270		0.269	

* Constrained Parameter

In order to maintain the deterministic nature of the model and avoid introducing randomness (and the associated need to do multiple runs to obtain an average result), rather than use random draws to realize the choice probabilities as is frequently done in activity-based approaches, a new synthetic population of households, broken out by number of vehicles, is created, using the probabilities of vehicle availability to re-weight the population. Comparisons of the number of household vehicles in the resulting synthetic and actual base year populations lead to some slight calibration adjustments to the ORL model"s bias constants.

Defining Tour and Stop Types

In traditional travel models, the various component models (trip generation, gravity models, mode split, time-of-day split, etc.) are segmented by trip purposes with separate component models for each trip purpose. In the new model design for the Knoxville region, the component models are segmented in a slightly different way. Mode and departure time choices are segmented by tour type, while destination choice is further segmented by stop (or activity) types. The generation of tours and the activities or stops which belong to them is accomplished by an initial group of regression models just as trips are produced in traditional trip generation, except that it is activities (or stops) and tours which are generated rather than trips. The following pages outline tour and stop types for the new Knoxville regional model, analogous to trip purposes in the current four-step model, based on the travel characteristics of the region from the combined 2000-2008 household survey data.

Tour Types

Tour types play an important role in the model. Both mode and time-of-day (or departure time) choice models are developed for each tour type, and the number of tour types is a critical determinate of the run time of the model.

Table 6. Tour Types

Tour Type	% Tours	Average Stops	% Stops	Frequency (/hh/day)	Frequency (/pers/day)
Work	33.6%	2.20	38.4%	0.96	0.40
UT	1.4%	1.81	1.3%	0.04	0.02
School	14.6%	1.54	11.6%	0.42	0.17
Non-Work	50.4%	1.85	48.7%	1.44	0.60
Visitor	*	1.50	*	1.20*	0.37*

* Tour & stop percentages are for resident travel; visitor tour frequencies are per travel party & per traveler.

Five tour types are used for the Knoxville regional model and displayed in Table 6: work tours, University of Tennessee (UT) tours, school tours, non-work tours and visitor tours. This division of tours offers a good balance between behavioral fidelity and run time, capturing a great deal of the temporal and modal variation with only five tours types. Visitor tour characteristics, representing travel by visitors to the Smokey Mountains tourism area, are taken from surveys of visitors to Lake Tahoe in 2004 and 2006. All other information is taken from Knoxville‟s combined 2000-2008 household survey data.

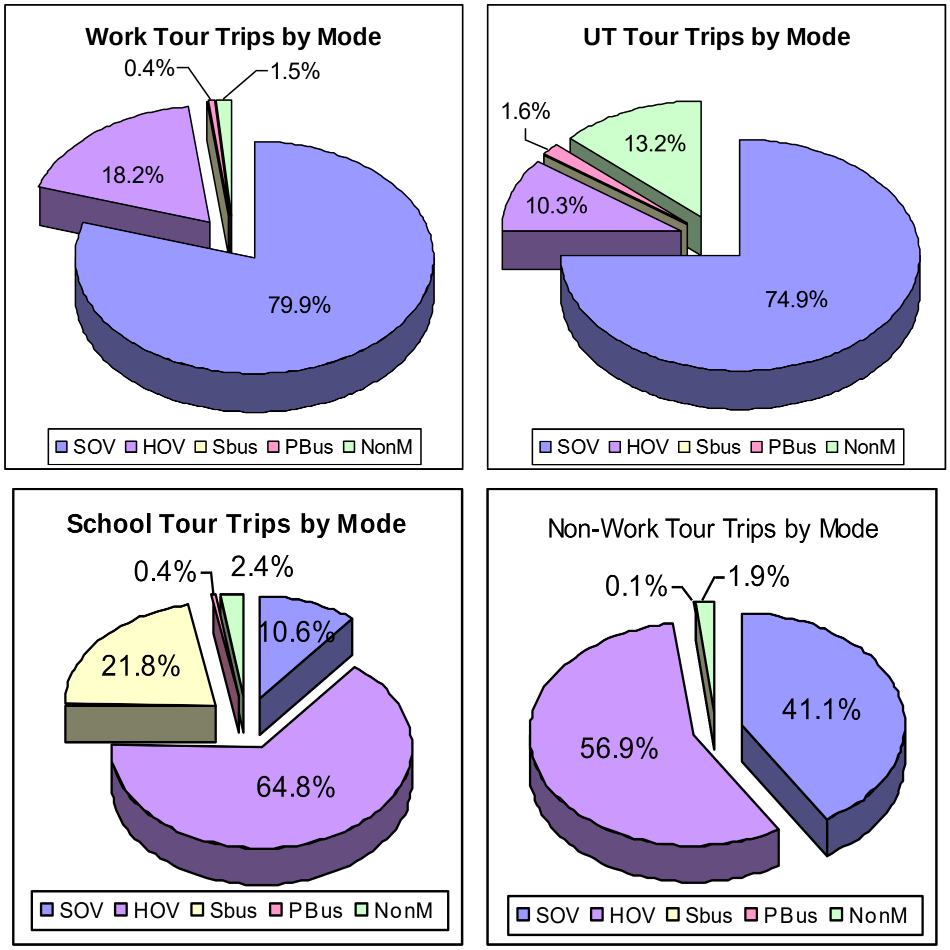

Figure 8. Mode Shares by Tour Type

The mode shares for each tour type, shown in Figure 8 above, are clearly distinct. Work tours are dominated by single occupancy vehicle (SOV) trips which comprise nearly 80% of all work tour trips. University of Tennessee tours, while also dominated by SOV, also show a very high share of non-motorized trips as well as notable transit. In (primary and secondary) school tours, in contrast, high occupancy vehicle (HOV) trips are most common, followed by school bus trips, with SOV trips comprising only about one in ten trips. Non-work tours are also predominantly HOV, like school tours, but with notably more SOV trips. Visitor tour modes (not displayed) are dominated by automobile (90.1%), with a notable 8.4% share for buses (mostly private coaches / shuttle buses), leaving 1.5% by bicycle/foot.

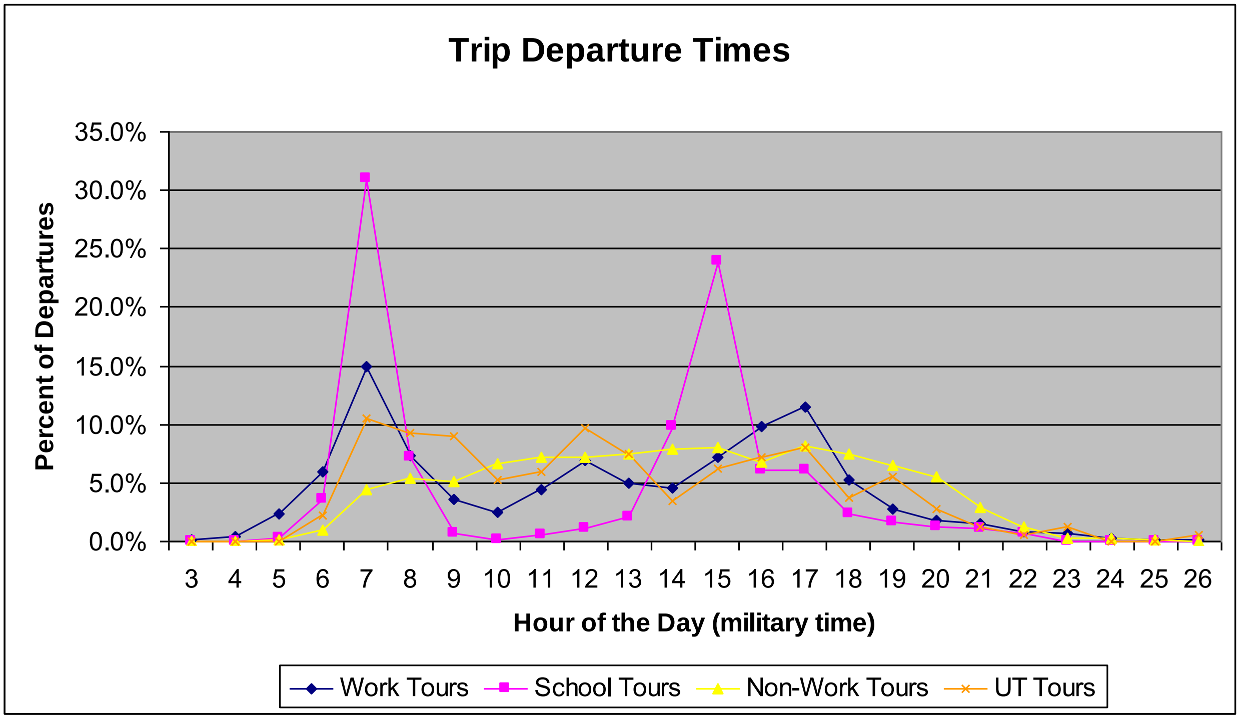

Figure 9. Trip Departure Times by Tour Type

The temporal distribution of trips, displayed in Figure 9, is also clearly distinct for each tour type. Work tour trip departures exhibit defined peaks at 7 A.M. and 5 P.M. corresponding to travelers departing home for work and work for home, as well as showing evidence of a smaller, but notable mid-day peak at 12 A.M. in connection with lunch. The distribution of UT tours is somewhat lumpy, largely owing to the small sample size and may require some smoothing for that reason. However, even with smoothing, it evidences three peaks: morning, mid-day and evening. The temporal profile of school tour trip departures are the most defined, with very sharp peaks at 7 A.M. and 3 P.M. in connection with the beginning and end of the school day. Non-work tour trip departures, in contrast, exhibit no peaking. They rarely begin before 7 A.M. From 7 A.M. they maintain a nearly constant frequency until 8 P.M., increasing only slightly in frequency very slowly throughout the day until 5 P.M. before slowly declining. The precise distribution of visitor tours is unavailable from Lake Tahoe, but resembles that of non-work tours.

Tours with both work and school stops were defined to be school tours and generally appeared to be high-school students with after-school jobs. Although distinct in many ways, given their relatively small number, non-UT college / university tours are treated as work tours, although these stops are a distinct stop type.

Stop Types

Stop types are defined by a combination of their purpose or activity type (work, university, school, maintenance, discretionary), their duration (more or less than 30 minutes) and traveler characteristics (income) as well as the type of tour to which they belong (work, UT, school or non-work). A total of eleven stop types, displayed in Table 7 below, are used in the Knoxville regional model.

Work tour stops are classified in four groups as low income (less than $25k/hh/year) work stops, other work stops, university stops and other (non-work) stops. UT tour stops are simply divided into UT stops and other stops. Similarly, school tour stops are divided into school stops and non-school stops. Non-work tour stops are categorized as short (less than 30 minutes) maintenance (shopping, personal business, service passenger, etc.) stops, long maintenance stops and discretionary (eat out, social/recreational, civic/religious, etc.) stops. Visitor tours have only one stop type, visitor stops.

Table 7. Stop Types

Stop Type		% Stops	Survey Activities and other Criteria	Frequency (/hh/day)	Frequency (/pers/day)
Work Tour		39.7%			
	Work (low income)	4.0%	Work outside of home if household income < $25k/year	0.22	0.09
	Work (other)	17.3%	Work outside of home if household income > $25k/year	0.95	0.40
	University	0.7%	School - junior college, college / university, vocational school	0.04	0.02
	Other	16.3%	Other Activities on Work Tours	0.90	0.38
UT Tour		1.3%			
	UT Studies	0.7%	Studies at U. of Tennessee	0.04	0.02
	Other	0.5%	Other Activities on UT Tours	0.03	0.01
School Tour		11.6%			
	School	7.7%	School – Daycare to high school	0.43	0.18
	Other	3.9%	Other Activities on School Tours	0.22	0.09
Non-Work Tour		48.7%			
	Short Maintenance	20.2%	Less than 30 minutes duration & Shopping (incidental or major), Personal Business, Medical / dental, Service passenger, Change mode	1.11	0.46
	Long Maintenance	12.0%	30 minutes or longer & Shopping (incidental or major), Personal Business, Medical / dental, Service passenger, Change mode	0.66	0.28
	Discretionary	16.6%	Volunteer Work, Eat Out, Social / Recreational, Civic, Church Activities, Loop trips	0.91	0.38

This framework, which defines stops by the type of tour to which they belong, does not allow travelers to change a stop from one tour type to another (e.g., shift a shopping stop from a work tour to a non-work tour), but it significantly simplifies the model, decreasing its development cost and run time, by avoiding the allocation of stops to tour types, taking advantage of the fact that, for each tour type, a stop sequence choice model will assign stops to tours so as to (stochastically) minimize total travel cost (so, for example, a shopping stop can shift from one non-work tour to another non-work tour). Stop allocation models could be developed at a later time, if desired, to allow for stops to be swapped between tour types, as an incremental model improvement.

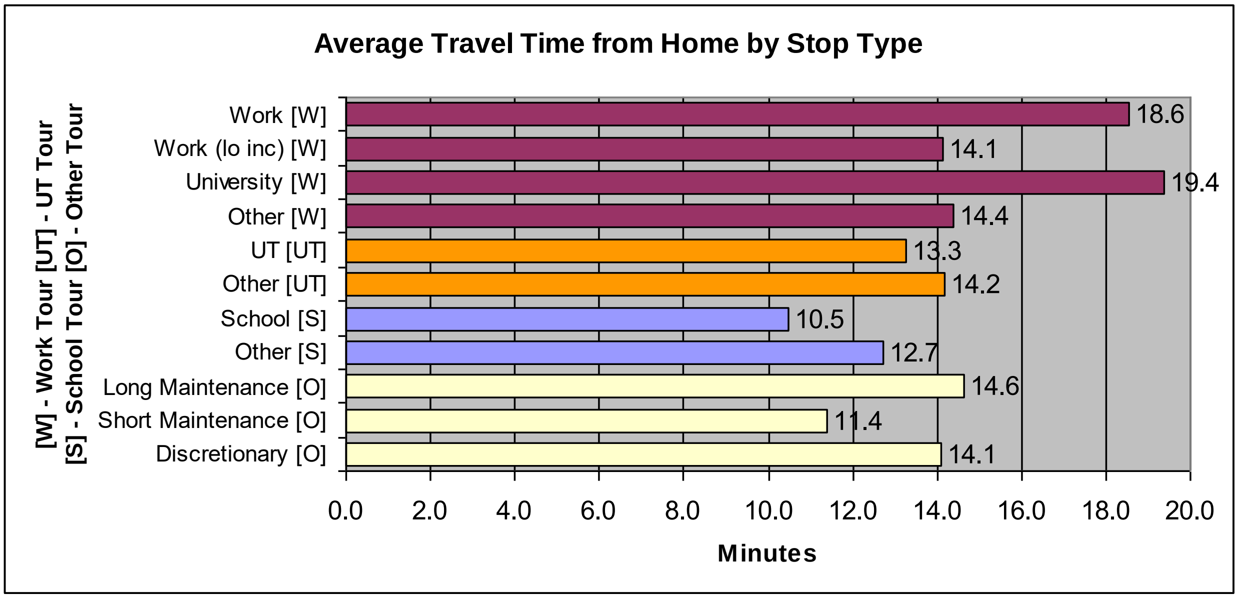

Figure 10. Average Travel Time from Home by Stop Type

The primary purpose of identifying stop types in terms of modeling travel behavior is to distinguish among stops with different spatial distributions, as destination or stop location choice models are developed for each stop type. The crucial variable in these models which describe the spatial distribution of stops is the travel time from the home location (even for stops not visited directly from home). Figure 10 above shows that each stop type has a distinct trip length. Work tour stops tend to be furthest from home, with non-work (other) stops somewhat closer to home than work stops and low income work stops closer to home than other general work stops or university stops. School tour stops are generally close to home, with non-school stops somewhat further from home than the school stops themselves. Non-work tour stops tend to be further than school tour stops but closer to home than work tour stops. Quick (short) maintenance stops are closest to home and long maintenance stops are furthest, with discretionary stops in between.

Tour and Stop Generation

The new Knoxville Regional Travel Model generates tours and stops rather than trips. The number of tours and stops of each type is estimated using multiple regression models applied to the disaggregate synthetic population of households. First, the number of tours, of each type, is estimated for each household. Then, for each stop type, the ratio of stops per tour is modeled and the total number of stops produced by multiplying this ratio by the number of tours.

In this framework, the modeled behavior is dominated by the tour generation equations, with the stop generation playing a secondary role (in some ways similar to, albeit simpler than, activity-based approaches which allow more tradeoffs). This is reflected in their goodness-of-fit which is quite good for the tour generation equations, but rather poor for stop generation since stop rates per tour are relatively constant. As mentioned previously, more elaborate model frameworks which allocate stops to tours may be developed at a later date, giving the model additional behavioral fidelity. However, the simple framework adopted here still offers improved sensitivity over traditional models.

While cross-classification models were once viewed as an advance over regression models for generating trips, this was due to their ability to reduce aggregation bias compared to regression models which were applied to zones as a whole. By applying regression models instead to a disaggregate population, aggregation bias is eliminated altogether in the approach adopted here. In this context, regression models offer two advantages over traditional cross-classification models used for generating trips. First, they allow the incorporation of more variables. While cross-classification models are limited to two or three variables at most, regression models can include more variables, introducing sensitivity in resulting trip rates to gas prices and accessibility variables in addition to the basic demographic characteristics. Second, the use of regression models allows the limitation of the non-linearities in the model‟s travel rates to the two with plausible behavioral explanation: satiation effects (e.g., decreasing marginal increase in trips for each additional household member) and interaction effects (e.g., vehicles and workers increasing together increasing travel more than either increasing by itself). Some satiation effects were incorporated in tour generation equations through the use of logarithmic transformations. Although interaction effects were widely tested, the only interaction effect which proved statistically significant was the interaction of gas prices and household income; increasing gas prices decreased certain stop rates, but only for low income households.

Table 8. Factors Affecting Household Tour and Stop Generation

	Workers	Non-Workers	Students	Seniors	Vehicles	Income	Gas Price	Access-ibility
Work Tours	+			-				+
Work Stops	+			-		+	-	+
Non-UT Univ Stops	+	+		-		-		+
Other Stops	+	-	+	-		+	-	+
School Tours		+	+					
School Stops			+					
Other Stops	+		+			+		
Other Tours		+			+	+		+
Short Maintenance Stops		+			+	+		+
Long Maintenance Stops		+	-	+	+	+		+
Discretionary Stops		+			+	+	-	+
Key	+	Variable (column) increases tour/stop rate (row)			-	Variable (column) decreases tour/stop rate (row)		

As Table 8 illustrates, the tour and stop generation models do offer sensitivity to considerably more variables than traditional cross-classification models. Each of these variables had a statistically significant effect and offers intuitive behavioral plausibility.

The number of work tours was mostly a simple function of the number of workers. Vehicle ownership and household income proved insignificant once accessibility was introduced into the model. A constant also proved insignificant, indicating that the model is largely effective in explaining the number of work tours. The presence of seniors in a household made work tours slightly less frequent, perhaps because senior workers are less likely to work full time. Accessibility, on the other hand, makes work tours marginally more frequent because it implies that commute times are shorter, so it is easier to get back and forth between home and work and workers can go home for lunch, return to work after dinner, on Saturday, if they forgot something, etc.

The number of work stops is first calculated for each household and then allocated to low income or other work stops based on the household‟s income. The number of work stops per work tour is relatively constant. However, the number of work stops per work tour decreases slightly with gas price and workers from high income (over $50,000/year) households make slightly more work stops per work tour on average. Both of these phenomenon likely reflect the probability of eating out for lunch or making some other mid-day sub-tour which results in two work stops (before and after lunch) which increases with income and decreases with gas prices.

This last hypothesis is partially supported by the fact that the number of other stops per work tour also decreases with gas prices, at least for low income workers. The number of other stops per work tour is also significantly increased by the number of household students from workers stopping to drop off students on the way to work and decreases with the number of non-workers in the household. This last fact has a variety of possible explanations, from workers needing to make less household maintenance stops, since they are made by non-workers on non-work tours, or because workers with non-workers at home are more motivated to return home after work and less likely to make stops on the way the there, etc. Non-UT college stops are relatively rare, but are more frequent for low income households with fewer workers but more adults (likely more students).

Knoxville‟s household travel surveys did capture over seventy UT students living off-campus and the stop rates for UT tours are taken from observations of their tours to UT. The tour rate per off-campus student was used based on students who attended UT during the survey. This rate agreed better with other sources, such as the *Indiana University Travel Demand Survey* (BLA, 1999), and corrected for the fact that UT students captured in Knoxville‟s household survey were more likely to be part-time students than the general student population. The household survey did not cover the travel behavior of students living on-campus. The tours generated by these students (through the enrollment variable) are based on basic rates observed in the IU survey noted above.

Table 9. Tour and Stop Generation Equations

Tour / Stop Type		Min	Coefficient	t-stat	Variable
Work Tours			0.5891	7.39	HH Workers
			0.0149	1.90	HH Workers x General Accessibility
			0.0135	5.80	General Accessibility
		0	-0.1295	-4.49	Presence of Seniors
	Work Stops / Work Tour		1.4619	29.64	Constant
			0.1855	4.82	High Income
		1	-0.1193	-5.93	Gas Price
	Non-UT University Stops / Work Tour		0.0721	5.02	Constant
			0.0182	1.89	Low Income
			0.0408	4.81	Ln(HH Persons)
		0	-0.0894	-5.73	Ln(HH Workers + 1)
	Other Stops / Work Tour		0.0438	0.14	Constant
			-0.1267	-3.37	HH Non-Workers
			0.1917	4.39	HH Students
			-0.0867	-2.38	Gas Price x Low Income
		0	0.0924	3.10	General Accessibility

Tour / Stop Type		Min	Coefficient	t-stat	Variable
UT Tours			1.1053		UT students
		0	0.3380		UT enrollment
	Campus stops / UT Tour	1.02	1.0223		Constant
	Other stops / UT Tour	0.78	0.7795		Constant
School Tours			0.5630	26.7	HH Students
		0	0.2023	13.6	HH Non-Workers
	School Stops / School Tour	1.02	1.0232		Constant
	Other Stops / School Tour		0.2834	3.95	Constant
			0.0875	2.19	HH Workers
		0	0.1344	2.05	High Income
Other Tours			-0.2803	-2.96	Constant (adjusted to -0.2000)
			0.7324	28.06	HH Non-Workers
			0.2044	5.86	IncomeLevel (1=Low,2=Mid,3=High)
		0	0.0531	5.59	Nearby Accessibility x Ln(HH Vehicles +1)
	Short Maintenance Stops / Other Tour		0.4303	3.53	Constant
			0.0074	2.56	HH Non-Workers x Nearby Accessibility
		0.43	0.3014	2.51	If HH Vehicles > 0
	Long Maintenance Stops / Other Tour		0.5421	17.90	Constant
			0.0059	2.68	HH Non-Workers x Nearby Accessibility
			-0.1586	-6.35	HH Students (adjusted to -0.2227)
		0	0.0697	1.85	Presence of Seniors
	Discretionary Stops / Other Tour		0.7451	25.03	Constant
			-0.0539	-3.51	HH Non-Workers
		0	-0.0446	-2.93	Gas Price x Low Income
Visitor Tours		0	0.6719		HotelRooms + RentalUnits
	Visitor stops / Visitor Tour	1.50	1.5000		Constant

The number of (primary and secondary) school tours is largely a simple function of the number of students in a household, although non-workers also generate “school tours”. This is due to a slight difference in the definition of student between the household surveys and the TAZ database/synthetic population. The surveys count pre-school children as “students” who can generate “school tours” to nursery school, etc. In the model, these pre-school tours are generated by non-workers since pre-school children are not counted as students in the zones/synthetic population.

The number of school stops per school tour is essentially constant at just over one. No explanatory variables available could significantly improve the model. Other stops on school tours were fairly constant, but were somewhat more common for students from households with higher income and more workers. The increase related to the number of workers could be related to students working part-time jobs or to a tendency to go to other places before home if all the adults are working and no one else is at home. Higher income students may have more money to spend, hence may make more shopping stops, etc.

The number of other non-work tours made by a household is most influenced by the number of non-workers in the household, as more non-workers generate more non-work tours. However, the non-work tours are also more frequent for households with more income and more vehicles, as well as for higher accessibility, urban households which experience lower travel costs to reach basic shopping and other destinations. The number of short (under 30 minutes) maintenance stops per non-work tour was largely constant, but somewhat higher for households with more non-workers and at least one vehicle. The number of long (over 30 minutes) maintenance stops per non-work tour was also fairly constant and increased with the number of non-workers and household vehicles; however, it also increased with the presence of seniors, who may have more time to spend, and decreased with the number of students, who may curtail long shopping activities. (Recalling the inclusion of small children as "students" in the survey, this required a calibration adjustment in application.) The number of discretionary stops per non-work tour decreased slightly with the number of non-workers, perhaps because the number of persons quickly increases the cost of many discretionary activities such as eating out, going to the movies, etc. Gas prices also decreased discretionary stops for low income households, indicating some competition for limited household resources between transportation and entertainment, etc.

The visitor tour generation rate is based on a rate per travel party taken from *Lake Tahoe Resident and Visitor Model, Model Description and Final Results* (PB, 2007), the assumption of one travel party per occupied hotel room/rental unit and the reported hotel room occupancy rate of 82% for Sevier County for July of 2006. The number of visitor stops per tour is also taken from Lake Tahoe. Following the Lake Tahoe model, these rates are not given per person but per travel party; the travel party is assumed to act as a single unit.

Table 10. Comparison of Basic Generation Rates

	NCHRP365 Averages	Knoxville 2000 Survey	Knoxville Previous Model*	Knoxville Combined Surveys	Knoxville New Model
tours/HH/day	3.47	2.66	2.85	2.86	2.87
stops/HH/day	5.54	5.60	5.56	5.51	5.62
trips/HH/day	9.00	8.25	8.42	8.37	8.49
stops/tour	1.60	2.11	1.95	1.93	1.96

*rates before application of under-reporting correction factors

The shift from generating trips to generating tours and stops makes direct comparisons between the new tour-based generation models and traditional trip-generation slightly more difficult. However, comparisons can be made at the level of daily travel using the following basic facts to convert trip rates to tour and stop rates. Every tour contains exactly two home-based trips. The number of trips is always equal to the number of tours plus the number of stops. (Unless otherwise noted, stops refer only to stops outside the home.) Using these equivalencies, average trip rates were converted to tour and stop rates and vice versa. Table 10 compares national averages from NCHRP 365, Knoxville‟s 2000 survey used to develop the previous model, the results of applying the previous model to the base year socioeconomic data, Knoxville‟s combined survey used to develop the new models presented here and the results of applying these models to the synthetic population for the base year. Differences arise between the averages resulting from the application of models and averages observed in the surveys used to develop them primarily because of differences between the characteristics of the survey sample as compared to the general population to which the models are applied.

The new model results in an average total trip rate which is closer to but still lower than the national average. There is good agreement on the overall stop rate per day, as well, although the new model"s applied rate is slightly higher than the other sources. Calibration of the previous Knoxville model required the application of significant correction factors for survey under-reporting, developed from GPS audited travel surveys in Ohio. However, the previous model also underrepresented four tire commercial vehicle trips. When these were increased in the new model, no underreporting factors were necessary. The rates reported above do not include any corrections for under-reporting, but do reflect two minor calibration adjustments, both noted in Table 9, one to account for differences in the definition of student between the survey and the model dataset, and one to ensure that the model application resulted in at least as many non-work tours on average as observed in the survey.

The main difference between the Knoxville model and nationally characteristic behavior is in the number of stops per tour. Both the previous and the new Knoxville surveys suggest that overall activity participation rates in Knoxville more or less follow the national average, but that the Knoxville region exhibits higher than average trip-chaining, and hence, lower tour generation rates. Both the previous and new Knoxville models reflect this.

In the new hybrid tour-based framework, there are no attraction generation models. Rather, attractions are modeled as part of the stop location choice models, instead of inputs to trip distribution. The model script does generates attractions, but only because TransCAD requires it. In fact, the actual attractions are part of the stop location choice models and are documented with them.

The airport was added as a "special generator," but not in the sense that it generates demand for activities (stops) as households do. Rather, it would be more appropriate to call the airport a special attractor, and as such, it is actually an adjustment factor which inflates the number of elemental alternatives by 4.9 per employee for the airport"s zone in the stop location choice model for long maintenance stops on other tours.

Tour Mode Choice

In the new Knoxville Regional Travel Model, as in activity-based models, the mode of travel is modeled in two stages: tour mode choice and trip mode choice. First, after tours are generated, they are assigned a primary mode by tour mode choice models. Later, after the spatial distribution of stops creates trips, individual trips are assigned a mode, based on the primary mode of the tour, in trip mode choice models.

The Knoxville model makes use of four primary or tour modes:

- Private automobile
- Public transit
- Walk / bike
- School bus

The primary mode or „tour mode‟ for a tour is determined by a simple set of definitions or rules.

- Any tour containing a school bus trip is a school bus tour.
- Any other (non-school bus) tour containing a public transit trip is a public transit tour.
- Any other (non-transit) tour containing a private automobile trip is an automobile tour.
- Any other tour, which contains **only** walk or bike trips, is a walk/bike tour.

In this framework, the primary choice determining transit mode share, etc., is tour mode choice. Trip mode choice ultimately reduces mostly to the determination of vehicle occupancy for automobile tours or the allocation of access modes for transit tours. Even in advanced activity-based models, fixed shares or other simple heuristics have been used for trip mode choice; whereas, tour mode choice models are more comparable to mode choice in traditional models.

The incorporation of behaviorally sensitive tour mode choice models in the new Knoxville Regional Travel Model represents significant added value as compared to the previous model in which mode shares were fixed and totally insensitive to demographics, levels-of-service, or any other policy variables. The new model produces, in addition to automobile trips by occupancy class, the system-level transit ridership, the number of transit trips generated by each residence zone and the total regional number of daily walk/bike trips. Moreover, the model architecture allows for the straightforward addition of future component models to produce transit and non-motorized trips at the route/street level. These component models and level of spatial fidelity were not part of the scope of this model development effort, but could be developed later.

Table 11 illustrates the variety of response variables incorporated into tour mode choice for each tour purpose. The variables are grouped into four broad categories: level-of-service variables, cost variables, demographic variables and built environment variables. The choice of primary mode for tours was sensitive to variables in each category for most tour types. The new model allows planners to test the impact of changes in these variables on transit system ridership and the amount of walking and biking in the region. The model for each tour purpose is presented in detail below.

Table 11. Factors Affecting Tour Mode Choice

	Level of Service			Costs		Demographics					Built Environment		
	Accessibility by mode	Distance to UT	% of TAZ Near Bus	Gas Price	Bus Fare	Workers	Students	Senior HH	Income	Vehicles per Person	Percent Sidewalks	Activity Diversity	Intersection Density
Work Tours													
Auto	+			-	+		+	+	+	+	-	-	
Bus	+			+	-		-	-	+	-	-	-	
Walk	+			+	+		+	-	-	-	+	+	
UT Tours													
Auto		+	-							+	-		
Bus		-	+							-	-		
Walk		-	-							-	+		
School Tours													
Auto	+			-					+	+			
Bus	+			+					-	+			
Walk	+			+					-	-			
School Bus	+			+					-	-			
Other Tours													
Auto	+			-		+	+	+		+		-	-
Bus	+			+		+	-	-		-		-	-
Walk	+			+		-	+	-		-		+	+

Key								
	+	Directly increases probability	+	Indirectly increases probability	-	Directly decreases probability	-	Indirectly decreases probability

The key difference between the tour mode choice models developed for the new Knoxville Regional Travel Model and those common in activity-based models is the way in which they measure the level-of-service provided by each competing mode and the related assumption of the hierarchy of travelers‟ choices (i.e., whether travelers‟ destination choices depend more on their mode choices or vice versa).

In activity-based models, as in traditional four-step models, (tour) mode choice is modeled conditional on (after) destination choice (or distribution) and can therefore use actual travel times between origins and destinations as level-of-service variables. This traditional model structure was first developed for very large metropolitan areas with significant choice rider markets and is more sensitive to changes in level-of-service provided by transit improvements and for testing their impacts on transit route ridership. However, it may be oversensitive to level-of-service variables and a source of optimism bias in transit forecasts, as this model structure is built on the assumption that travelers are more likely to change mode than destination. This may well be the case for affluent choice riders for their work commute in large cities; however, there are many situations in which it seems more reasonable to assume to the contrary that travelers are more likely to change destinations than mode.

Local household survey and KAT on-board survey data offer some support (discussed below) of this general assumption for the Knoxville region that travelers are more likely to change destination than mode of travel. In general, this assumption seems more appropriate in markets like Knoxville with few choice riders where mode choice is generally a foregone conclusion on which destination choice is conditioned (i.e., either the traveler has access to a car and does not even think of riding transit or they do not have access to a car and rely on transit, choosing their destinations, possibly even workplace, based on where the transit system can get them). "Reverse hierarchy" models such as those developed for the new Knoxville Regional Travel Demand Model, which represent destination (or stop location) choice conditional on mode choice, still take the level-of-service provided by competing modes into account and allow for changes in ridership based on improvements to transit or highway modes. However, they measure the level-of-service provided by each mode not directly by the travel times between origins and destinations but indirectly by the accessibility to various types of destination provided by each mode to a residence zone.

Traditional Hierarchy

Assumption: Travelers are more likely to change ***mode*** than ***destination***.

1. Destination Choice:
   Where will I go?

↓

2. Mode Choice:
   How will I go (drive, walk, bus, etc.)?

Reverse Hierarchy

Assumption: Travelers are more likely to change ***destination*** than ***mode***.

1. Mode Choice:
   How will I go (drive, walk, bus, etc.)?

↓

2. Destination Choice:
   Where will I go?

The accessibility variables used in tour mode choice are logsums based on a simplified, gravity version of the utility of the stop location choice models. These logsum accessibilities include only the impedance and attraction (or size) variables; whereas, the actual destination choice models used include other variables, as well. The stop location choice models were estimated first and the inclusion of these accessibilities as proxy variables for their expected utility in the tour mode choice models allows for the interpretation of the two component models as a single nested logit model of the combined choice of tour mode and stop location. There is some loss of statistical efficiency in estimating the models sequentially in this manner, rather than simultaneously; however, simultaneous estimation of such models remains an advanced practice and is not possible with commercially available software. The combination of these two models in this fashion allows for reciprocal sensitivity of mode choice to destination choice as well as vice versa but at the cost of requiring the feedback of these accessibility variables in addition to travel times in the model application.

The results of the model estimation from the combined household survey data and incorporating observations from the KAT on-board survey, performed using ELM software (www.elm-works.com) and presented in detail below, provide some evidence for the reverse hierarchy and the assumption that travelers in the region are more likely to change destinations than mode. This claim is based on the fact that, for each tour purpose, the sequentially estimated maximum likelihood parameter on the logsum accessibility variable lies within the acceptable range (i.e. between zero and the parameter on the nest of modes above). This fact stands in rather stark contrast to the combined mode and destination choice models of the traditional hierarchy which seemingly inevitably require the constraint of the mode choice logsum parameters in destination choice – equivalent to the imposition by fiat of the assumption that travelers are more likely to change mode than destination. The Knoxville models imposed no such behavioral assumption, in contrast, their "reverse" assumption on the magnitude of the mode and destination choice elasticities was simply supported by the data as evidenced by the logsum accessibility parameter estimates in Table 12 through Table 15.

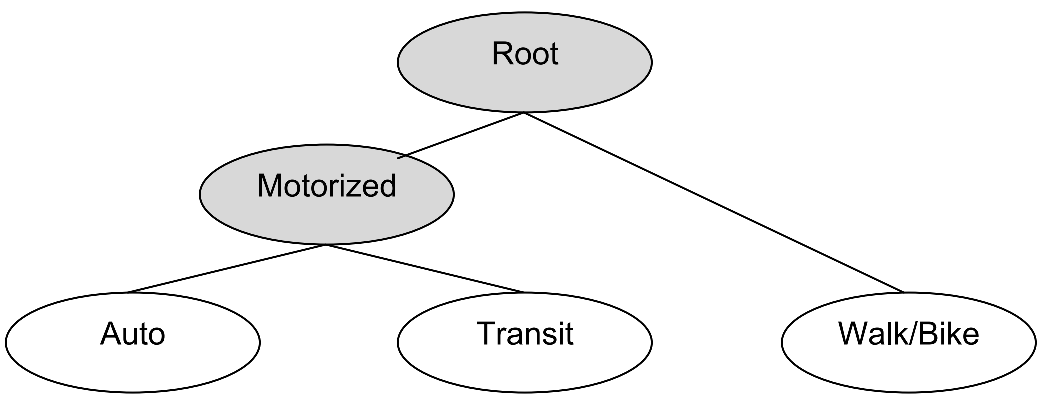

Figure 11. Nesting of Travel Mode for Work and Other Tours

The choice of primary mode for work tours was modeled using a nested logit model, grouping the private automobile and public transit alternatives together as motorized modes. Although the estimated nesting coefficient was not statistically significantly different from one, it was judged to be different enough to justify the nesting structure. This structure implies that people who drive to work are more likely to switch to take a bus than to walk/bike and transit riders are more likely to switch to driving than to walking/biking. This seems reasonable, particularly for work tours when travel time is more important, suggesting that workers who commute by foot or by bike are different or special in some way, likely in that they live very close to work.

The parameter on accessibility was highly significant, implying that the level-of-service (travel times) provided by the competing modes are important in the choice among them. The number of household students decreased the probability that workers would commute by bus, suggesting the need/desire to drop children off at school which is more easily facilitated by private auto. The presence of seniors marginally decreased the probability of transit and walk/bike modes for commuting (e.g., in the case of senior workers, an increased effort/cost associated with walking, generally necessary to access transit, as well). This variable was retained, even though it was not particularly statistically significant in the final model estimation, as it exhibited higher significance in a variety of other specifications. Higher income levels were found to decrease the probability of walking/biking to work but did not have any significant impact on bus use once the level of vehicle ownership was taken into account. The number of household vehicles per person decreased both the probabilities of transit and of non-motorized modes. Considering cost variables, higher gas prices decrease the probability of private automobile use and higher bus fares decrease the probability of bus use. Built environment variables (for the residence zone) including activity diversity (mixed land uses) and the percent of streets with sidewalks increased the probability of walking or biking to work. Overall, the model"s goodness-of-fit statistics suggest that the model does a good job explaining commuting mode choices in the region, but much of the behavior is explained by the models constants which correspond to travelers" biases regarding unobserved or unquantifiable characteristics of the modes.

Table 12. Disaggregate Nested Logit Model of Work Tour Mode Choice

Variable	Alternative	Parameter	t-statistic
-- Logsum Parameters			
Motorized Nest	Auto, Transit	0.5262	-0.42
-- Generic Parameters			
Logsum Accessibility of Gravity Work Location Choice	All	0.0457	3.14
-- Alternative Specific Parameters			
CONSTANT	Transit	-0.0917	*
CONSTANT	WalkBike	-5.2258	*
Household Students	Transit	-1.3181	-2.98
Presence of Seniors in Household	Transit	-0.7682	-1.37
Presence of Seniors in Household	WalkBike	-0.7682	"
Income Group (1-3)	WalkBike	-0.7381	-2.18
Gas Price (year 2006 $)	Auto	-0.1150	**
Bus Fare (year 2006 $)	Transit	-0.0690	**
Activity Diversity	WalkBike	3.0949	1.63
Percent of Zone's Streets with Sidewalks	WalkBike	2.8035	4.03
Household Vehicles per Person	Transit	-2.3673	-5.69
Household Vehicles per Person	WalkBike	-1.259	-1.82

-- Model Statistics			
Log Likelihood at Zero		-3074.2	
Log Likelihood at Constants		-205.1	
Log Likelihood at Convergence		-148.0	
Rho Squared w.r.t. Zero		0.952	
Rho Squared w.r.t Constants		0.278	

* Constants were adjusted in calibration in order to reproduce observed mode shares; the original estimated constants were 0.2196 and -4.9641 for Transit and Walk/Bike, respectively.
** Parameters for gas price and bus fare were constrained in calibration in order to produce elasticities consistent with observations. Original estimated parameters were larger in magnitude and highly significant.

The choice of primary mode for University of Tennessee (UT) student tours was represented using a simple, aggregate multinomial logit model applied to at the zonal level (since the UT student population is not represented in the synthetic population). There were slightly less than one hundred such tours observed in the household survey, and there is reason to believe they may not be generally representative of all UT student tours, over-representing off-campus students. Given these data limitations, the resulting model is simple and did rely on the heuristic calibration of several parameter values. The percent of the student‟s residence zone within ½ mile of a bus route was used essentially as a transit availability variable, which basically disallowed the choice of transit for zones with little or no transit availability. The distance to the UT campus was asserted as increasing the likelihood of private automobile use although the limited data did not support this. The magnitude of the effect was determined heuristically to attain mode shares at distances from campus roughly consistent to those observed in the *Indiana University Travel Demand Survey* (BLA, 1999). The data did support the significance of the percent of students‟ residence zone‟s streets with sidewalks as increasing the likelihood of walking/biking to campus. The data also supported the effect of vehicle ownership decreasing the probabilities of transit and walk/bike modes, although it was necessary to constrain the relationship between these effects in order to obtain this result. The model‟s goodness-of-fit statistics reflect the simple aggregate model structure and limited data available for model estimation. However, the model was able to be calibrated to offer reasonable sensitivity to transit availability, distance from campus, the built environment (sidewalks) and vehicle ownership and to reproduce the observed base year mode shares.

Table 13. Aggregate Multinomial Logit Model of University of Tennessee Student Tour Mode Choice

Variable	Alternative	Parameter	t-statistic
-- Alternative Specific Parameters			
CONSTANT	Transit	-99999.9706	*
CONSTANT	WalkBike	-2.0813	*
Percent of Zone within ½ mile of Bus Route	Transit	99998.0693	*
Distance (mi) to UT campus	Auto	0.2000	**
Percent of Zone’s Streets with Sidewalks	WalkBike	1.8526	3.82
Zonal Vehicles per Person	Transit	-0.3059	-1.95
Zonal Vehicles per Person	WalkBike	-0.9177	***

-- Model Statistics			
Log Likelihood at Zero		-113.2	
Log Likelihood at Constants		-43.1	
Log Likelihood at Convergence		-38.2	
Rho Squared w.r.t. Zero		0.663	
Rho Squared w.r.t Constants		0.114	

* Constants and the Percent of Zone within ½ mile of Bus Route (transit availability) were adjusted in calibration to produce observed mode shares, the original estimated parameter values for transit and walk/bike constants and transit availability were -4.84419E+12, -1.8359, 4.84419E+12, respectively.
** The distance to campus variable was asserted, as discussed in the text.
*** The effect of vehicle availability on walk/bike was constrained to be 1/3 its effect on transit.

The choice of primary mode for school tours was modeled using a nested logit model, grouping the walk/bike, public transit and school bus alternatives together as non-auto modes and the data supported the statistically significant similarity of these modes. This structure implies that students who take a non-automobile mode (walk/bike, public or school bus) to school are more likely to switch to another non-automobile mode than to driving/being driven to school. This seems reasonable for school travel, suggesting that students who are driven or drive are different in some way, likely in their parents work schedules, etc.

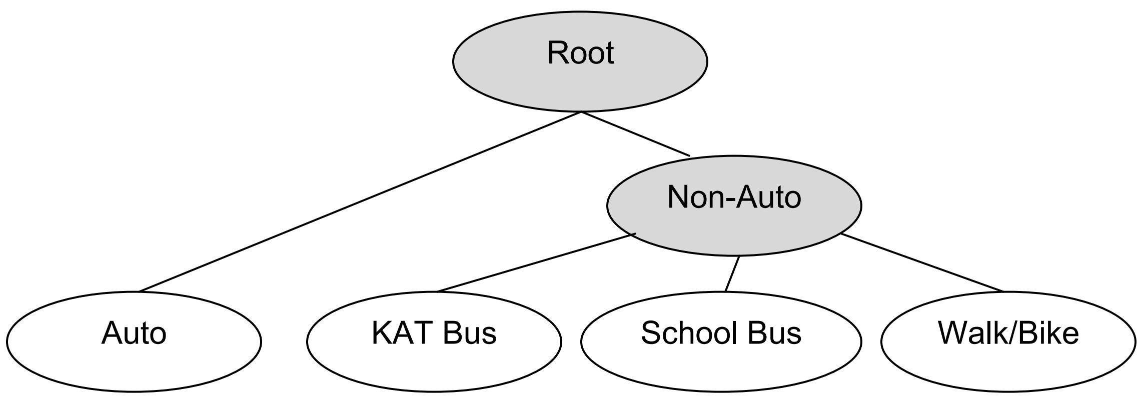

Figure 12. Nesting of Travel Mode for School Tours

As in the case of work tours, the parameter on accessibility was significant, implying that the level-of-service (travel times) provided by the competing modes are important in the choice among them. As there was no school bus network with which to calculate accessibilities for this mode, the general automobile accessibility was used as it seemed reasonable that it would correlate fairly well with school bus accessibility. However, this accessibility is surely higher than the true school bus accessibility given dwell times, and therefore causes the school bus bias constant to be less than it would otherwise be.

The model is sensitive to household vehicle availability which decreases the probability of walking/biking or school bus. It also reveals that higher gas prices decrease the probability of students being driven / driving to school for low and middle income households. This estimated effect was highly significant but was revised downward in calibration in light of evidence from other models that the effects of gas prices were overstated in the data due to data collection issues (more lower income observations late in data collection when gas price was higher). There were very few observations of public bus use for school tours, and hence, the data did not support these or other effects on public bus use. It has been observed that the age of students is likely to affect mode choice for school tours as students of driving age have different options than younger students. However, student‟s age was unavailable for inclusion in these models, since the variable was not generated for the synthetic population.

Table 14. Disaggregate Nested Logit Model of School Tour Mode Choice

Variable	Alternative	Parameter	t-statistic
-- Logsum Parameters			
Non-Auto	PubBus, SchlBus, WalkBike	0.4506	-2.59
-- Generic Parameters			
Logsum Accessibility of Gravity School Location Choice		0.1497	2.15
-- Alternative Specific Parameters			
CONSTANT	PubBus	-2.3413	*
CONSTANT	WalkBike	-1.1811	*
CONSTANT	SchlBus	-1.0170	*
Household Vehicles per Person	WalkBike	-1.2367	-2.31
Household Vehicles per Person	SchlBus	-1.1989	-3.94
Gas Price (year 2006 $) for Low Income Households	Auto	-0.2330	**
Gas Price (year 2006 $) for Middle Income Households	Auto	-0.0950	**
-- Model Statistics			
Log Likelihood at Zero		-1698.8	
Log Likelihood at Constants		-659.9	
Log Likelihood at Convergence		-611.7	
Rho Squared w.r.t. Zero		0.640	
Rho Squared w.r.t Constants		0.073	

* Constants were adjusted in calibration in order to reproduce observed mode shares; the original estimated constants were -1.6482, -0.9436 and -0.9783 for Transit, Walk/Bike and School Bus, respectively.
** Parameters for gas price were constrained in calibration in order to produce elasticities consistent with observations. Original estimated parameters were larger in magnitude and highly significant.

The choice of primary mode for other tours was modeled using a nested logit model, grouping the private automobile and public transit alternatives together as motorized modes as for work tours and in this case the data supported the statistically significant similarity of these modes. (Refer to Figure 11.) This structure implies that people who drive are more likely to switch to take a bus than to walk/bike and transit riders are more likely to switch to driving than to walking/biking. This seems reasonable suggesting that travelers who walk or bike are different or special in some way, likely in that their activity purpose is recreational.

As in the case of work and school tours, the parameter on accessibility was significant, implying that the level-of-service (travel times) provided by the competing modes are important in the choice among them. A variety of demographic variables were also significant to varying degrees. The number of household workers decreased the likelihood of walk/bike tours, perhaps indicating less time for recreation in these households. The number of students decreased the likelihood of transit, as taking children on a bus/leaving them represents an additional challenge to travelers. The presence of seniors in the household decreased the probability of transit or non-motorized modes, probably due to the increased effort of walking for seniors, and vehicle availability decreased the likelihood of bus and walk/bike. The built environment was a factor, as well, with residents of zones with greater street connectivity (higher intersection approach density, more grid and less cul-de-sac streets) and more mixed land uses (activity diversity) more likely to make walk/bike tours. The price of gas was also a factor, decreasing the probability of automobile tours. A small and statistically insignificant effect of bus fare on low and middle income travelers was observed but not ultimately included.

Table 15. Disaggregate Nested Logit Model of Other Tour Mode Choice

Variable	Alternative	Parameter	t-statistic
-- *Logsum Parameters*			
Motorized	Auto, Transit	0.361	-2.54
-- *Generic Parameters*			
Logsum Accessibility of Gravity Other Stop Location Choice		0.1466	2.21
-- *Alternative Specific Parameters*			
CONSTANT	Transit	-0.6576	*
CONSTANT	WalkBike	-3.1150	*
Household Workers	WalkBike	-0.5134	-3.07
Household Students	Transit	-0.3897	-1.27
Presence of Seniors in Household	Transit	-0.5644	-1.93
Presence of Seniors in Household	WalkBike	-0.5644	“
Gas Price (year 2006 $)	Auto	-0.1420	**
Activity Diversity (mixed land uses)	WalkBike	1.3101	1.78
Household Vehicles per Person	Transit	-2.3295	-1.33
Household Vehicles per Person	WalkBike	-1.1225	-3.38
Urban Design (Intersection Approach Density)	WalkBike	1.3979	2.15
-- *Model Statistics*			
Log Likelihood at Zero		-4627.4	
Log Likelihood at Constants		-398.6	
Log Likelihood at Convergence		-342.7	
Rho Squared w.r.t. Zero		0.926	
Rho Squared w.r.t Constants		0.140	

* Constants were adjusted in calibration in order to reproduce observed mode shares; the original estimated constants were -0.026 and -2.9734 for Transit and Walk/Bike, respectively.

** The parameter for gas price was constrained in calibration in order to produce elasticities consistent with observations. Original estimated parameters were larger in magnitude and statistically significant.

For visitor tours, no data was available, so fixed mode shares were taken from *Lake Tahoe Resident and Visitor Model, Model Description and Final Results* (PB, 2007). The Lake Tahoe mode split was 90.05% private automobile, 1.31% public transit and 1.51% walk/bike/horseback. The remaining 7.13% were travel by private shuttles/buses which are not currently represented in the Knoxville model. If this is a cause of under-loading in the Sevier County tourism areas, the private automobile mode share may be adjusted upwards to count these private shuttles as private automobiles.

The models‟ bias constants were adjusted in calibration to reproduce the observed mode shares from the combined survey data and 2006 system ridership for KAT. The survey and base year model mode shares are displayed in Table 16.

Table 16. Observed and Calibrated Mode Shares by Tour Purpose

	Work Tours		**UT Tours***		**School Tours**		**Other Tours**		**Visitor Tours**
	Survey	*Model*	*Survey*	*Model*	*Survey*	*Model*	*Survey*	*Model*	
Auto	98.79%	98.77%	*90.01%*	79.06%	81.15%	81.15%	98.19%	98.18%	90.05%
Transit	0.62%	0.64%	*1.95%*	3.74%	0.18%	0.18%	0.10%	0.11%	1.31%
Walk / Bike	0.60%	0.59%	*8.05%*	17.20%	1.07%	1.08%	1.71%	1.71%	1.51%
School Bus					17.59%	17.58%			
** The UT Tours calibration also used data from IU with less auto (see text below).*									

All of the models reproduced the observed mode shares with relatively small adjustments to their bias constants. The one notable exception in which the modeled mode share was not forced to reproduce the survey was for UT tours. As noted above, there were very few UT tours and reason to believe that they may not have been a representative sample. In particular, there is reason to believe there the survey sample included more off-campus students, who are presumably less likely to walk/bike than the student population in general. The mode split used represents a compromise between the mode split observed in the Knoxville surveys (90% auto) and the mode split observed from an actual survey of university students (75% auto in the *Indiana University Travel Demand Survey* cited earlier).

The tour mode choice models were also validated against observed 2006 KAT system ridership. Based on KAT total weekly ridership data for 2006, average weekday ridership was approximately 9,390 unlinked trips per weekday when UT was in session, based on the assumption of an equivalent of 323 weekdays per year (equivalent to the assumption that Saturday has 70% the ridership of a weekday and Sunday has 50% of a weekday‟s ridership). The base year model predicts just over 11,500 trips on transit tours, of which, 60.9% are actually by transit (this is the trip mode split), yielding just under 7,100 linked transit trips per weekday (the model assumes UT is in session). Assuming 1.3 boardings per linked trip, or three transfers per ten linked trips, this implies that the modeled transit trips correspond to approximately 9,220 unlinked trips. (Although the model also predicts visitor transit trips in Sevier County, these are not reported or included in this total, as they have not been able to be validated and would be made on a separate transit system.) In conclusion, it seems that the model‟s 7,094 daily linked transit trips are approximately equivalent to 9,222 daily unlinked trips which is in substantial agreement with KAT 9,393 daily unlinked transit trips for 2006 and consistent within the range of reasonable assumptions on equivalent weekdays per year and average number of transfers per linked trip.

The response properties or elasticities of the model were also able to be validated against observed data from "natural experiments" as gas prices and bus fare have varied over the past several years. The model‟s response properties are measured in terms of elasticities of demand with respect to an input variable. Elasticities are simply normalized (unit-less) measures of the response of an output variable to a change in an input variable. There general formula for elasticity is given below.

$$elasticity = \frac{\%\ change\ in\ output\ variable}{\%\ change\ in\ input\ variable}$$

An important distinction is made in economics between short-run and long-run elasticities, since markets and demand (the output variable) respond to a change in circumstances (the input variable) over time, it is typical for elasticities measured over short periods of time to be smaller than those measured over longer periods of time up to some point at which the elasticity stabilizes. The maximum elasticity to which observed elasticities converge over longer periods of time, or long-run elasticity, is generally the appropriate elasticity for travel forecasting models since they are used primarily for long range planning. However, elasticities observed over the past three years or less are short or mid-run elasticities and should therefore be equal to or somewhat lower than elasticities in the model.

For instance, weekly KAT ridership data is available for 2006 and 2008 and weekly gas prices for the Knoxville area were provided for the same time periods by Gasbuddy.com. If the elasticity of KAT ridership with respect to gas prices is calculated for an eight week period from late-January to late-March in 2006 vs. 2008, the elasticity is 0.16. However, the elasticity comparing the whole of 2006 and 2008 is 0.32. The 0.16 number is a short-run elasticity, whereas the 0.32 observation may be approaching the long-run elasticity of transit demand with respect to gas price. Replicating the change in gas price from the late-January to late-March period from 2006 to 2008 ($2.19/gallon to $2.95/gallon), the model exhibits an elasticity of 0.33, similar to the longer-run elasticity observed comparing the years of 2006 and 2008. The model should generally be expected to reflect long-run elasticities, because it is estimated using essentially cross-sectional data (household travel surveys) which is presumably an observation of the travel market essentially in equilibrium.

KAT increased its base bus fare from $1.00/ride to $1.25/ride in January 2009. Weekly KAT ridership data was made available for eight weeks from late January to late March of 2009. Elasticities could therefore be calculated comparing the ridership to the same period in 2006 and in 2008. The comparison to 2006 may actually be better than to 2008 since gas prices were more similar to 2009 in 2006 than in 2008. The resulting elasticities are -0.17 (using 2006 as the reference) and -0.28 (using 2008). These are very much short-run elasticities since they measure travelers responses only within the first three months following the fare change. It is expected that travelers would continue to respond to the change and the long-run elasticity should be somewhat higher. Based on the relationship between the gas price elasticities for the same period (which also roughly corresponding to the beginning of the gas price spike in 2008) and the entire years of 2006 and 2008, it seems reasonable to suppose that the long-run elasticity is at least twice as large as the -0.17 elasticity observed. In response to the change in bus fare, the model predicts an elasticity of KAT ridership to bus fare of -0.47. This may be slightly high, but is judged to be within the range of a reasonable long run elasticity.

Table 17. Observed vs. Modeled Transit Ridership (late January - late March)

Year	Gas Price / gallon		Bus Fare		Actual Ridership	Model Ridership
	Nominal $	2006 $	Nominal $	2006 $		
2006	$ 2.19	$ 2.19	$ 1.00	$ 1.00	10,554	10,401
2008	$ 2.95	$ 2.76	$ 1.00	$ 0.94	10,939	11,220
2009	$ 1.75	$ 1.66	$ 1.25	$ 1.18	10,259	9,625

Table 17 illustrates the predicted versus observed transit ridership for the late January to late March period in 2006, 2008 and 2009 (data for 2007 was unavailable). The model is clearly in general agreement with the observations, but somewhat over-predicts travelers‟ short term responses to changes in gas price and bus fare. If, however, the model actually represents travelers long-run responses, its predictions may represent what bus ridership would be if gas prices and bus fare stabilized at these levels for a long period of time. The modeled ridership numbers seem consistent with this interpretation, implying the reasonableness of its elasticities for long range planning. Further sensitivity analysis comparing the model to other data observations, particularly over longer periods of time, could either further validate the model or be used to adjust the model, if necessary.

Stop Location Choice

The new Knoxville Regional Travel Model is the first model to produce a spatial distribution of trips using a double destination choice framework of stop location and stop sequence choice models. The theory behind this approach was developed in Vince Bernardin, Jr.‟s doctoral dissertation at Northwestern University, *A Trip-Based Travel Demand Framework Consistent with Tours and Stop Interaction*. The stop location choice models which are the subject of this chapter are more practical versions of those featured in the paper "Enhanced Destination Choice Models Incorporating Agglomeration related to Trip-Chaining while Controlling for Spatial Competition," coauthored by Bernardin, Koppelman and Boyce and due to appear in *Transportation Research Record* later in 2009.

The double destination choice framework adopted here offers a substantial improvement over traditional trip-based models such as the previous Knoxville regional model. The spatial distribution of trips in traditional models, based on a single gravity model for each trip purpose, is open to several serious critiques. Most crucially, traditional trip distribution models are not consistent with the basic physical requirement that (essentially) all daily travel is conducted in closed tours and can therefore produce travel patterns which are physically impossible. This is a serious problem with traditional models. Only slightly less serious is the problem that traditional models are insensitive to trip-chaining efficiencies (e.g., the tendency of travelers to group their stops together into convenient tours, such as stopping at restaurants near their workplace or frequent shopping locations, etc.). The double destination choice framework employed in the new Knoxville Regional Travel Model addresses both of these problems with traditional models and does so in a different way than activity-based models have. For formal demonstrations of this refer to the sources cited above.

The basic behavioral framework implied by the double destination choice of stop locations and sequences is straightforward. First, travelers choose all the destinations or locations at which they will stop during the day – where they will go. Next, travelers choose an origin for each destination they will visit – where they will go from. The choice of origins must obey the constraint that each place that they visit is an origin exactly as many times as it is a destination. This "traveler conservation constraint" requires that as many travelers arrive at as leave each location every day so that travelers are never created or destroyed in the model. This constraint, together with the basic structure of the model, ensures that it will produce physically possible trips consistent with closed tours. The implementation of this constraint on stop sequences is addressed in the following chapter.

This chapter, focused on the stop location choice models, addresses the incorporation of convenience and trip-chaining efficiencies among other effects. These effects, in particular, are incorporated by introducing special accessibility variables measuring a destination‟s convenience to other probable stop locations (complementary destinations) into the choice of stop locations. This, however, is only one of several effects incorporated in this destination choice which are generally excluded from traditional gravity models. The destination or stop location choice models presented here are of a general (universal or mother) logit form and can be considered as generalizations of more traditional gravity models. The general logit formula for the probability of a stop location, j, for a residence location, h, is given below.

$$P_{j|h} = \frac{e^{V_{j|h}}}{\sum_{j'} e^{V_{j'|h}}}$$

Here, $V_{j|h}$ represents the utility or attractiveness of location *j* to a resident of *h*. It is straightforward to demonstrate that the formula reduces to that of a singly constrained gravity model in the case below where A_j are the number of attractions to *j* and $f_{j|h}$ is the friction factor for the destination *j* and origin *h*.

$$V_{j|h} = \ln(\mathrm{A_j}) + \ln(\mathrm{f_{hj}})$$

It can further be shown (Daly, 1982) that the doubly constrained gravity model can be represented by introducing a third term to the utility (a shadow price corresponding to the lagrangian multiplier for the attraction constraint). Destination choice models, such as the stop location choice models presented here, build from this basic gravity model by simply adding terms for other variables or factors in the utility or attractiveness of destinations ($V_{j|h}$). This flexible general approach allows not only for the incorporation of trip-chaining efficiencies but for any number of response variables. The stop location choice models for the Knoxville Regional Travel Model incorporate the effects of various impedances, not only travel times but also the psychological boundary represented by political boundaries and river crossings, the effects of traditional attraction or size variables such as employment, enrollment, etc., as well as the effects of other destination qualities such as their accessibility to complements and to substitutes, their degree of activity diversity (mixed uses) and the cost of parking and the effects of traveler characteristics such as income or the centrality (accessibility) of their residence.

Table 18. Factors Affecting Stop Location Choice

	Impedance					Destination qualities						Destination size (Attractions)							
	Time	Accessibility from Home	River Crossing	County Line Crossing	Intra-zonal	General Accessibility	Access to Complements	Access to Substitutes	Bus Availability	Activity Diversity	Pay Parking	Basic Employment	Industrial Employment	Retail Employment	Service Employment	University Employment	UT Student Residents	K-12 Enrollment	HH or HH Population
Work Tours																			
Work (lo inc)	-	-	-	-	+				+			+	+	+	+				
Work	-	-	-	-	+	+						+	+	+	+				
College	-	-		-	-											+			
Non-work	-	-	-	-	+		+	-						+	+			+	
UT Tours																			
UT campus																+			
Other	-	-		-	+		+	-		+				+	+		+		

	Impedance					Destination qualities						Destination size (Attractions)							
	Time	Accessibility from Home	River Crossing	County Line Crossing	Intra-zonal	General Accessibility	Access to Complements	Access to Substitutes	Bus Availability	Activity Diversity	Pay Parking	Basic Employment	Industrial Employment	Retail Employment	Service Employment	University Employment	UT Student Residents	K-12 Enrollment	HH or HH Population
School Tours																			
School	-	-	-	-	+	+												+	
Other	-	-	-		+		+			+				+	+			+	+
Other Tours																			
Short Maint.	-	-	-		+		+	-		+	-			+	+				
Long Maint.	-	-	-		+	+								+	+				
Discretionary	-	-	-	-	+	+				+				+	+				+

Most of the effects are incorporated in the model by adding terms to the utility function ($V_{j|h}$). However, the traveler heterogeneity effects related to income and residence location are handled differently. Analysis of average travel times from home to stop locations of the various types by income group indicated that the only statistically significant difference was between low income and other work locations. Income was therefore simply used to segment the model and estimate separate work location choice models for low income workers and other workers.

The incorporation of the accessibility of travelers‟ residence location reflects the fact that when people choose their residence location, they also effectively choose how far they are willing to travel. Travelers who live in dense, urban (high accessibility) areas are likely to have shorter trip lengths than travelers who live in remote, rural (low accessibility) areas. In the stop location choice models developed here, travelers‟ willingness-to-travel, and hence, trip lengths, vary as a function of the accessibility of their residence. In many gravity models, a gamma function is used as the friction factor function. In many destination choice models, an exponential function of travel time (t) is used as the friction factor function ($f_{hj} = e^{\beta_t t_{hj}}$) so that the term in the utility simplifies ($\beta_t t_{hj}$) and the willingness-to-travel parameter, β_t, can be easily estimated. However, in the models adopted here, travel time is interacted with the accessibility of the residence zone (a_{0h}) so that the friction factor term in the utility function becomes $\beta_t a_{0h} t_{hj}$ (the friction factor would be given, $f_{hj} = e^{\beta_t a_{0h} t_{hj}}$). The results of model estimation, documented in detail for each stop type below, support the general hypothesis that rural residents visit locations further from their homes than urban residents. In general, the willingness-to-travel of residents of the most urban (most accessible) areas was about 10% lower than the regional average; whereas, the willingness-to-travel of residents of the most rural (least accessible) areas was about 200% higher or twice the regional average for most stop types.

The travel times which are interacted with residence accessibility do include terminal times, generally assumed at two minutes, except for the downtown areas with pay parking where the terminal time is assumed to be four minutes.

Table 19. Work Location Choice Model for Low Income Households

Variable	Parameter	t-statistic
--Size Parameters		
Basic Employment (A_{1j})	1	*
Industrial Employment (A_{2j})	1.0037	1.61
Retail Employment (A_{3j})	1.3761	2.36
Service Employment (A_{4j})	1.3893	2.46
--Generic Parameters		
Travel Time x Residence Accessibility ($a_{0h}t_{hj}$)	-0.0137	**
River Crossings (x_{1hj})	-0.4159	-2.87
County Line Crossings (x_{2hj})	-0.4405	-3.27
Percent of Destination Zone within ½ Mile of Bus (x_3)	1.1906	4.58
Intrazonal (x_0)	0.4872	***
--Model Statistics		
Log Likelihood at Zero	-3725.4	
Log Likelihood at Estimation	-2908.0	
Log Likelihood at Application	-2940.6	
Rho-Squared w.r.t. Zero	0.211	

*One size/attraction variable must be constrained (not all can be identified).

** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0114, (t-stat 15.89).

***The intrazonal parameter was adjusted in calibration; the original estimated parameter was 0.0875.

The work location choice models for low income and for other households use fairly standard attraction or size variables, employment by broad industry categories. In estimation, the parameters for the different industry categories were allowed to vary in order to capture any tendency of low income workers to be employed in different industries. In application, the attractions are calculated slightly differently. The total attractions for all work stops is simply the total employment for a zone. The attractions are apportioned between low income and other work stops based on the ratio of attractions predicted using the parameters from estimation, and balanced to the number of stops produced for each stop type in generation. Hence, the total work attractions are proportional to the total employment for a zone, but low income workers are more likely to be employed in the retail sector and less likely to work in the industrial or service sectors. Both the low income and other work location choice models are "doubly constrained" such that the models must assign exactly one stop for every attraction. This double constraint amounts to the addition of an additional term in the utility function for row factors or shadow prices (s_j). The utility function for a work location for low income households is therefore given by the following equation:

$$V_{j|h} = \ln(\mathrm{A_j}) + \ln(\mathrm{bs_j}) - 0.0137\mathrm{a_{0h}t_{hj}} - 0.4159x_{\mathrm{1hj}} - 0.4405x_{\mathrm{2hj}} + 1.1906x_{\mathrm{3j}} + 0.4892x_0$$

Where the number of attractions, A_j, for low income work stops is estimated as described above (and balanced to productions, where b is the balancing factor):

$$A_j = Total\ Emp_j \left(\frac{A_{1j} + 1.0037A_{2j} + 1.3761A_{3j} + 1.3893A_{4j}}{2A_{1j} + 3.0965A_{2j} + 2.5973A_{3j} + 3.6030A_{4j}} \right)$$

Similarly, the number of attractions, A_j, for other work stops is estimated as described above (and balanced to productions, where the balancing factor, b, is included elsewhere in the utility):

$$A_j = Total\ Emp_j \left(\frac{A_{1j} + 2.0928A_{2j} + 1.2212A_{3j} + 2.2137A_{4j}}{2A_{1j} + 3.0965A_{2j} + 2.5973A_{3j} + 3.6030A_{4j}} \right)$$

So that the utility for other work stop locations is given:

$$V_{j|h} = \ln(\mathrm{A_j}) + \ln(\mathrm{bs_j}) - 0.0103\mathrm{a_{0h}t_{hj}} - 0.1038x_{1\mathrm{hj}} - 0.3906x_{2\mathrm{hj}} + 0.9545a_{0\mathrm{j}} + 0.8435x_0$$

Given these utility functions, the probability of a work stop location for low income or other households can be calculated using the general logit formula introduced earlier.

Table 20. Work Location Choice Model for Middle and Upper Income Households

Variable	Parameter	t-statistic
--Size Parameters		
Basic Employment (A_{1j})	1	*
Industrial Employment (A_{2j})	2.0928	5.74
Retail Employment (A_{3j})	1.2212	3.15
Service Employment (A_{4j})	2.2137	6.26
--Generic Parameters		
Travel Time x Residence Access ($a_{0h}t_{hj}$)	-0.0103	**
River Crossings (x_{1hj})	-0.1038	-1.92
County Line Crossings (x_{2hj})	-0.3906	-7.96
General Accessibility of Destination (a_{0j})	0.9545	7.39
Intrazonal (x_0)	0.8435	***
--Model Statistics		
Log Likelihood at Zero	-16768.9	
Log Likelihood at Estimation	-13031.7	
Log Likelihood at Application	-13085.3	
Rho-Squared w.r.t. Zero	0.220	

*One size/attraction variable must be constrained (not all can be identified).
** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0101, (t-stat 33.24).
***The intrazonal parameter was adjusted in calibration; the original estimated parameter was -0.131.

The travel time, interacted with residence accessibility as described above, was found to be highly significant in both the low income and other work location choice models indicating that all travelers prefer work locations closer to home, but urban residents do more so than rural residents. River crossings and county line crossings were also found to decrease the utility or attractiveness of a location, acting as additional impedance variables. Based on the value of (travel) time for travelers residing in average accessibility areas, a river crossing was equivalent to an additional 3.3 minutes of travel time for low income workers or 0.9 minutes for other workers and a county line crossing was equivalent to approximately an additional 3.5 minutes of travel time for workers (regardless of income).

The work location choice model for low income workers also shows that zones with greater access to KAT bus routes are more attractive work locations for these workers. This stands to reason, as low income workers are less likely to own cars and more likely to depend on public transit service for transportation, making locations served by transit more attractive.

The work location choice model for other workers incorporated the general accessibility of destinations as a variable, making it a competing destinations model (Fotheringham, 1983, 1986). The highly significant positive parameter associated with this variable indicates significant agglomeration effects, or in other words, that work locations near other work locations (such as those in downtown Knoxville) are generally more attractive than isolated locations for middle and higher income workers.

Both work location choice models for low income and other households are statistically superior to gravity models, but are still limited in explanatory power without more detailed information about the precise industries at locations and the income/occupations of workers.

Table 21. Stop Location Choice Model for non-UT College Studies

Variable	Parameter	t-statistic
--Size Parameters		
Non-UT college enrollment	1	*
--Generic Parameters		
Travel Time x Residence Access	-0.0112	**
County Line Crossings	-0.8935	-2.72
Intrazonal	-5.0000	***
--Model Statistics		
Log Likelihood at Zero	-495.9	
Log Likelihood at Estimation	-126.6	
Log Likelihood at Application	-124.3	
Rho-Squared w.r.t. Zero	0.749	

*One size/attraction variable must be constrained (not all can be identified).
** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0064, (t-stat 3.44).
***The intrazonal parameter could not be estimated statistically, it was calibrated.

The stop location choice model for non-UT college/university stops is based on a small number of observations and is therefore necessarily simple. However, these stop locations are determined largely by the location of non-UT college enrollment (the attraction variable) to which the model is constrained and so the relatively simple model still performs quite well. The model incorporated only the effect of travel time (by residence accessibility), county line crossings (which in this case were quite significant deterrents equivalent to nearly thirteen minutes of additional travel time) and a factor for intrazonal stops.

The attraction variables for non-work stops on work tours include retail and service employment as well as elementary and secondary school enrollment. While retail and service employment clearly are attracting shopping and other household maintenance and discretionary activities, the enrollment clearly is related to workers dropping off (and picking up) students at school on their way to/from work. The significance of this attraction variable in non-work stop location choice on work tours is consistent with the significance of the number of household students in contributing to the number of these stops generated by a household. This model, unlike the preceding work location choice models, is not doubly constrained, nor is there any difference in the calculation of attractions between estimation and application other than balancing.

Table 22. Stop Location Choice Model for Non-work Stops on Work Tours

Variable	Parameter	t-statistic
--Size Parameters		
Retail Employment (A_{3j})	2.8529	26.62
Service Employment (A_{4j})	1	*
K-12 Enrollment (A_{5j})	1.7144	13.75
--Generic Parameters		
Travel Time x Residence Access ($a_{0h}t_{hj}$)	-0.0148	**
River Crossings (x_{1hj})	-0.1728	-2.55
County Line Crossings (x_{2hj})	-0.0983	-1.84
Accessibility of Destination to Employment (a_{1j})	0.6949	6.20
Accessibility of Destination to Substitutes (a_{2j})	-1.6879	-11.06
Intrazonal (x_0)	0.6641	***
--Model Statistics		
Log Likelihood at Zero	-16536.4	
Log Likelihood at Estimation	-12047.5	
Log Likelihood at Application	-12645.5	
Rho-Squared w.r.t. Zero	0.235	

*One size/attraction variable must be constrained (not all can be identified).
** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0156, (t-stat 42.91).
***The intrazonal parameter was adjusted in calibration; the original estimated parameter was 1.8346.

In addition to the attraction variables, the choice of non-work stop locations on work tours depends significantly on the travel time (interacted with residence accessibility) and on the number of river and county line crossings. However, these latter psychological barriers are less significant here than for work location choice, representing on average an equivalent of 1 and 0.6 additional minutes of travel time, respectively.

The model of non-work stop location choice on work tours also incorporated the potential stop location‟s accessibility to employment and to substitutes (similar and presumably competing nearby attractions), making it an agglomerating and competing destination choice model (Bernardin *et al.*, 2009). The positive (highly significant) parameter on the accessibility to employment indicates that workers prefer non-work stop locations on work tours which are close to probable work locations. This measure of locations‟ convenience to workplaces means the model does reflect trip-chaining efficiencies in the choice of non-work stop locations on work tours. Moreover, it also reflects differential spatial competition among locations through the accessibility to substitutes variable which is also highly significant. If only a single destination accessibility variable is included in the model, the differential spatial competition mask the trip-chaining effects since both of these effects operate over similar distances in this case and the spatial competition effects are stronger. The use of two destination accessibility variables allows for the identification of both effects.

For clarity and completeness, the utility function for non-work stop locations on work tour is

$$V_{j|h} = \ln\left(2.8529\mathrm{A}_{3\mathrm{j}} + \mathrm{A}_{4\mathrm{j}} + 1.7144\mathrm{A}_{5\mathrm{j}}\right) + \ln(\mathrm{b}) - 0.0148\mathrm{a}_{0\mathrm{h}}\mathrm{t}_{\mathrm{hj}} - 0.1728x_{1\mathrm{hj}} - 0.0983x_{2\mathrm{hj}} + 0.6949a_{1\mathrm{j}} - 1.6879a_{2\mathrm{j}} + 0.6641x_{0}$$

The balancing factor (b) is necessary for application in TransCAD even for singly constrained models but does not affect the probability of locations, since it is applied to all of them. Since the utility function of other subsequent stop location choice models can be determined from the tables documenting their parameters, just as this one can from Table 22, the utility functions for subsequent stop location choice models will not be written out in equation form.

The general explanatory power of the model of non-work stop locations on work tours remains limited by lack of data on the price, quality and precise nature of the goods and services available at various locations and the inherent stochasticity of human behavior. However, with the additional factors it incorporates, this model offers approximately a nine percent increase over the explanatory power of a gravity model.

A choice model is not necessary for University of Tennessee (UT) campus/study stops since their location is known. They are simply apportioned to the campus based on the UT enrollment (which was partially redistributed based on parking locations on campus).

The stop location choice model for non-UT stops on UT student tours was based on limited observations which may be biased, including a disproportionate number of off-campus students. The model unsurprisingly, therefore, has somewhat limited explanatory power in general. However, it does successfully incorporate a variety of effects. The attraction variables include university enrollment as well as retail and service employment, perhaps indicating a significant number of social activities. Travel time from home (interacted with residence accessibility) was highly significant. River crossings were not found to be a significant deterrence, but county line crossings, equivalent on average to approximately 5.9 minutes of additional travel time, were included despite their marginal statistical significance. It is likely that the low significance in this case merely reflects the small sample size.

Table 23. Stop Location Choice Model for Non-UT Stops on UT Student Tours

Variable	Parameter	t-statistic
--Size Parameters		
Retail Employment	3.0523	5.93
Service Employment	1	*
University Enrollment	2.3775	4.71
--Generic Parameters		
Travel Time x Residence Access	-0.0107	**
County Line Crossings	-1.0384	-1.50
Accessibility of Destination to Complements	1.3717	2.37
Accessibility of Destination to Substitutes	-1.0977	-5.07
Activity Diversity (mixed uses)	2.2670	2.10
Intrazonal	0.6858	***
--Model Statistics		
Log Likelihood at Zero	-617.4	
Log Likelihood at Estimation	-447.1	
Log Likelihood at Application	-542.1	
Rho-Squared w.r.t. Zero	0.122	

*One size/attraction variable must be constrained (not all can be identified).

** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0160, (t-stat 7.44).

***The intrazonal parameter was adjusted in calibration; the original estimated parameter was 4.2305.

The model incorporated both a location‟s accessibility to different or complementary locations as well as to similar locations or substitutes, making it also an agglomerating and competing destination choice model. This model does, therefore, reflect trip-chaining effects related to the convenience of destinations. The model also plausibly found that locations with diverse activities (mixed land uses) were more attractive.

Table 24. School Location Choice Model

Variable	Parameter	t-statistic
--Size Parameters		
K-12 Enrollment	1	*
Accessibility of Destination to Enrollment	3.7232	40.75
--Generic Parameters		
Travel Time x Residence Access	-0.0257	**
River Crossings	-0.7093	-4.00
County Line Crossings	-0.9423	-6.44
Intrazonal	0.9580	***
--Model Statistics		
Log Likelihood at Zero	-6864.5	
Log Likelihood at Estimation	-3131.3	
Log Likelihood at Application	-3194.3	
Rho-Squared w.r.t. Zero	0.535	

*One size/attraction variable must be constrained (not all can be identified).
** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0238, (t-stat 31.76).
***The intrazonal parameter was adjusted in calibration; the original estimated parameter was 0.9530.

The school location choice model used an accessibility variable in a different way, as an attraction variable. The data set revealed a considerable number of observations of school activities reported in zones with no enrollment, but immediately adjacent to or relatively nearby zones with enrollment. The reason for this is likely at least two or threefold. First, there was likely some discrepancy in the address matching/geo-coding of school enrollment (done several years ago in development of the TAZ layer in earlier model development efforts) and in the address matching/geo-coding of school activities from the household surveys (done as part of this model development work). There were many cases in which school enrollment and school activities appeared on opposite sides of the street dividing two zones perhaps suggesting the use of different street networks in geo-coding, or alternately the use of cross-streets to locate activities rather than addresses. There was also, however, a number of cases where private school enrollment had clearly been omitted from the TAZ database. Further, there was a problem of the definition of school activities, which in the survey included pre-school/day care, which are not necessarily precisely co-located with enrollment. For this reason, service employment (including day care providers) was introduced as an attraction variable, but it proved insignificant. The approach ultimately adopted here, instead, was to introduce accessibility to enrollment as an attraction variable, so that school stops would be attracted not only to zones with school enrollment but also to zones very nearby. This approach produced a model which performed very well, explaining more than half the variation in school location choices and addressing both problems with using enrollment alone for attractions.

The model also included travel time from home (interacted with residence accessibility) which was highly significant. Both river crossings and county lines, in particular, presented significant barriers for school location choice as well, which stands to reason, since school districts respect county lines (and often rivers) and only private school students generally attend school out of their district. On average, river crossings represented an additional 2.7 minutes of travel time and county lines represented an additional 3.6 minutes of travel time (both of which are quite significant given the average travel time from home of only 10.1 minutes).

Table 25. Stop Location Choice Model for Non-school Stops on School Tours

Variable	Parameter	t-statistic
--Size Parameters		
Retail Employment	2.6043	10.23
Service Employment	1	*
K-12 Enrollment	1.3245	4.61
HH Population	0.6076	2.27
--Generic Parameters		
Travel Time x Residence Access	-0.0210	**
River Crossings	-0.6098	-3.49
Accessibility of Enrollment	0.9436	5.79
Activity Diversity (mixed uses)	0.9837	2.65
Intrazonal	0.7853	***
--Model Statistics		
Log Likelihood at Zero	-4092.4	
Log Likelihood at Estimation	-2600.0	
Log Likelihood at Application	-2616.0	
Rho-Squared w.r.t. Zero	0.361	

*One size/attraction variable must be constrained (not all can be identified).
** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0216, (t-stat 26.21).
***The intrazonal parameter was adjusted in calibration; the original estimated parameter was 1.9198.

The stop location choice model for non-school stops on school tours included retail and service employment, K-12 enrollment and household population as attraction variables. Enrollment is included because many of these stops/activities are after school extracurricular activities at or nearby the school. Household population is an attraction due both to social activities and baby-sitting/day care (when not classified as school). The model also includes travel time from home (interacted with residence accessibility) which is highly significant. County line crossings did not prove significant, but river crossings did, representing on average an equivalent of 2.6 additional minutes of travel time. The model found that locations with diverse activities (mixed land uses) are more attractive. The accessibility to enrollment, measuring a location‟s convenience to school activities, is also significant and incorporates trip-chaining behavior in this model of the choice of non-school stop locations on school tours.

The model of short (less than 30 minute) maintenance stop locations on other tours includes retail and service employment as attraction variables. The travel time from home (interacted with residence accessibility) was highly significant, but its parameter had to be increased in magnitude further in calibration in order to replicate the observed distribution‟s mean in application. County line crossings did not prove significant, but river crossings did, representing for average travelers an additional 1.1 minute of travel time.

Table 26. Stop Location Choice Model for Short (< 30 min) Maintenance Stops on Other Tours

Variable	Parameter	t-statistic
--Size Parameters		
Retail Employment	1.7185	25.22
Service Employment	1	*
--Generic Parameters		
Travel Time x Residence Access	-0.0329	**
River Crossings	-0.2641	-3.81
Accessibility to Nearby Attractions	0.9460	12.07
Activity Diversity (mixed uses)	0.5051	2.93
Probable Parking Fee	-2.5327	-4.64
Intrazonal	0.9721	***
--Model Statistics		
Log Likelihood at Zero	-20965.4	
Log Likelihood at Estimation	-13701.7	
Log Likelihood at Application	-14784.7	
Rho-Squared w.r.t. Zero	0.295	

*One size/attraction variable must be constrained (not all can be identified).
** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0221, (t-stat 62.54).
***The intrazonal parameter was adjusted in calibration; the original estimated parameter was -0.2101.

Accessibility to nearby destinations, measuring the convenience of a location, was also incorporated in the model so that the model reflects travelers‟ preference for trip-chaining efficiencies. It is likely that these effects may actually be larger than represented by the model, as the effects captured here are the net trip-chaining agglomeration effects and differential spatial competition effects. An agglomerating and competing destination choice model could possibly represent the trip-chaining more accurately by controlling for the spatial competition effects, but this approach would require more finely defined employment categories than were available for inclusion in this model.

The model also found that diverse locations (with more mixed land uses) are more likely short maintenance stop locations, perhaps because the traveler is more likely to make another stop in the same zone. A probable parking fee, in contrast, decreased the attractiveness of a location for short maintenance stops. This effect makes particular sense for this stop type, given its short duration. The probable parking fee is calculated as the percent of pay parking within a zone multiplied by the average hourly parking fee (assumed to be $2 in 2006) divided by two (based on the duration of these stops). Comparing the willingness-to-travel to the disutility of a parking fee implies an average value of travel time of $5.76/hour which may be slightly low, but still seems generally reasonable given the average regional wage rate of $16.80.

Table 27. Stop Location Choice Model for Long (> 30 min) Maintenance Stops on Other Tours

Variable	Parameter	t-statistic
--Size Parameters		
Retail Employment	2.5731	32.17
Service Employment	1	*
--Generic Parameters		
Travel Time x Residence Access	-0.0205	**
River Crossings	-0.1819	-2.41
General Accessibility of Destination	0.7694	5.38
Intrazonal	0.4864	***
--Model Statistics		
Log Likelihood at Zero	-12250.3	
Log Likelihood at Estimation	-8559.1	
Log Likelihood at Application	-8681.1	
Rho-Squared w.r.t. Zero	0.291	

*One size/attraction variable must be constrained (not all can be identified).
** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0167, (t-stat 42.18).
***The intrazonal parameter was adjusted in calibration; the original estimated parameter was 0.0790.

The model of long (greater than 30 minute) maintenance stop locations on other tours also includes retail and service employment as attraction variables. Again, the travel time from home (interacted with residence accessibility) was highly significant, but its parameter had to be increased in magnitude further in calibration in order to replicate the observed distribution‟s mean in application. As with short maintenance stops, county line crossings did not prove significant, but river crossings did, representing for average travelers an additional 1.0 minute of travel time.

The general accessibility of destinations, measuring the convenience of a location over a somewhat larger area than the accessibility variable used for short maintenance stop locations, was also incorporated in the model so that the model reflects travelers‟ preference for trip-chaining efficiencies. As in the case of short maintenance stops, it is likely that these effects may actually be larger than represented by the model, and incorporating an accessibility to substitutes variable could improve this if more finely defined employment categories were available.

Table 28. Stop Location Choice Model for Discretionary Stops on Other Tours

Variable	**Parameter**	**t-statistic**
--Size Parameters		
Retail Employment	2.1769	18.19
Service Employment	1	*
Households	1.4669	12.64
--Generic Parameters		
Travel Time	0.0817	2.56
Travel Time x Residence Access	-0.0276	**
River Crossings	-0.3301	-4.94
County Line Crossings	-0.0567	-1.14
General Accessibility of Destination	0.8170	9.01
Activity Diversity (mixed uses)	1.2516	8.18
Intrazonal	0.7572	***
--Model Statistics		
Log Likelihood at Zero	-16547.9	
Log Likelihood at Estimation	-11883.3	
Log Likelihood at Application	-12128.5	
Rho-Squared w.r.t. Zero	0.267	

*One size/attraction variable must be constrained (not all can be identified).
** The willingness-to-travel parameter was adjusted in calibration, the original value was -0.0240, (t-stat 7.99).
***The intrazonal parameter was adjusted in calibration; the original estimated parameter was -0.0730.

The model of discretionary stop locations on other tours also includes households in addition to retail and service employment as attraction variables. It also includes a different form of friction factor or impedance with not only the interaction term between travel time from home and residence accessibility but also a fixed, constant effect of travel time. Although the positive parameter on travel time may initially seem counter-intuitive, the resulting disutility of the combined two terms over the range of observed residence accessibilities (and somewhat beyond) is always negative and allowed a stronger interaction effect which performed better statistically. Both major river crossings and county lines effects were included, as well, despite the fact that the latter were not particularly significant in themselves, equivalent to only 0.3 minutes of additional travel time on average, because the overall model specification performed significantly better when they were controlled for. River crossings, on the other hand, represented an additional 1.8 minutes of travel time for average travelers.

The general accessibility of destinations, measuring the convenience of a location, was also again incorporated in the model so that the model reflects travelers‟ preference for trip-chaining efficiencies. As in the case of maintenance stops, it is likely that these effects may actually be larger than represented by the model, and incorporating an accessibility to substitutes variable could improve this if more finely defined employment categories were available. This model also shows that more diverse locations (with more mixed land uses) are more attractive locations for discretionary stops.

The stop locations for visitor tours are produced by a gravity model. The attractions are adapted from the Ohio Statewide Visitor Travel Model and adjusted for the Sevier County tourism area. The model only allows visitor attractions within the zones flagged as tourist TAZ. There was no data available to calibrate the model against, but some adjustments were made for reasonableness. This component model, and the visitor models, in general, would greatly benefit from additional data collection efforts aimed at observing visitor travel behavior in the area.

Table 29. Gravity Model Parameters Assumed for Visitor Stop Locations

Variable	Parameter
Area (sq. mi.)	76.57
Retail Employment	1.37
Service Employment	1.61
Travel Time Sensitivity	-0.10

The other estimated stop location choice models were calibrated, as noted above, in order to reproduce the observed mean travel time from home for each stop time (trip length in the case of home-based trips) and the observed percentage of intrazonal stops from the combined household travel surveys. The other exception besides visitor stops was for UT student tours which were not forced to reproduce the survey observations, given the aforementioned concerns that the survey observations largely missed on-campus students.

Table 30. Calibration Statistics for Stop Location Choice Models

	Mean Travel Time from Home (min)			Percent Intrazonal		
	Observed	Modeled		Observed	Modeled	
		Estimated	Calibrated		Estimated	Calibrated
Work Tours						
Work (lo inc)	15.3	16.6	15.3	3.3	2.0	3.3
Work	18.5	18.8	18.5	3.0	1.2	3.0
College	20.8	23.6	21.6	0.0	0.3	0.1
Non-work	14.6	13.6	14.6	4.2	10.6	4.2
UT Tours						
UT campus	17.9	13.1	13.1	0.0	18.2	18.2
Other	15.9	10.3	13.9	4.2	51.1	4.2
School Tours						
School	10.1	11.2	10.1	11.3	4.1	11.3
Other	12.4	11.3	12.4	8.8	21.4	8.8
Other Tours						
Short Maintenance	11.7	15.4	11.7	7.6	1.6	7.5
Long Maintenance	15.0	17.2	15.0	3.4	1.6	3.4
Discretionary	14.2	16.6	14.2	6.6	2.2	6.6

It was generally found necessary to adjust the attractiveness of intrazonal stop locations (stop locations in the same zone as the residence) for most of the stop types. The adjustment was necessary not only to reproduce the percentage of intrazonal stops but also to reproduce the mean travel time from home. Too many or too few intrazonal stops in the estimated model was generally the primary reason of too short or too long average travel times from home. The willingness-to-travel was also generally adjusted, but by varying amounts for different tour and stop types. Most stop types required minimal adjustments, but the stops on Other (non-work) tours, in particular, required somewhat more significant adjustments. The reason for this is not clear, but in the end, the stop location choice models were able to be calibrated to reproduce key characteristics of the observed distributions mostly simply by adjusting the probability of intrazonal stops, with modest adjustments to the willingness-to-travel for stops on other tours.

County level work flows from the model were compared to the 2000 Census Transportation Planning Package (CTPP)"s Journey to work (JTW) flows as well as to previous models. The poor ability of the 2004 version of the KRTM to replicate the CTPP inter-county JTW flows was one of the motivations for the 2008 update of the KRTM. The updated 2008 KRTM was able to reproduce the CTPP JTW flows much better, but only through the incorporation of ad hoc k-factors.

Table 31. Percent of Inter-county Journeys to Work

	Total Journeys to Work		% Inter-county			
County	**2000 CTPP**	**2009 KRTM**	**2000 CTPP**	**2009 KRTM**	**2008 KRTM**	**2004 KRTM**
Anderson	28,730	34,203	30.3%	27.5%	38.0%	13.3%
Blount	47,429	57,886	34.0%	36.5%	33.6%	33.9%
Grainger	5,990	4,808	49.4%	62.6%	59.1%	34.2%
Jefferson	15,480	16,055	41.8%	34.0%	38.6%	26.5%
Knox	179,010	212,657	11.6%	12.0%	11.9%	3.3%
Loudon	15,455	20,009	42.1%	54.2%	55.3%	43.8%
Sevier	33,479	43,019	24.2%	22.5%	22.9%	20.8%
Union	6,965	7,923	63.0%	67.9%	37.2%	64.7%
All	332,538	396,561	22.3%	22.8%		

The results of the new KRTM"s work location choice models can be compared directly to the CTPP JTW data without the problems of trip purpose definitions in traditional model (due to HBO trips on work tours). However, when comparing the absolute number of journeys to work, it is important to keep in mind that the CTPP numbers reflect the year 2000, whereas, the new 2009 KRTM has (and the 2008 KRTM had) a base year of 2006. A larger absolute number of trips should therefore be expected in the 2009 KRTM.

It is clear from Table 31 and Table 32 that the distribution from the 2004 KRTM, produced by a doubly constrained gravity model, could not reproduce the observed CTPP inter-county flows. The tables also show that the 2008 KRTM was able to reproduce the observed flows fairly well, but only by using significant k-factors. The largest and most notable problem in both models is the interaction between Anderson and Knox counties. The original 2004 KRTM grossly under-predicts the interaction and even the 2008 KRTM, after the use of k-factors, notably over-predicts the interaction. Both the 2004 and 2008 models mis-predict the balance of flows between the two counties, as well. The 2004 model predicts more commuters from Anderson to Knox than vice versa and the 2008 model predicts more or less balanced commuting in both directions. Only the new 2009 KRTM accurately reproduces the observed CTPP pattern with more commuters from Knox County to Oak Ridge and other destinations in Anderson County.

Table 32. Selected Major Inter-county Work Flows

Residence	Workplace	2000 CTPP	2009 KRTM	2008 KRTM	2004 KRTM
Blount	**Knox**	13,610	16,397	16,208	16,920
Knox	**Anderson**	11,015	11,677	13,834	2,752
Anderson	**Knox**	8,114	8,694	12,290	4,098
Sevier	**Knox**	6,520	5,792	7,951	6,998
Knox	**Blount**	5,329	6,569	4,895	2,796
Loudon	**Knox**	4,580	7,793	8,211	5,263
Jefferson	**Knox**	4,380	2,723	5,175	805
Union	**Knox**	3,558	3,795	4,648	3,953
Grainger	**Knox**	2,064	1,778	2,106	1,377
Jefferson	**Sevier**	1,755	2,182	2,373	3,139

The new 2009 KRTM reproduces the CTPP JTW flows as well as, if not better than, the 2008 model. However, unlike its predecessor, the 2009 KRTM contains no special calibration factors in order to achieve this. The added value of the more sophisticated stop location choice models is clear. They accurately predict the observed inter-county work flows by incorporating observable, measureable variables like river crossings, traveler‟s income and residence accessibility, etc., while the gravity model must fall back on ad hoc k-factors to reproduce the regional commuting patterns.

Stop Sequence Choice

Stop sequence choice models comprise the second half of the double destination choice framework in the new Knoxville Regional Travel Model. These models, which are more procedural than behavioral, simply “connect the dots” produced by stop location choice to form trips and tours.

There is one stop sequence choice model for each tour purpose. All the stop location matrices produced by the stop location choice models for one tour purpose are added together to create a table (matrix) of all the out-of-home stops, by location, for each residence location. The number of tours of that purpose is then added to the diagonal to account for stops at home. Each row vector, corresponding to a residence zone, in the stop location matrix for the tour purpose then becomes the row and column marginal vector to which a gravity model is constrained. This procedure enforces the traveler conservation constraint and ensures that all travel takes place in closed tours. The stop sequence choice model is therefore essentially only a doubly constrained gravity model, applied to each residence zone, in which both the row and columns are constrained to the same vector.

There are only three subtle differences between the gravity models used to perform stop sequence choice and traditional gravity models. The first is that they are applied once for *each* residence zone, rather than once for *all* residence zones. The second is the need for a special shadow price or factor to account for the split between in-home stops and out-of-home stops within the home zone in order to preserve the number of trips and tours. The third difference is the interpretation and treatment of travel times in this context.

It is important to remember that within the context of stop sequence choice, the stop locations are fixed as an input to which the stop sequence choice is constrained. The role of travel time in stop sequence choice is therefore not to determine where travelers will go, but rather which stops, at what distances from each other, travelers will combine into trips and tours. This sequencing or combining of stops pertains mainly to the generation of non-home-based trips, since the residence location and stop locations already essentially define home-based trips. In this context, the main function of travel time is to ensure nearby out-of-home stops are combined into trips and tours to generate non-home-based trips of appropriate length. For this purpose, travel time functions relatively similarly to traditional models and its parameter should be expected to be negative since travelers prefer to combine stops into tours with shorter non-home-based trips (to minimize their total travel time for the tour). However, for home-based trips in stop sequence choice, the stochastic minimization of travel time has already been accomplished (in stop location choice) so any travel time effects are to correct for the home-based trip ends being closer or farther from home than other stop locations for a given tour type. The parameter on travel time for home-based trips should therefore be expected to be small in magnitude, but unlike in traditional models may be either positive or negative.

Table 33. Stop Sequence Choice Model Parameters

Trip Type	Travel Time	Intrazonal
Work Tours - Home-Based Trips	0.070	-1.743
Work Tours - Non-Home-Based Trips	-0.194	
UT Tours - Home-Base Trips	0.000	-3.963
UT Tours - Non-Home-Base Trips	-0.055	
School Tours - Home-Based Trips	-0.080	-3.912
School Tours - Non-Home-Based Trips	-0.119	
Other Tours - Home-Based Trips	0.030	-2.064
Other Tours - Non-Home-Based Trips	-0.146	

Given the limited number of model parameters, presented in Table 33, they were simply calibrated to reproduce observed trip lengths as is standard practice for gravity models rather than formally statistically estimated. The residence zone intrazonal factors are presented as shadow prices (in units of utility or „utils‟). The resulting calibration statistics, including the log likelihood and rho-squared goodness-of-fit statistics, are presented in Table 34. The models reproduce the average observed trip lengths well. The one exception is UT student trips, which depart from the survey observations in order to compensate for the over-representation of off-campus students in the survey.

Table 34. Stop Sequence Choice Model Calibration Statistics

	Average Travel Time		Percent Diagonal		Log Likelihood		Rho Square
Trip Type	Observed	Model	Observed	Model	@ Model	@ Zero	v. Zero
Work Tours	**14.9**	**14.8**	**5.1**	**4.7**	**-91158.8**	**-104838.9**	**0.130**
Work Tours - Home-Based	16.3	16.2	4.1	3.6	-58477.6	-66476.9	0.120
Work Tours - Non-Home	12.4	12.5	7.0	6.6	-31691.7	-38362.0	0.174
UT Tours	**15.0**	**12.8**	**1.2**	**11.7**	**-3254.5**	**-4177.5**	**0.221**
UT Tours - Home-Base	16.3	13.0	0.6	8.2	-2265.5	-2893.7	0.217
UT Tours - Non-Home	12.1	12.0	2.7	25.8	-1040.6	-1283.8	0.189
School Tours	**10.5**	**10.6**	**10.7**	**12.2**	**-26245.4**	**-34886.2**	**0.248**
School Tours - Home-Based	10.3	10.4	11.0	11.6	-19599.3	-26606.3	0.263
School Tours - Non-Home	11.2	11.3	9.8	15.1	-6557.2	-8279.9	0.208
Other Tours	**12.1**	**12.0**	**8.5**	**6.9**	**-123978.6**	**-150184.6**	**0.174**
Other Tours - Home-Based	12.7	12.7	7.6	7.2	-87572.2	-105684.6	0.171
Other Tours - Non-Home	10.6	10.6	10.8	6.2	-35431.4	-44500.0	0.204
Total All Resident Trips					**-244637.4**	**-294087.2**	**0.168**
Total All Trips OLD MODEL					**-256916.5**	**-294087.2**	**0.126**

The total daily person trip table (summing all trip/tour types) was compared against the observed trip table from the combined household survey as well as against the total daily person trip table (summing all trip purposes) from the previous trip-based Knoxville Regional Travel Model which was not consistent with tours, trip-chaining, etc. Any comparison between the old and new models must be made at this level because the old trip purposes in the previous model are not consistent with the tour-based trip types in the new model. The gravity models in the previous model, taken as a whole, offered a 12.6% improvement over the assumption of total randomness (the equal probability of all trips). The new stop location and sequence choice models, in contrast, offered a 16.8% improvement over the assumption of total randomness, representing a 33% increase in the explanatory power of the new model over its predecessor.

While explaining just under 17% of the observed variation in trips may not initially seem like an impressive statistic, it is important to recognize that a fairly high degree of randomness is likely inherently inexplicable in trip-making, given observable variables, as is the case in many human behaviors. Moreover, the new model‟s claim to superiority over the previous model is based not only in its ability to explain more of the observed variation in behavior, but also in its more realistic assumptions regarding the random or unexplained behavior. This latter fact should manifest itself in the model‟s response properties or elasticities, which should be more realistic in the new model than in the old. Sensitivity analyses to test the response properties of the model were beyond the scope of the model development, and there is currently no data available capturing local travelers‟ responses to specific stimuli (the change in travel times from a single new facility, the introduction of a single new development, etc.) with which to compare the model‟s responses. However, sensitivity analyses performed on stop location choice models of the type adopted here as part of Dr. Bernardin‟s dissertation research at Northwestern demonstrated that in general these models do respond more realistically than gravity models. In particular, the effects of new developments are more appropriately localized and complementary between developments can create halo effects in which new developments create new stops in other nearby zones with complementary activities/land uses. Such halo effects are well known to occur around real developments, but traditional models without trip-chaining effects cannot reproduce them. The consistency with tours provided by the stop sequence models also guarantees the physical possibility of model responses – which traditional models unfortunately cannot. In the end, the added value of the new stop location and sequence choice models comes from a combination of these factors – the guarantee of physically possible trip patterns, the promise of more realistic model response properties and the ability of the model to explain more of travelers‟ observed behavior.

Trip Mode Choice

As stated earlier, in the new Knoxville Regional Travel Model, as in activity-based models, the mode of travel is modeled in two stages: tour mode choice and trip mode choice. First, after tours are generated, they are assigned a primary mode by tour mode choice models. Then, after the stop location and sequence choice models create trips, these trips are assigned a mode, based on the primary mode of the tour, in trip mode choice models.

Trip mode choice models were only developed for private automobile tours according to the scope of this model development effort. In this context, trip mode choice reduces primarily to the determination of vehicle occupancy. The Knoxville model generally uses six trip modes for automobile tours:

- Walk
- Drive Alone
- HOV2
- HOV3
- HOV4
- HOV5+

Although there is not likely to be a need to differentiate among higher vehicle occupancies for planning purposes, and only a single HOV vehicle class is used in the assignment model, the model is designed with higher occupancy alternatives both because differentiating among them allows the model to estimate vehicle occupancies more accurately and to allow for their possible use in future versions of the model.

The trip mode shares are predicted by aggregate multinomial (or, in some cases, nested) logit models for the home-based and non-home-based trips of each tour purpose. These models are applied to entire trip tables, based on the aggregate characteristics of the origin and destination zones associated with trips. There is, therefore, significant information loss, and the models do not perform as well as disaggregate models might. However, they do manage to predict vehicle occupancy (as well as walk trips on auto tours), incorporating a variety of plausible effects related to gas price, trip length, urban design, general accessibility, degree of commercial vs. residential activity, parking costs, tourist attractions, average zonal household size, average zonal vehicle availability, average zonal presence of seniors, and K-12 and university enrollment.

In the framework of this model design, time is only introduced and dealt with in the departure time choice models, applied after trip mode choice. Despite the use of the term „sequence" which generally implies time, the stop location and sequence choice models do not incorporate time. They produce trips consistent with tours, but do not determine the direction of tours or trips. Origins and destinations are arbitrarily defined at this stage (and the trip tables are symmetric so that trips in one direction are equally probable as in the opposite direction). Thus, any zonal variables used in trip mode choice are applied to both trip ends.

Table 35. Factors Affecting Trip Mode Choice

	Gas Price	Walk Time	Intersection Density	General Accessibility	Employment to Population Ratio	Percent Pay Parking	Tourist TAZ	Average HH Size	Vehicles per HH	Senior HH	Enrollment	UT Students
Work Tour Home Based												
Walk	+	-	+									
SOV				-								
HOV2					-			+			+	
HOV3					-			+			+	
HOV4					-			+			+	
HOV5					-			+			+	
Work Tour Non-Home Based												
Walk	+	-	+			+						
SOV												
HOV2	+				-	+						
HOV3	+				-	+						
HOV4	+				-	+						
HOV5	+				-	+						
UT Student Tours												
Walk		-										+
SOV												
HOV2												
HOV3												
HOV4												
HOV5												
School Tour Home Based												
Walk		-							-			
SOV									+			
HOV2				+				+	+		-	
HOV3				+				+			-	
HOV4				+				+			-	
HOV5				+				+			-	
School Tour Non-Home Based												
Walk		-	+	-								
SOV												
HOV2											-	
HOV3											-	
HOV4											-	
HOV5											-	
Other Tour Home Based												
Walk		-							-	-		
SOV	-					-			+			
HOV2							+	+		+	+	
HOV3							+	+			-	
HOV4							+	+			-	
HOV5					-		+	+			-	
Other Tour Non-Home Based												
Walk		-				+						
SOV	-											
HOV2					-	+						
HOV3					-	+						
HOV4					-	+						
HOV5					-	+						
Key	+	Direct Increase		Indirect Increase	-	Direct Decrease		Indirect Decrease				

The trip mode choice models are segmented first by tour type, following the earlier component models, and second by the more traditional home-based, non-home-based distinction. As in traditional models, non-home-based trips (which can no longer be tied to the trip-maker or their residence zone after this information is discarded in stop sequence choice) are more difficult to explain and relate to model variables. However, unlike in traditional models, these models do have the advantage of being segmented by tour type and retaining that information about the tour"s primary purpose, and perhaps owing to this fact, the non-home-based models performed comparably to the home-based trip mode choice models.

All of the trip mode choice models, beginning with the home-based trips on work tours, show that walk time (or its log transform) decreases the probability of walk trips. This stands to reason, as walk trips, particularly on tours using an automobile, will tend to be short. These trips comprise less than two tenths of a percent of the home-based trips on work tours with an automobile, but close to two percent of the non-home-based trips, probably mostly short mid-day trips for a nearby lunch, etc. Intersection approach density, measuring the connectivity or walk-ability of the street network, also increases the probability of walk trips, as does higher gas prices.

Table 36. Work Tour Home-Based Trip Mode Choice Model

Variable	Alternative	Parameter	t-statistic
-- Alternative Specific Parameters			
CONSTANT	Walk	-8.4035	*
CONSTANT	HOV2	-5.2925	*
CONSTANT	HOV3	-7.8178	*
CONSTANT	HOV4	-9.1838	*
CONSTANT	HOV5+	-11.2714	*
Ln(Walk Time)	Walk	-0.9548	-3.3
Zonal Average Household Size	HOV2	0.3037	4.5
Zonal Average Household Size	HOV3, HOV4, HOV5+	0.602	5.2
K-12 Enrollment	HOV2	0.0003	5.0
K-12 Enrollment	HOV3, HOV4, HOV5+	0.0004	6.1
Employment to Population Ratio	HOV2	-0.0014	-2.0
Employment to Population Ratio	HOV3, HOV4, HOV5+	-0.005	-2.1
General Accessibility	DriveAlone	-0.0821	-3.7
Intersection Approach Density	Walk	0.0008	1.7
Gas Price (2006 $)	Walk	1.7238	2.9
-- Model Statistics			
Log Likelihood at Zero		-8603.9	
Log Likelihood at Constants		-3037.7	
Log Likelihood at Convergence		-2962.2	
Rho Squared w.r.t. Zero		0.656	
Rho Squared w.r.t Constants		0.025	

*Constants were adjusted in calibration. The original estimated values were -8.1898 for walk, -5.0788 for HOV2, -7.6041 for HOV3, -8.9701 for HOV4, and -11.0577 HOV5+.

The home-based trips on work tours also show that larger average household sizes increase the probability of carpooling, since most carpooling is done among members of the same household. Primary and secondary school enrollment also increase the probability of carpooling, presumably related to workers dropping their children off at school. More commercial areas, as indicated by the employment to population ratio, are less likely to attract carpools, again owing to the fact most carpooling is related to shared travel by families. General accessibility, however, which measures both the commercial and residential opportunities nearby, decreases the probability of driving alone (thereby increasing the probability of carpooling).

As in the case of the home-based trips, non-home-based trips on work tours with a private automobile are more likely to be walking trips if the walk time is short, there is good street connectivity (high intersection approach density) and gas prices are high. The percent pay parking within a zone also increased the probability of walking for non-home-based trips, and slightly increased the probability of carpooling, as did higher gas prices. More commercial locations (as measured by the employment to population ratio) slightly decreased the probability of carpooling.

Table 37. Work Tour Non-Home-Based Trip Mode Choice

Variable	Alternative	Parameter	t-statistic
-- Alternative Specific Parameters			
CONSTANT	Walk	-4.3247	-6.2
CONSTANT	HOV2	-2.2110	-12.6
CONSTANT	HOV3	-3.5815	-18.1
CONSTANT	HOV4	-5.0921	-18.6
CONSTANT	HOV5+	-6.1646	-15.3
WalkTime	Walk	-0.0551	-5.2
Employment to Population Ratio	HOV2	-0.0010	-1.9
Employment to Population Ratio	HOV3, HOV4, HOV5+	-0.0037	-2.2
Intersection Approach Density	Walk	0.0007	3.6
Percent Pay Parking	Walk	4.6858	5.2
Percent Pay Parking	HOV2, HOV3, HOV4, HOV5+	0.9602	2.1
Gas Price (2006 $)	Walk	0.7275	3.3
Gas Price (2006 $)	HOV2, HOV3, HOV4, HOV5+	0.2240	3.4
-- Model Statistics			
Log Likelihood at Zero		-4956.7	
Log Likelihood at Constants		-2030.9	
Log Likelihood at Convergence		-1887.7	
Rho Squared w.r.t. Zero		0.619	
Rho Squared w.r.t Constants		0.071	

The trip mode choice models for UT student tours are necessarily simpler than for other tour types, since they are supported by less data. A single model is used for both home-based and non-home-based trips and the higher vehicle occupancy alternatives are collapsed into HOV3+.

The only two factors which proved statistically significant, are the length of the trip, as measured by the walk time and the number of UT students, which largely measures proximity to campus. Both of these factors increase the probability of walk trips (on tours with a private automobile), and together they explain a good deal of the variation in the data. For trips that are made by private automobile, none of the available variables proved statistically significant, so the split between single occupancy and higher occupancy alternatives is fixed by the model constants.

Table 38. Trip Mode Choice for UT Student Tours

Variable	Alternative	Parameter	t-statistic
-- Alternative Specific Parameters			
CONSTANT	Walk	-1.4279	-1.2
CONSTANT	HOV2	-2.0961	-10.9
CONSTANT	HOV3+	-4.0177	-8.4
Walk Time	Walk	-0.1430	-2.1
UT Student Population	Walk	0.0004	3.0
-- Model Statistics			
Log Likelihood at Zero		-418.0	
Log Likelihood at Constants		-197.2	
Log Likelihood at Convergence		-152.4	
Rho Squared w.r.t. Zero		0.635	
Rho Squared w.r.t Constants		0.227	

Trip mode choice for other school tours is predicted by nested logit models, with the automobile alternatives grouped together, indicating that walking is a different, special alternative. For home-based trips, the probability of carpooling is increased by zonal average household size and by general accessibility. Zonal average vehicle ownership, on the contrary, increases the probability or driving alone (for high school students) or HOV2 (presumably a parent or older sibling escorting a single child). Primary and secondary school enrollment likewise decreases the vehicle occupancy. This may seem counter-intuitive, but the locations for these trips which are attracted to enrollment are already fixed, and here for trip mode choice, the enrollment generally is simply an indicator of the presence of a high school. High schools typically have significantly higher enrollment and are the only locations which can attract students driving alone.

Table 39. School Tour Home-based Trip Mode Choice

Variable	Alternative	Parameter	t-statistic
-- Logsum Parameters			
Drive		0.7769	-0.4368
-- Generic Parameters			
-- Alternative Specific Parameters			
CONSTANT	Walk	-0.5883	*
CONSTANT	HOV2	-0.6620	*
CONSTANT	HOV3	-1.3307	*
CONSTANT	HOV4	-3.5317	*
CONSTANT	HOV5+	-6.9577	*
Walk Time	Walk	-0.0229	-3.6163
Zonal Average Household Size	HOV2	0.0893	0.7134
Zonal Average Household Size	HOV3	0.3884	2.5978
Zonal Average Household Size	HOV4	0.7014	3.7415
Zonal Average Household Size	HOV5+	1.2781	4.6701
Zonal Average Vehicle Ownership	Drive Alone, HOV2	0.2076	2.0303
K-12 Enrollment	HOV2	-0.0002	-4.2467
K-12 Enrollment	HOV3	-0.0004	-6.5584
K-12 Enrollment	HOV4	-0.0005	-6.237
K-12 Enrollment	HOV5+	-0.0007	-5.1921
General Accessibility	HOV2, HOV3, HOV4, HOV5+	0.0556	1.981
-- Model Statistics			
Log Likelihood at Zero		-3135.0	
Log Likelihood at Constants		-2498.4	
Log Likelihood at Convergence		-2430.4	
Rho Squared w.r.t. Zero		0.225	
Rho Squared w.r.t Constants		0.027	

*Constants were adjusted in calibration. The original estimated values were -0.3674 for walk, -0.4411 for HOV2, -1.1098 for HOV3, -3.3108 for HOV4, and -6.7368 HOV5+.

The model for non-home-based trips on school tours with an automobile also shows that higher vehicle occupancies are less likely where higher enrollment indicates the presence of a high school. It also shows that walking is more likely for short trips, in accessible areas with good street connectivity. This last effect was not statistically significant, but was retained in the model since it was consistent with findings regarding this effect in the models for other tour and trip types.

Table 40. School Tour Non-home-based Trip Mode Choice

Variable	Alternative	Parameter	t-statistic
-- Logsum Parameters			
Drive		0.9079	-0.1
-- Alternative Specific Parameters			
CONSTANT	Walk	12.1325	*
CONSTANT	HOV2	1.3795	*
CONSTANT	HOV3	1.0616	*
CONSTANT	HOV4	0.3346	*
CONSTANT	HOV5+	-0.0721	*
WalkTime	Walk	-0.0481	-2.6
K-12 Enrollment	HOV2	-0.0003	-3.3
K-12 Enrollment	HOV3	-0.0005	-4.5
K-12 Enrollment	HOV4, HOV5+	-0.0007	-4. 8
General Accessibility	Walk	-0.5982	-2.7
Intersection Approach Density	Walk	0.0009	0.8
-- Model Statistics			
Log Likelihood at Zero		-942.9	
Log Likelihood at Constants		-765.4	
Log Likelihood at Convergence		-732.1	
Rho Squared w.r.t. Zero		0.224	
Rho Squared w.r.t Constants		0.044	

*Constants were adjusted in calibration. The original estimated values were 12.2417 for walk, 1.4887 for HOV2, 1.1780 for HOV3, 0.4438 for HOV4, and 0.0371 HOV5+.

As for other tour and trip types, the model for home-based trips on other tours with an automobile shows that walking is more likely for shorter trips to and from zones with lower vehicle ownership and less households with seniors. The presence of seniors also increases the probability of HOV2 trips, in particular. In general, carpooling is more likely to and from zones with larger average household size. Trips to and from zones with higher vehicle ownership are very slightly more likely to be drive alone. This marginal effect was retained in the model although it was not statistically significant given its general plausibility. Driving along is slightly less likely with higher gas prices and more pay parking. More commercial zones (with higher employment to population ratios) are less likely to see very high occupancy vehicle trips (with five or more persons per vehicle), while carpooling any kind is more likely in the Sevier County tourism area. Primary and secondary enrollment was incorporated in two ways, both directly and with a log transform. The direct effect on higher occupancy trips (three or more persons per vehicle) is negative, likely again due to the high school effect. The log transform, on the other hand, less influenced by the large enrollment numbers of high schools shows an increase in occupancy with the log of enrollment, likely capturing the service student passenger activities.

Table 41. Other Tour Home-based Trip Mode Choice

Variable	Alternative	Parameter	t-statistic
-- Alternative Specific Parameters			
CONSTANT	Walk	-1.0559	-1.7
CONSTANT	HOV2	-1.0167	-5.5
CONSTANT	HOV3	-1.7349	-9.9
CONSTANT	HOV4	-3.1367	-10.1
CONSTANT	HOV5up	-3.8668	-11.9
Walk Time	Walk	-0.0071	-2.7
Zonal Average Household Size	HOV2, HOV3	0.1153	2.1
Zonal Average Household Size	HOV4, HOV5+	0.2446	3.1
Zonal Average Vehicle Ownership	Walk	-0.6726	-3.1
Zonal Average Vehicle Ownership	DriveAlone	0.0314	0.5
Zonal Percent of HH with Seniors	Walk	-1.2730	-1.4
Zonal Percent of HH with Seniors	HOV2	0.3321	2.6
Employment to Population Ratio	HOV5+	-0.0723	-2.7
Tourist TAZ	HOV2, HOV3, HOV4, HOV5+	0.4074	4.0
Percent Pay Parking	DriveAlone	-1.0763	-2.3
Gas Price (2006 $)	DriveAlone	-0.0727	-2.3
K-12 Enrollment	HOV3, HOV4, HOV5+	-0.0002	-4.8
Log of K-12 Enrollment	HOV2, HOV3	0.0113	2.0
Log of K-12 Enrollment	HOV4, HOV5+	0.0277	2.4
-- Model Statistics			
Log Likelihood at Zero		-13668.7	
Log Likelihood at Constants		-9789.5	
Log Likelihood at Convergence		-9720.9	
Rho Squared w.r.t. Zero		0.289	
Rho Squared w.r.t Constants		0.007	

For non-home-based trips on other tours with an automobile, walking is more likely for shorter trips in areas with more pay parking. Carpooling is less likely to and from more commercial zones with higher employment to population ratios, and driving alone is less likely with higher gas prices.

Table 42. Other Tour Non-home-based Trip Mode Choice

Variable	Alternative	Parameter	t-statistic
-- Alternative Specific Parameters			
CONSTANT	Walk	-3.4784	*
CONSTANT	HOV2	-0.6003	*
CONSTANT	HOV3	-1.7717	*
CONSTANT	HOV4	-3.0223	*
CONSTANT	HOV5up	-3.4825	*
WalkTime	Walk	-0.0167	-3.2
Employment to Population Ratio	HOV2, HOV3	-0.0010	-2.4
Employment to Population Ratio	HOV4, HOV5+	-0.0051	-1.9
Percent Pay Parking	Walk	4.4209	2.8
Percent Pay Parking	HOV2	1.2386	2.1
Percent Pay Parking	HOV3	1.5763	2.3
Gas Price (2006 $)	DriveAlone	-0.2705	-5.4
-- Model Statistics			
Log Likelihood at Zero		-5754.1	
Log Likelihood at Constants		-3988.3	
Log Likelihood at Convergence		-3951.3	
Rho Squared w.r.t. Zero		0.313	
Rho Squared w.r.t Constants		0.009	

*Constants were adjusted in calibration. The original estimated values were -3.5128 for walk, -0.6347 for HOV2, -1.8061 for HOV3, -3.0567 for HOV4, and -3.5169 HOV5+.

Since visitor tours and stops were defined and generated per travel party rather than per person, there is no conversion from person to vehicle trips or adjustment for vehicle occupancy. Based on the Lake Tahoe‟s 2004 summer and winter visitors travel surveys, 93% of travel parties are assumed to have more than one visitor and constitute HOV trips.

Although the goodness-of-fit of these models is low, consistent with their aggregate design, the models did very well replicating the observed split between SOV and HOV trips. Several models required no calibration adjustment. Others required very small adjustments to the model constants, noted above. The observed and calibrated split between single and high occupancy vehicle trips is displayed in Table 43.

Table 43. Trip Mode Choice Calibration

Trip Type	Trip Mode	Observed	Model
Work Tours – Home-Based Trips	SOV	91.46%	91.14%
	HOV	8.54%	8.86%
Work Tours – Non-Home-Based Trips	SOV	89.77%	89.89%
	HOV	10.23%	10.11%
UT Student Tours	SOV	93.82%	93.79%
	HOV	6.18%	6.21%
School Tours – Home-Based Trips	SOV	35.21%	35.12%
	HOV	64.79%	64.88%
School Tours – Non-Home-Based Trips	SOV	42.04%	41.77%
	HOV	57.96%	58.23%
Other Tours – Home-Based Trips	SOV	64.32%	64.16%
	HOV	35.68%	35.84%
Other Tours – Non-Home-Based Trips	SOV	59.72%	59.96%
	HOV	40.28%	40.04%

Departure Time Choice

The new Knoxville Regional Travel Model includes departure time choice models which distribute trips throughout the day. The models are capable not only of producing the traditional AM, PM and off peak trip tables for standard assignments, but also can produce trip tables for any or all 15-minute periods from 6 am to 9 pm. These 15-minute trip tables should be of significant value for traffic micro-simulations and could be used in the future in conjunction with a dynamic network assignment.

In addition to adding temporal resolution, the departure time choice models add sensitivity to new variables, most notably travel times and accessibility. The new models will reflect shifts in travelers‟ departure times in order to avoid longer travel times. This effect, commonly referred to as peak-spreading as travelers leave earlier or later to avoid peak traffic, was modest, but already statistically significant in the household survey data. The effect was evident for all tour types but was most significant for Other Tours, which, in general, presumably have more flexibility in the timing of their activities than tours including work, university or school activities.

The models also incorporate accessibility variables which allow departure times to vary geographically in the model, e.g., lower accessibility, rural travelers might generally leave for work earlier (since they have further to go to get to work).

The models are also sensitive to the distributions of population and employment, as in traditional models, so that trips on work tours tend to flow from residential areas to employment areas in the morning and vice versa in the evening, etc. However, this effect is accomplished differently in these models than in traditional models, through the use of a „return ratio‟ variable. The „return ratio‟ is not actually the ratio of inbound and outbound trips from home, but a related explanatory variable defined as the log of the ratio of the employment to population ratio at the origin versus the employment to population ratio at the destination. Hence, more residential destinations (smaller denominator) and more commercial origins (larger numerator) are associated with higher return ratios, so the model predicts more work/school-related trips later in the day; whereas, more commercial destinations (larger denominator) and more residential origins (smaller numerator) are associated with lower return ratios, so the model predicts more work/school-related trips earlier in the day.

Home-based and non-home-based trips for each tour type are represented by different models, since the first and last trips of a tour have different temporal distributions compared with mid-tour non-home-based trips. This is segmentation is particularly important for midday/lunch traffic which is associated primarily with shorter, mid-tour non-home-based trips, as opposed to the am and pm peaks which are more associated with longer home-based trips.

Differences in the timing of SOV and HOV trips are also reflected in the models through the incorporation a binary variable in the departure time choice models.

The distribution of traffic throughout the day is also indirectly responsive to a number of variables which are not included in the departure time choice models directly but affect the number of trips and tours of various types. These variables include the number of workers, students, seniors, etc. These effects can be significant even though they are indirect, as the model will, for instance, reflect a decrease in am and pm peak departures with an increase in the number of seniors, since they generate fewer work tours.

The departure time choice models are multinomial logit pseudo-continuous discrete choice models. Although applied as familiar MNL discrete choice models, the models are mathematically consistent with a continuous interpretation/representation of time. Models of this type have been used in some activity-based models, such as for San Francisco, and can theoretically be used to predict the number of trips for any arbitrary period of time, of any duration (see Abou Zeid *et al.*, 2004). The consistency with a continuous treatment of time is accomplished through the interaction of explanatory bias variables with trigonometric functions of time. Although this results in a large number of variables, the number of variables is actually less than would be needed to incorporate the bias effects directly. Given this structure, the best measure of statistical significance of an explanatory variable is given by the chi-squared test on the full set of interaction terms. However, t-tests were still used to eliminate unnecessary terms wherever possible. The estimated models and relevant statistics are displayed in Table 44 through Table 50.

The trigonometric functions are identified in the tables below by a postscript of one through six which refers to the length of their period (e.g., SIN3). The postscript, P, is included in the trigonometric function (to produce periods of various lengths) in the following way:

$$SINP \stackrel{\text{def}}{=} \sin\left(\frac{2\pi P}{24} t\right)$$

where t is the time of the day in hours (and fractions of hours) from midnight.

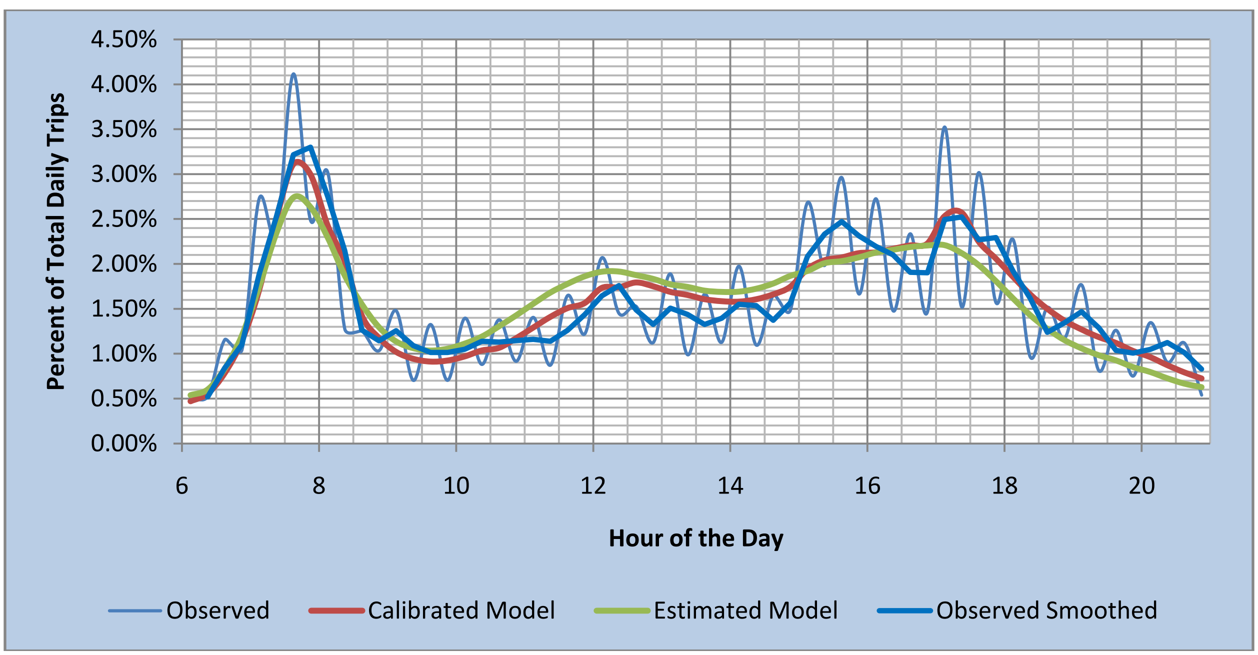

Figure 13. Daily Distribution of Departure Times

Figure 13 displays the distribution for all household auto trips, comparing the observations from the combined household survey with the predictions of the model. A smoothed version of the observed distribution is also presented to take into account the fact that departure times are more frequently reported exactly on the hour or half-hour due to rounding by survey participants. The model results are presented both with and without the shadow prices introduced in calibration.

Figure 14 through Figure 17 display the distributions for each tour type. It is clear from these graphs that the model is successful in reproducing the distinct distribution associated with each type of tour.

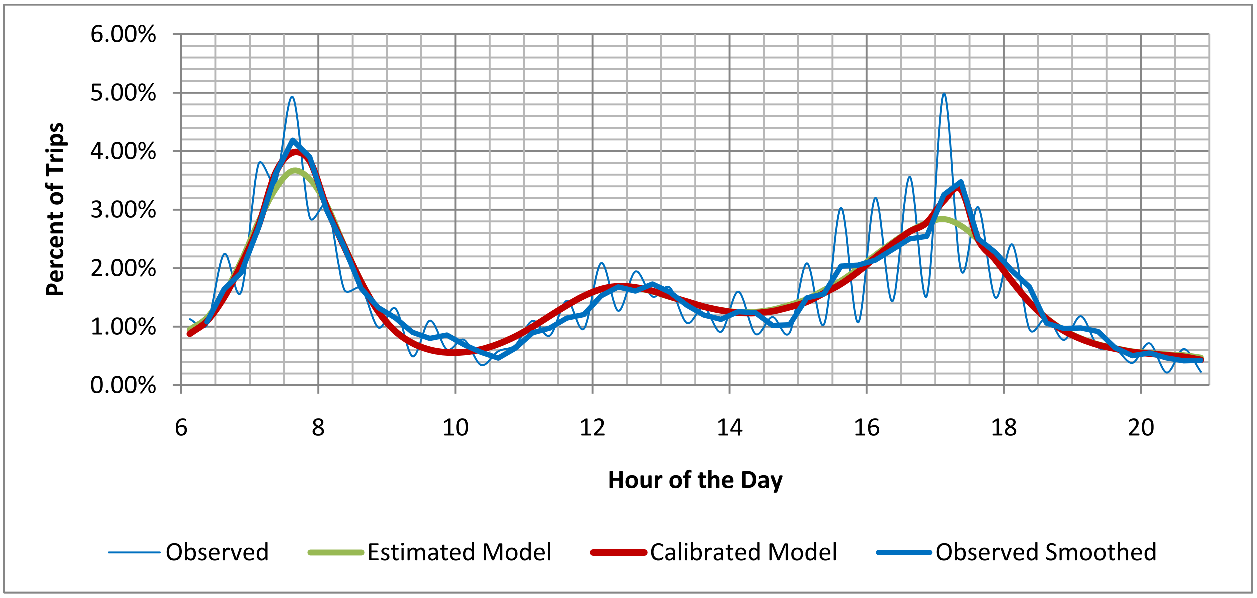

Figure 14. Daily Distribution of Work Tour Trip Departure Times

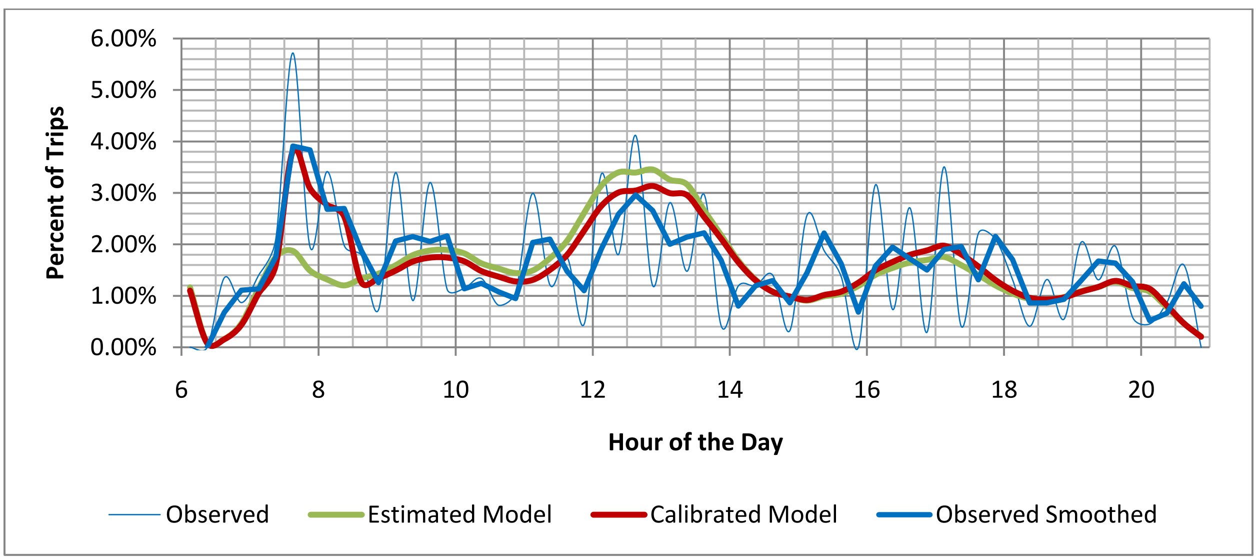

Figure 15. Daily Distribution of UT Tour Trip Departure Times

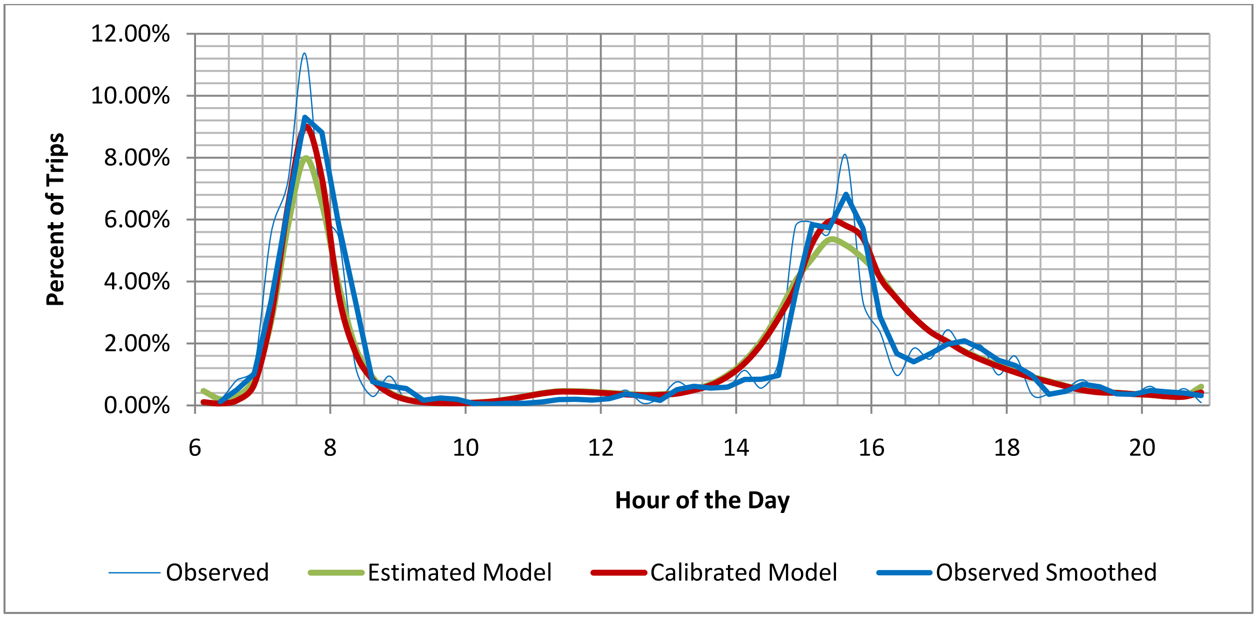

Figure 16. Daily Distribution of School Tour Trip Departure Times

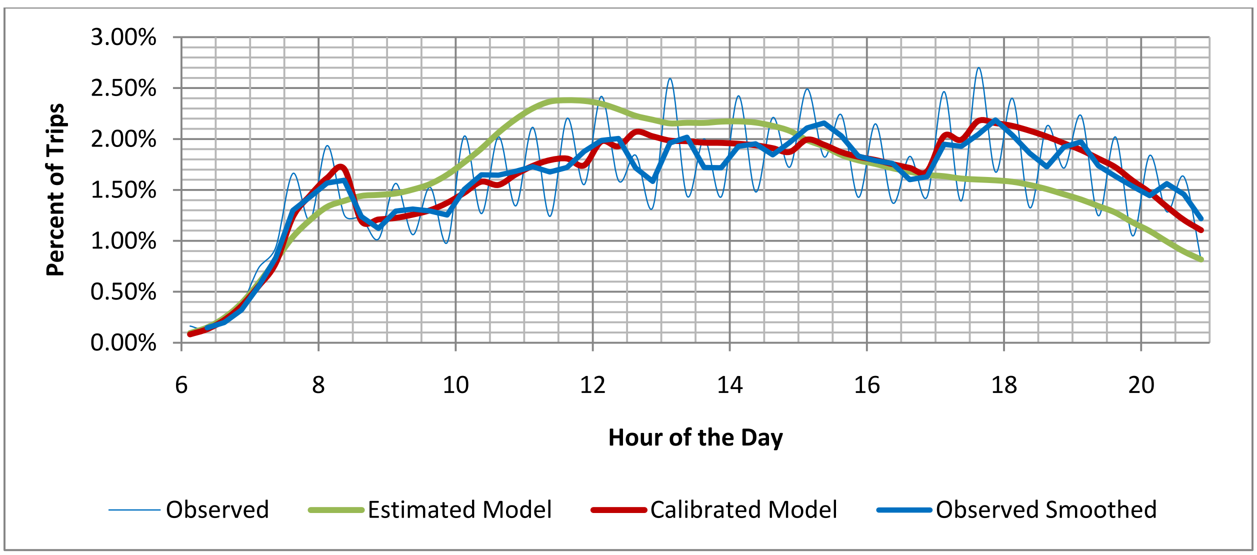

Figure 17. Daily Distribution of Other Tour Trip Departure Times

Table 44. Estimated Departure Time Choice Model for Home-based Trips on Work Tours

Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter			*-- Generic Parameter*		
SIZ	1	*	Travel Time	-0.0880	-3.06
-- Bias Parameters					
SIN1	1.8268	1.48	Origin Accessibility x SIN2	0.2352	8.96
SIN2	1.6154	1.20	Origin Accessibility x SIN3	0.2121	7.89
SIN3	-1.1180	-1.92	Origin Accessibility x SIN4	0.0970	3.56
SIN4	-2.5904	-3.25	Origin Accessibility x COS1	-0.0853	-1.54
SIN5	-2.0644	-2.56	Origin Accessibility x COS2	-0.1664	-3.13
SIN6	-1.2049	-3.01	Origin Accessibility x COS3	-0.2167	-4.08
COS1	-2.9602	-3.68	Origin Accessibility x COS4	-0.1421	-2.75
COS2	-5.5679	-2.92	Origin Accessibility x COS5	-0.0659	-1.54
COS3	-5.0220	-2.13	Origin Accessibility x COS6	0.0465	1.59
COS4	-3.5811	-2.08	Destination Accessibility x SIN1	-0.1490	-1.20
COS5	-1.7541	-2.21	Destination Accessibility x SIN2	-0.2995	-2.46
COS6	0.0144	0.05	Destination Accessibility x SIN4	0.2513	2.57
HOV x SIN1	-1.4753	-5.63	Destination Accessibility x SIN5	0.2064	2.10
HOV x SIN2	-1.3088	-5.37	Destination Accessibility x SIN6	0.1098	2.27
HOV x SIN4	1.2450	6.69	Destination Accessibility x COS1	0.1360	1.50
HOV x SIN5	0.7151	4.64	Destination Accessibility x COS2	0.4875	2.31
HOV x SIN6	0.1706	1.67	Destination Accessibility x COS3	0.5895	2.31
HOV x COS2	1.1160	3.80	Destination Accessibility x COS4	0.3709	2.10
HOV x COS3	2.1309	6.62	Destination Accessibility x COS5	0.1192	1.64
HOV x COS4	1.0385	4.88	Destination Accessibility x COS6	-0.0813	-3.33
Return Ratio x SIN1	-0.1921	-18.02	Return Ratio x COS3	-0.0345	-2.46
Return Ratio x SIN3	0.0203	1.73	Return Ratio x COS4	-0.0295	-1.52
Return Ratio x SIN5	0.0250	2.62	Return Ratio x COS5	-0.0553	-3.07
Return Ratio xCOS1	0.0524	3.14	Return Ratio x COS6	-0.0381	-2.78
-- Model Statistics					
Log Likelihood at Zero					-19802.9
Log Likelihood at Constants					-17857.0
Log Likelihood at Convergence					-17064.8
Rho Squared w.r.t. Zero					0.138

* One size variable must be constrained, not all can be identified.

Table 45. Estimated Departure Time Choice Model for Non-home-based Trips on Work Tours

Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter					
SIZ	1	*	*-- Bias Parameters*		
-- Bias Parameters			Origin Accessibility x SIN2	0.1156	5.04
SIN1	2.6468	1.97	Origin Accessibility x SIN4	-0.1163	-4.43
SIN2	3.9050	2.23	Origin Accessibility x SIN5	-0.1058	-4.14
SIN3	2.3127	1.90	Origin Accessibility x COS1	-0.3865	-1.72
SIN4	0.6915	1.12	Origin Accessibility x COS2	-0.4469	-2.29
SIN5	-0.5546	-1.34	Origin Accessibility x COS3	-0.5287	-3.24
SIN6	-0.7074	-4.32	Origin Accessibility x COS4	-0.3486	-2.73
COS1	-9.7997	-3.82	Origin Accessibility x COS5	-0.1744	-2.06
COS2	-10.5718	-4.10	Origin Accessibility x COS6	-0.1147	-2.60
COS3	-8.5644	-3.38	Destination Accessibility x SIN2	-0.1499	-5.81
COS4	-6.6683	-3.43	Destination Accessibility x SIN3	-0.0520	-1.81
COS5	-3.5722	-3.32	Destination Accessibility x COS1	0.5108	1.75
COS6	-0.6449	-1.45	Destination Accessibility x COS2	0.6192	2.49
HOV x SIN1	-11.8008	-3.66	Destination Accessibility x COS3	0.5321	2.74
HOV x SIN2	-12.8505	-3.45	Destination Accessibility x COS4	0.4045	2.91
HOV x SIN3	-5.0962	-2.47	Destination Accessibility x COS5	0.2108	2.44
HOV x SIN4	2.5316	1.85	Destination Accessibility x COS6	0.1219	2.76
HOV x SIN5	3.9829	3.38	HOV x COS3	18.9664	3.69
HOV x SIN6	1.6311	3.45	HOV x COS4	13.6679	3.69
HOV x COS1	5.9939	3.63	HOV x COS5	5.5188	3.39
HOV x COS2	15.6211	3.72	HOV x COS6	1.0898	2.72
-- Model Statistics					
Log Likelihood at Zero				-11168.2	
Log Likelihood at Constants				-10634.8	
Log Likelihood at Convergence				-10644.0	
Rho Squared w.r.t. Zero				0.047	

* One size variable must be constrained, not all can be identified.

Table 46. Estimated Departure Time Choice Model for Trips on UT Tours

Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter			*-- Generic Parameter*		
SIZ	1	*	Travel Time	-0.2531	-1.80
-- Bias Parameters					
SIN1	-5.4896	-1.31	COS1	-43.0984	-3.49
SIN2	-15.9014	-2.90	COS2	-49.7917	-3.77
SIN3	-28.1108	-4.56	COS3	-33.4792	-2.80
SIN4	-28.1290	-3.84	COS4	-15.0056	-1.97
SIN5	-18.2564	-3.43	COS5	0.2742	0.07
SIN6	-5.5398	-2.39	COS6	4.8864	2.21
HOV x SIN1	10.0083	1.54	Origin Accessibility x SIN1	-0.3092	-2.99
HOV x SIN2	13.2081	1.52	Origin Accessibility x SIN4	-0.1202	-1.13
HOV x SIN3	10.1337	1.62	Origin Accessibility x SIN6	-0.1805	-1.97
HOV x SIN4	3.4489	1.40	Origin Accessibility x COS2	0.6801	5.36
HOV x SIN6	-1.2469	-2.08	Origin Accessibility x COS4	0.1749	1.71
HOV x COS1	3.1926	1.32	Origin Accessibility x COS6	0.1220	1.32
HOV x COS2	-5.2323	-0.80	Destination Accessibility x SIN2	0.7433	2.85
HOV x COS3	-10.3977	-1.16	Destination Accessibility x SIN3	2.6006	4.34
HOV x COS4	-11.0032	-1.42	Destination Accessibility x SIN4	3.2412	4.38
HOV x COS5	-7.0908	-1.62	Destination Accessibility x SIN5	2.1461	4.14
HOV x COS6	-2.9531	-1.95	Destination Accessibility x SIN6	0.8805	4.34
Return Ratio x SIN1	1.3309	3.24	Destination Accessibility x COS1	3.9421	3.31
Return Ratio x SIN2	1.6884	3.44	Destination Accessibility x COS2	4.8812	3.98
Return Ratio x SIN3	0.8783	3.35	Destination Accessibility x COS3	4.3276	4.20
Return Ratio x SIN5	-0.2355	-2.41	Destination Accessibility x COS4	2.0221	3.33
Return Ratio x SIN6	-0.0699	-1.08	Destination Accessibility x COS5	0.2062	0.62
Return Ratio x COS2	-1.2773	-3.64	Destination Accessibility x COS6	-0.5822	-2.76
Return Ratio x COS3	-1.8170	-3.46	Return Ratio x COS5	-0.5725	-2.84
Return Ratio x COS4	-1.4030	-3.36	Return Ratio x COS6	-0.1945	-3.14
-- Model Statistics					
Log Likelihood at Zero				-1155.2	
Log Likelihood at Constants				-1076.6	
Log Likelihood at Convergence				-1004.5	
Rho Squared w.r.t. Zero				0.131	

* One size variable must be constrained, not all can be identified.

Table 47. Estimated Departure Time Choice Model for Home-based Trips on School Tours

Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter			*-- Generic Parameter*		
SIZ	1	*	Travel Time	-0.2313	-2.23
-- Bias Parameters					
SIN1	-3.7320	-0.68	Origin Accessibility x SIN1	-0.9553	-3.56
SIN2	-4.4511	-0.70	Origin Accessibility x SIN2	-0.8541	-3.05
SIN3	-2.6620	-0.68	Origin Accessibility x SIN3	-0.6453	-3.59
SIN4	0.2436	0.09	Origin Accessibility x SIN6	0.1649	3.02
SIN5	0.8849	0.43	Origin Accessibility x COS1	0.5345	1.87
SIN6	-0.2936	-0.31	Origin Accessibility x COS2	0.9461	2.52
COS1	0.6780	0.23	Origin Accessibility x COS3	0.9903	2.43
COS2	3.8185	0.53	Origin Accessibility x COS4	0.8847	2.85
COS3	7.8419	0.89	Origin Accessibility x COS5	0.3930	2.44
COS4	4.1320	0.63	Origin Accessibility x COS6	0.1556	1.79
COS5	2.7503	0.89	Destination Accessibility x SIN1	0.9887	1.83
COS6	1.4478	1.45	Destination Accessibility x SIN2	1.2029	1.71
HOV x SIN1	4.2049	1.18	Destination Accessibility x SIN3	1.1819	2.29
HOV x SIN2	4.1000	1.26	Destination Accessibility x SIN4	0.3278	1.80
HOV x SIN4	-2.2608	-0.98	Destination Accessibility x SIN6	-0.2618	-3.88
HOV x SIN5	-2.4783	-1.19	Destination Accessibility x COS1	-0.6495	-2.46
HOV x SIN6	-0.8935	-1.09	Destination Accessibility x COS2	-1.0595	-1.86
HOV x COS1	-5.6889	-2.66	Destination Accessibility x COS3	-1.4636	-1.90
HOV x COS2	-10.0063	-1.77	Destination Accessibility x COS4	-1.4147	-2.14
HOV x COS3	-9.6309	-1.49	Destination Accessibility x COS5	-1.0021	-2.72
HOV x COS4	-6.1199	-1.53	Destination Accessibility x COS6	-0.3857	-2.84
HOV x COS5	-2.2575	-1.73	Return Ratio x SIN5	0.4072	3.90
HOV x COS6	-0.4957	-2.02	Return Ratio x COS1	0.9635	5.85
Return Ratio x SIN1	-0.1860	-1.90	Return Ratio x COS2	0.9379	5.20
Return Ratio x SIN2	0.6265	5.18	Return Ratio x COS3	0.4425	3.21
Return Ratio x SIN3	0.8666	4.77	Return Ratio x COS5	-0.3234	-4.52
Return Ratio x SIN4	0.7996	4.72	Return Ratio x COS6	-0.1473	-2.36
-- Model Statistics					
Log Likelihood at Zero				-7062.3	
Log Likelihood at Constants				-5577.9	
Log Likelihood at Convergence				-5300.9	
Rho Squared w.r.t. Zero				0.249	

* One size variable must be constrained, not all can be identified.

Table 48. Estimated Departure Time Choice Model for Non-home-based Trips on School Tours

Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter			*-- Generic Parameter*		
SIZ	1	*	Travel Time	-0.2662	-2.02
-- Bias Parameters					
SIN1	37.7269	1.65	Origin Accessibility x SIN1	1.2807	3.38
SIN2	58.0663	1.53	Origin Accessibility x SIN2	2.4927	3.65
SIN3	49.2258	1.29	Origin Accessibility x SIN3	3.4608	4.27
SIN4	27.7736	1.07	Origin Accessibility x SIN4	2.5286	3.99
SIN5	7.7895	0.70	Origin Accessibility x SIN5	1.3299	3.91
SIN6	-1.1324	-0.44	Origin Accessibility x SIN6	0.3092	2.36
COS1	-4.9201	-1.77	Origin Accessibility x COS1	0.3045	1.22
COS2	-15.8669	-2.06	Origin Accessibility x COS3	-0.8651	-2.87
COS3	-22.6462	-1.70	Origin Accessibility x COS4	-1.8414	-3.74
COS4	-20.9168	-1.42	Origin Accessibility x COS5	-1.3034	-3.02
COS5	-12.5200	-1.23	Origin Accessibility x COS6	-0.7116	-3.66
COS6	-2.2840	-0.65	Destination Accessibility x SIN1	-1.2453	-2.80
HOV x SIN1	-40.9467	-1.89	Destination Accessibility x SIN2	-1.2329	-2.63
HOV x SIN2	-67.1663	-1.85	Destination Accessibility x SIN3	-0.7689	-3.07
HOV x SIN3	-66.5008	-1.78	Destination Accessibility x COS2	1.0999	2.95
HOV x SIN4	-43.1247	-1.69	Destination Accessibility x COS3	1.4552	2.98
HOV x SIN5	-17.2379	-1.58	Destination Accessibility x COS4	1.3069	3.64
HOV x SIN6	-2.3802	-1.02	Destination Accessibility x COS5	0.4700	2.68
HOV x COS2	7.9686	2.11	Destination Accessibility x COS6	0.2702	2.58
HOV x COS3	19.2974	2.05	HOV x COS5	15.0837	1.70
HOV x COS4	22.3985	1.85	HOV x COS6	4.6349	1.54
-- Model Statistics					
Log Likelihood at Zero				-2105.9	
Log Likelihood at Constants				-1782.8	
Log Likelihood at Convergence				-1800.1	
Rho Squared w.r.t. Zero				0.145	

* One size variable must be constrained, not all can be identified.

Table 49. Estimated Departure Time Choice Model for Home-based Trips on Other Tours

Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter			*-- Generic Parameters*		
SIZ	1	*	Travel Time	-0.1232	-4.65
-- Bias Parameters					
SIN1	4.5267	3.43			
SIN2	5.1426	3.73	Origin Accessibility x SIN1	-0.4292	-2.81
SIN3	1.7449	2.78	Origin Accessibility x SIN2	-0.3325	-2.37
SIN4	-1.7195	-2.12	Origin Accessibility x SIN4	0.3004	2.86
SIN5	-3.0570	-4.13	Origin Accessibility x SIN5	0.3456	3.53
SIN6	-1.7434	-5.52	Origin Accessibility x SIN6	0.1477	3.59
COS1	-8.6975	-10.11	Origin Accessibility x COS1	0.5903	5.36
COS2	-11.6700	-5.90	Origin Accessibility x COS2	0.9178	3.68
COS3	-12.1501	-5.18	Origin Accessibility x COS3	0.8740	3.04
COS4	-9.2818	-5.80	Origin Accessibility x COS4	0.6053	3.26
COS5	-4.1119	-6.49	Origin Accessibility x COS5	0.2319	3.62
COS6	-0.8977	-5.47	Origin Accessibility x COS6	0.0909	4.97
HOV x SIN1	-0.7225	-5.51	Destination Accessibility x SIN1	-0.3151	-3.79
HOV x SIN3	0.8435	3.53	Destination Accessibility x SIN2	-0.4572	-4.48
HOV x SIN4	1.1331	3.95	Destination Accessibility x SIN3	-0.2531	-3.62
HOV x SIN5	0.5488	3.80	Destination Accessibility x SIN4	-0.0886	-2.70
HOV x COS1	0.7875	4.75	Destination Accessibility x SIN6	0.0300	2.16
HOV x COS2	0.9254	3.10	Destination Accessibility x COS2	0.2812	4.28
HOV x COS3	0.8742	3.76	Destination Accessibility x COS3	0.4998	5.60
HOV x COS5	-0.5118	-3.95	Destination Accessibility x COS4	0.4293	6.27
HOV x COS6	-0.2618	-2.94	Destination Accessibility x COS5	0.1940	5.60
Return Ratio x SIN1	0.0446	2.69	Return Ratio x COS1	0.1901	7.16
Return Ratio x SIN2	0.1366	5.65	Return Ratio x COS2	0.1037	5.27
Return Ratio x SIN3	0.0979	3.02	Return Ratio x COS4	-0.0522	-2.31
Return Ratio x SIN4	0.0694	3.05	Return Ratio x COS5	-0.0545	-2.28
Return Ratio x SIN6	-0.0174	-1.76	Return Ratio x COS6	-0.0195	-1.74
-- Model Statistics					
Log Likelihood at Zero				-31195.1	
Log Likelihood at Constants				-30247.4	
Log Likelihood at Convergence				-30056.7	
Rho Squared w.r.t. Zero				0.037	

* One size variable must be constrained, not all can be identified.

Table 50. Estimated Departure Time Choice Model for Non-home-based Trips on Other Tours

Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter					
SIZ	1	*			
-- Bias Parameters					
SIN1	2.6743	1.12	Origin Accessibility x SIN1	0.1881	1.75
SIN2	1.9145	0.63	Origin Accessibility x SIN2	0.4786	2.34
SIN3	-0.4080	-0.16	Origin Accessibility x SIN3	0.4945	1.73
SIN4	-1.4950	-0.73	Origin Accessibility x SIN4	0.3077	1.28
SIN5	-1.0704	-0.86	Origin Accessibility x SIN5	0.1395	1.18
SIN6	-0.4631	-0.96	Origin Accessibility x SIN6	0.0352	0.84
COS1	-8.3223	-5.11	Origin Accessibility x COS1	0.3620	2.38
COS2	-9.2829	-3.15	Origin Accessibility x COS2	0.2729	2.49
COS3	-8.0988	-2.28	Origin Accessibility x COS4	-0.1413	-1.11
COS4	-5.1084	-1.86	Origin Accessibility x COS5	-0.1472	-1.03
COS5	-1.8106	-1.16	Origin Accessibility x COS6	-0.0789	-1.15
COS6	-0.7182	-1.19	Destination Accessibility x SIN1	-0.8303	-4.34
HOV x SIN1	-4.9275	-2.07	Destination Accessibility x SIN2	-0.8965	-4.30
HOV x SIN2	-4.6855	-2.09	Destination Accessibility x SIN3	-0.3488	-3.71
HOV x SIN3	-1.3412	-2.38	Destination Accessibility x COS2	0.7285	4.45
HOV x SIN4	1.7654	1.29	Destination Accessibility x COS3	0.9048	4.28
HOV x SIN5	2.1179	1.82	Destination Accessibility x COS4	0.5803	4.20
HOV x SIN6	0.6289	1.62	Destination Accessibility x COS5	0.2312	3.53
HOV x COS1	3.5595	2.52	Destination Accessibility x COS6	0.1341	3.83
HOV x COS2	6.9733	1.93	HOV x COS4	5.5571	2.23
HOV x COS3	8.0690	1.98	HOV x COS5	1.6314	2.25
-- Model Statistics					
Log Likelihood at Zero				-13076.6	
Log Likelihood at Constants				-12585.4	
Log Likelihood at Convergence				-12508.1	
Rho Squared w.r.t. Zero				0.044	

* One size variable must be constrained, not all can be identified.

Most of the estimated models did quite well at replicating the observed temporal distributions. However, there were several issues which did motivate the introduction of shadow prices in calibration to correct for a few issues. Although the use of the trigonometric functions worked very well on the whole, they were clearly not able to represent the sharpness of the peaks with the periods used, and it was not clear that the data would support more functions with shorter periods. Also, the resulting distribution for Other Tours, while a general unimodal distribution, did not fit the observed distribution particularly well, for reasons that remain unclear. Relatively small shadow prices, displayed in Table 51 (in utils), were used in order to better reproduce the observed distributions. Although they are of questionable consistency with a continuous representation of time, they seem reasonable, especially to compensate for the method‟s inability to represent the sharpness of the real peak periods. It is important to represent the peaks well since they are often of more interest and importance in reproducing observed traffic and in generating performance measures.

Table 51. Departure Time Choice Model Shadow Prices from Calibration

Period	Work	UT	School	Other	Period	Work	UT	School	Other
Overnight	-0.09	-0.76	-0.56	0	1:00 PM				-0.1
6:00 AM					1:15 PM				-0.1
6:15 AM					1:30 PM				-0.1
6:30 AM					1:45 PM				-0.1
6:45 AM					2:00 PM				-0.1
7:00 AM			0.2		2:15 PM				-0.1
7:15 AM	0.1		0.2		2:30 PM				-0.1
7:30 AM	0.1	0.8	0.2	0.2	2:45 PM				-0.1
7:45 AM	0.1	0.8	0.2	0.2	3:00 PM			0.15	
8:00 AM		0.8		0.2	3:15 PM			0.15	
8:15 AM		0.8		0.2	3:30 PM			0.15	
8:30 AM				-0.2	3:45 PM			0.15	
8:45 AM				-0.2	4:00 PM				
9:00 AM				-0.2	4:15 PM				
9:15 AM				-0.2	4:30 PM				
9:30 AM				-0.2	4:45 PM				
9:45 AM				-0.2	5:00 PM	0.1			0.2
10:00 AM				-0.2	5:15 PM	0.2			0.2
10:15 AM				-0.2	5:30 PM				0.3
10:30 AM				-0.3	5:45 PM				0.3
10:45 AM				-0.3	6:00 PM				0.3
11:00 AM				-0.3	6:15 PM				0.3
11:15 AM				-0.3	6:30 PM				0.3
11:30 AM				-0.3	6:45 PM				0.3
11:45 AM				-0.3	7:00 PM				0.3
12:00 PM				-0.2	7:15 PM				0.3
12:15 PM				-0.2	7:30 PM				0.3
12:30 PM				-0.1	7:45 PM				0.3
12:45 PM				-0.1	8:00 PM				0.3
					8:15 PM				0.3
					8:30 PM				0.3
					8:45 PM				0.3

External Model

Trips with at least one trip-end outside the study area are considered external trips. External trips are further classified as External-Internal (EI) trips if only one trip-end falls outside the study area and as external-external (EE) trips if both trip-ends fall outside the study area. These external trips require special treatment in the travel demand modeling process.

The Knoxville regional model has 29 external stations where traffic can enter or exit the model‟s roadway network to and from the surrounding areas (Figure 18). An external origin-destination survey was conducted for 6 major external stations, including 5 Interstate locations and one location on US-11E, in September of 2007. This survey used video license plate matching to identify survey respondents and included the 24-hour traffic count by vehicle type. The vehicle types are auto, Single Unit (SU) truck and Multiple Unit (MU) truck. The survey EE trip table was developed by vehicle type for these six major external stations.

The following steps were taken to update the external trip table for each vehicle type,

- Determining daily O and D trips at each external station from the most recent AADT traffic counts,
- Obtaining EE trip percentages for each external station from the 2000 original model,
- Calculating preliminary EE O and D trips and balancing EE O and D trips for all external stations by the *Weighted Sum* (50% O to 50% D) *method in TransCAD,*
- Computing the preliminary EE O-D matrix by applying the balanced EE O and D to the 2000 original EE O-D matrix using *growth factor (Fratar Balancing) method*,
- Calculating and balancing major EE O and D trips for 6 major external stations based on the AADT data and the survey results,
- Computing the major EE O-D matrix by applying the major EE O and D to the survey EE trip table using *growth factor (Fratar Balancing) method,*
- Obtaining the final EE O-D matrix by updating the preliminary EE O-D matrix with the major EE O-D matrix.

For an external station, external-internal trips of each vehicle type are equal to the difference between the AADT and the number of external-external trips (if any) of the vehicle type; and were, therefore, derived from the final external-external trip table and the AADT data of the vehicle type.

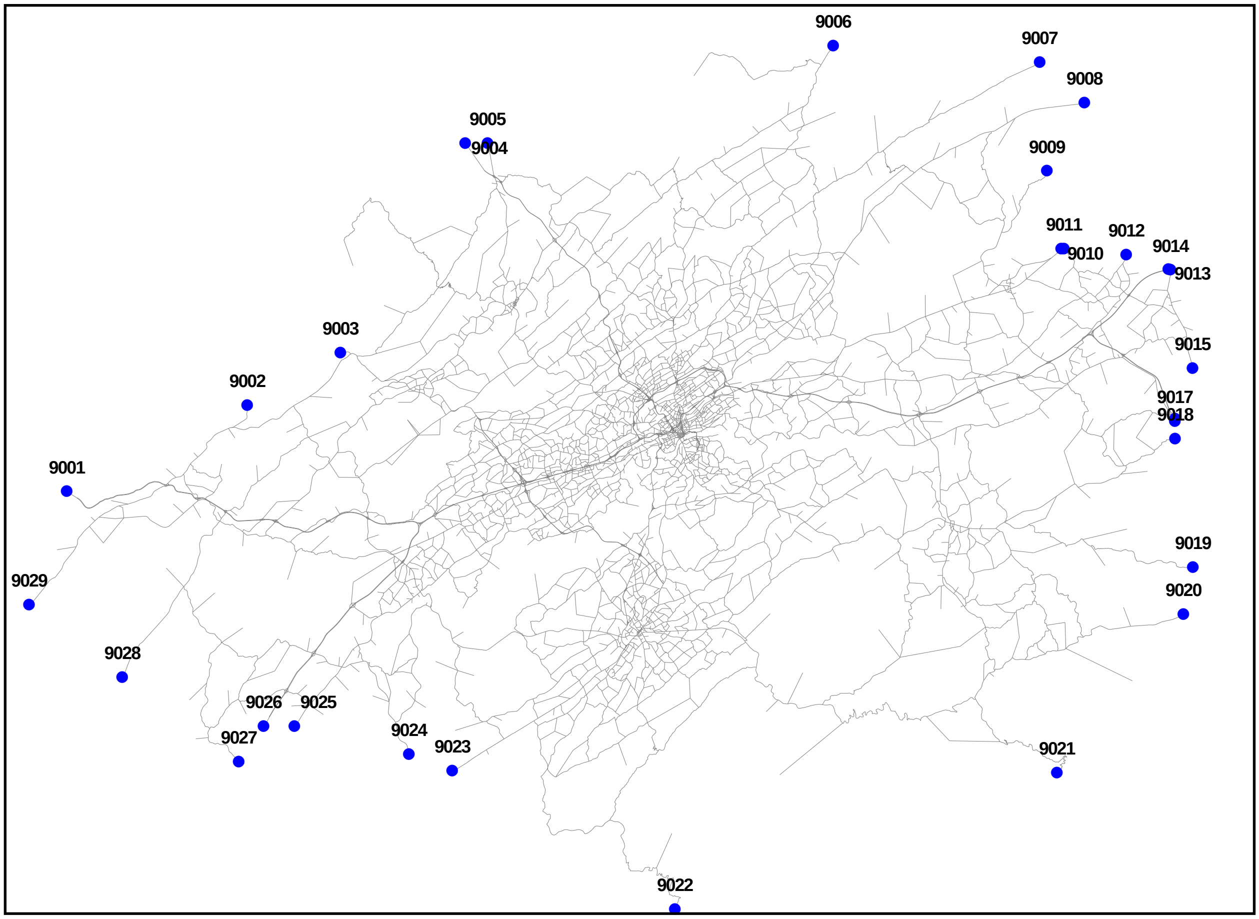

Figure 18. External Stations

The twenty-nine external station locations, along with the number of external-external and external-internal auto and truck trips at each station, are displayed in Figure 18. Six of the twenty-nine external stations in the Knoxville model serve over 20,000 daily trips (the five interstate stations and the station for US11E) while seven external stations (the five interstate stations and the two stations for US 25E) serve over 5,000 daily external-external trips. All of the remaining twenty-two stations carry less than 500 external-external trips. Seven of the remaining twenty-two stations carry between 100 and 497 while the remaining fifteen serve less than 100 through trips a day. The auto trip exchanges between the fourteen stations with more than 100 total daily external-external trips are displayed in Table 52, and the SU and MU truck trip exchanges for these stations are presented in Table 53 through Table 55.

Table 52. External Station Summary

External Station	Road Name	Location	AADT	External-External			External-Internal		
				Auto	SU Truck	MU Truck	Auto	SU Truck	MU Truck
9001	**I-40**	**W**	**40,830**	**4,127**	**1,411**	**2,711**	**24,285**	**1,222**	**7,072**
9002	US 27	NE	3,830	361	22	113	3,238	16	78
9003	Winter Gap R	NW	9,289	63	0	0	8,853	186	186
9004	**I-75**	**NW**	**42,120**	**3,338**	**960**	**4,259**	**25,304**	**1,567**	**6,691**
9005	Hwy 116	N	3,900	21	2	2	3,722	76	76
9006	Hwy 33	N	8,242	358	18	43	7,359	137	326
9007	SR 131	NE	1,287	6	0	0	1,191	64	26
9008	US 11 W	E	5,533	30	2	4	5,005	164	328
9009	SR 375	NE	1,658	0	0	0	1,575	66	17
9010	**US 11 E**	**E**	**21,525**	**208**	**56**	**114**	**20,671**	**159**	**317**
9011	Hwy 341	N	2,244	167	27	7	1,987	39	14
9012	Hwy 66	N	4,102	137	17	7	3,841	64	33
9013	**I-81**	**E**	**33,802**	**3,069**	**1,122**	**2,369**	**20,931**	**568**	**5,742**
9014	US 25E	N	11,045	6,715	262	190	3,800	70	31
9015	US 25E	S	8,057	6,745	262	190	745	60	52
9016	**I-40**	**SE**	**28,716**	**3,326**	**454**	**2,698**	**14,478**	**407**	**7,353**
9017	US 25W	SE	5,960	0	0	0	5,762	78	120
9018	US 411	E	6,634	46	0	3	6,123	133	328
9019	SR 339	E	1,548	0	0	0	1,533	15	0
9020	US 321	E	5,256	0	0	0	5,150	53	53
9021	US 441	S	6,373	23	0	0	6,219	30	100
9022	US 129	S	1,020	1	0	0	978	20	20
9023	US 411	SW	11,458	151	7	26	9,931	336	1,005
9024	Hwy 72	S	5,514	178	16	40	4,564	205	511
9025	US 11	SW	3,537	16	0	0	3,061	106	354
9026	**I-75**	**SW**	**40,532**	**3,686**	**1,559**	**3,368**	**24,688**	**466**	**6,764**
9027	SR 322	S	1,486	0	0	0	1,456	15	15
9028	SR 58	SW	1,536	0	0	0	1,444	31	61
9029	US 27	SW	4,302	350	40	82	3,565	89	176

Table 53. Major External-External Auto Trip Interchanges

	9001	9002	9004	9006	9010	9011	9012	9013	9014	9015	9016	9023	9024	9026	9029
9001	0.00	13.64	151.38	21.03	36.81	0.10	0.90	760.15	0.00	0.36	867.10	3.82	37.28	137.57	12.45
9002	13.63	0.00	3.04	0.48	1.03	0.00	0.00	21.01	0.00	0.00	7.02	0.03	0.28	6.83	127.32
9004	151.33	3.04	0.00	11.45	13.90	0.03	0.24	52.44	0.00	1.11	461.34	5.50	22.82	921.99	6.25
9006	21.03	0.48	11.45	0.00	0.14	0.00	0.00	4.03	0.00	0.00	19.30	1.39	0.61	118.75	1.17
9010	36.79	1.03	13.90	0.14	0.00	0.05	0.04	13.82	0.00	0.11	3.60	4.84	0.78	24.89	3.19
9011	0.10	0.00	0.03	0.00	0.05	0.00	0.01	32.90	0.00	0.00	50.36	0.01	0.01	0.48	0.00
9012	0.90	0.00	0.24	0.00	0.04	0.01	0.00	30.80	0.00	0.10	32.00	0.07	0.03	4.72	0.00
9013	759.82	21.01	52.43	4.03	13.82	32.88	30.79	0.00	0.00	12.53	71.03	48.66	4.82	451.90	6.47
9014	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3093.00	0.00	0.00	0.00	0.00	0.00
9015	0.39	0.00	1.20	0.00	0.12	0.00	0.10	13.47	3622.21	0.00	0.42	0.00	0.00	0.09	0.00
9016	866.80	7.02	461.31	19.30	3.60	50.35	32.00	71.04	0.00	0.39	0.00	7.22	0.47	125.25	4.55
9023	3.82	0.00	5.50	1.39	4.84	0.01	0.07	48.71	0.00	0.00	7.23	0.00	0.12	2.61	1.25
9024	37.27	0.28	22.82	0.61	0.78	0.01	0.03	4.82	0.00	0.00	0.47	0.12	0.00	20.70	0.73
9026	137.56	6.83	922.20	118.79	24.89	0.48	4.72	452.06	0.00	0.08	125.28	2.61	20.70	0.00	7.43
9029	12.44	127.32	6.25	1.17	3.18	0.00	0.00	6.47	0.00	0.00	4.55	1.25	0.73	7.43	0.00

Table 54. Major External-External Single Unit (SU) Truck Trip Interchanges

	9001	9002	9004	9006	9010	9011	9012	9013	9014	9015	9016	9023	9024	9026	9029
9001	0.00	3.72	39.39	2.27	13.54	0.18	0.89	320.22	0.00	0.00	159.84	1.18	5.68	147.17	11.10
9002	3.72	0.00	0.00	0.00	0.00	0.00	0.00	0.44	0.00	0.00	0.13	0.00	0.00	0.53	6.17
9004	39.38	0.00	0.00	0.24	3.27	0.01	0.05	10.40	0.00	0.00	34.64	0.33	0.68	388.93	1.67
9006	2.27	0.00	0.24	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.13	0.02	0.00	6.28	0.00
9010	13.54	0.00	3.27	0.00	0.00	0.01	0.00	0.96	0.00	0.00	1.39	0.25	0.02	8.55	0.00
9011	0.18	0.00	0.01	0.00	0.01	0.00	0.01	7.08	0.00	0.00	6.26	0.00	0.00	0.45	0.00
9012	0.89	0.00	0.05	0.00	0.00	0.01	0.00	3.54	0.00	0.00	2.14	0.01	0.00	2.36	0.00
9013	320.14	0.44	10.40	0.05	0.96	7.08	3.54	0.00	0.00	0.00	7.47	1.68	0.08	208.40	0.73
9014	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	131.00	0.00	0.00	0.00	0.00	0.00
9015	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	131.00	0.00	0.00	0.00	0.00	0.00	0.00
9016	159.81	0.13	34.65	0.13	1.39	6.26	2.14	7.47	0.00	0.00	0.00	0.14	0.00	14.50	0.33
9023	1.18	0.00	0.33	0.02	0.25	0.00	0.01	1.68	0.00	0.00	0.14	0.00	0.00	0.39	0.00
9024	5.68	0.00	0.68	0.00	0.02	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	1.53	0.00
9026	147.18	0.53	389.07	6.28	8.55	0.45	2.36	208.47	0.00	0.00	14.51	0.39	1.53	0.00	0.00
9029	11.09	6.17	1.67	0.00	0.00	0.00	0.00	0.73	0.00	0.00	0.33	0.00	0.00	0.00	0.00

Table 55. Major External-External Multiple Unite (MU) Truck Trip Interchanges

	9001	9002	9004	9006	9010	9011	9012	9013	9014	9015	9016	9023	9024	9026	9029
9001	0.00	16.47	122.98	4.59	14.16	0.01	0.12	589.37	0.00	0.00	516.29	1.39	9.75	72.82	5.75
9002	16.47	0.00	0.00	0.00	0.00	0.00	0.00	7.00	0.00	0.00	3.71	0.00	0.00	2.26	27.56
9004	123.00	0.00	0.00	2.98	20.77	0.00	0.04	116.37	0.00	0.00	680.36	2.34	7.05	1170.12	5.26
9006	4.59	0.00	2.98	0.00	0.01	0.00	0.00	0.36	0.00	0.00	1.69	0.10	0.03	12.24	0.00
9010	14.16	0.00	20.76	0.01	0.00	0.00	0.00	3.61	0.00	0.00	9.16	0.61	0.07	8.61	0.00
9011	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.55	0.00	0.00	2.40	0.00	0.00	0.03	0.00
9012	0.12	0.00	0.04	0.00	0.00	0.00	0.00	1.71	0.00	0.00	1.81	0.00	0.00	0.31	0.00
9013	589.37	7.00	116.35	0.36	3.61	1.55	1.71	0.00	0.00	0.00	86.46	7.08	0.51	369.55	1.36
9014	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	95.00	0.00	0.00	0.00	0.00	0.00
9015	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	95.00	0.00	0.00	0.00	0.00	0.00	0.00
9016	516.17	3.71	680.08	1.69	9.16	2.40	1.81	86.44	0.00	0.00	0.00	1.02	0.05	45.12	1.08
9023	1.39	0.00	2.34	0.10	0.61	0.00	0.00	7.07	0.00	0.00	1.02	0.00	0.01	0.44	0.00
9024	9.75	0.00	7.05	0.03	0.07	0.00	0.00	0.51	0.00	0.00	0.05	0.01	0.00	2.53	0.00
9026	72.80	2.26	1169.58	12.23	8.61	0.03	0.31	369.45	0.00	0.00	45.12	0.44	2.53	0.00	0.00
9029	5.75	27.55	5.26	0.00	0.00	0.00	0.00	1.36	0.00	0.00	1.08	0.00	0.00	0.00	0.00

The number of external-internal trips at each external station is given by the difference between the AADT and the total external-external trips. However, modeling is required to locate the internal origins/destinations which correspond to these trips. In the Knoxville Regional Travel Model, the internal trip ends are modeled in a two step process, and then connected to an external station with a doubly-constrained gravity model.

First, an initial set of car and truck internal attractions are modeled as a function of employment, households and lodgings (hotel rooms and short term rental units).

$$Internal\ Car\ Attractions = 22.89\sqrt{Employment} + 0.28 * Households + 0.34 * Lodging$$

$$\begin{aligned} Internal\ Truck\ Attractions \\ &= 0.35 * Basic\ Employment + 0.28 * Industrial\ Employment \\ &+ 0.27 * Retail\ Employment + 0.11 * Service\ Employment \end{aligned}$$

The truck attractions are simply one end of an inter-regional truck trip. These car attractions can be thought of as related to long distance trips which occur infrequently, such as long distance business travel or tourism. However, in some parts of the Knoxville region, daily commute and shopping trips to locations just outside the model area become external-internal trips in the model. These are accounted for with a special binary choice model which predicts the probability that an external destination will be chosen for a stop based on the residence"s accessibility to internal activities versus their accessibility to external-internal trip ends at the external stations. Figure 19 displays the resulting probabilities for the base year network and TAZ.

$$\begin{aligned} Probability\ of\ an\ External\ Stop\ Location \\ &= 1 - \frac{1}{1 + e^{Access\ to\ Externals - Access\ to\ Internals}} \end{aligned}$$

This probability is then used to reallocate a portion of the daily stops generated as a part of work and other tours to external stations as external-internal attractions. These are combined with the initial internal car attractions associated with less frequent travel to become the attractions in a doubly constrained gravity model. The friction factors for the gravity model are given by a gamma function with alpha = 150000, beta = 0.7 and gamma = 0.05.

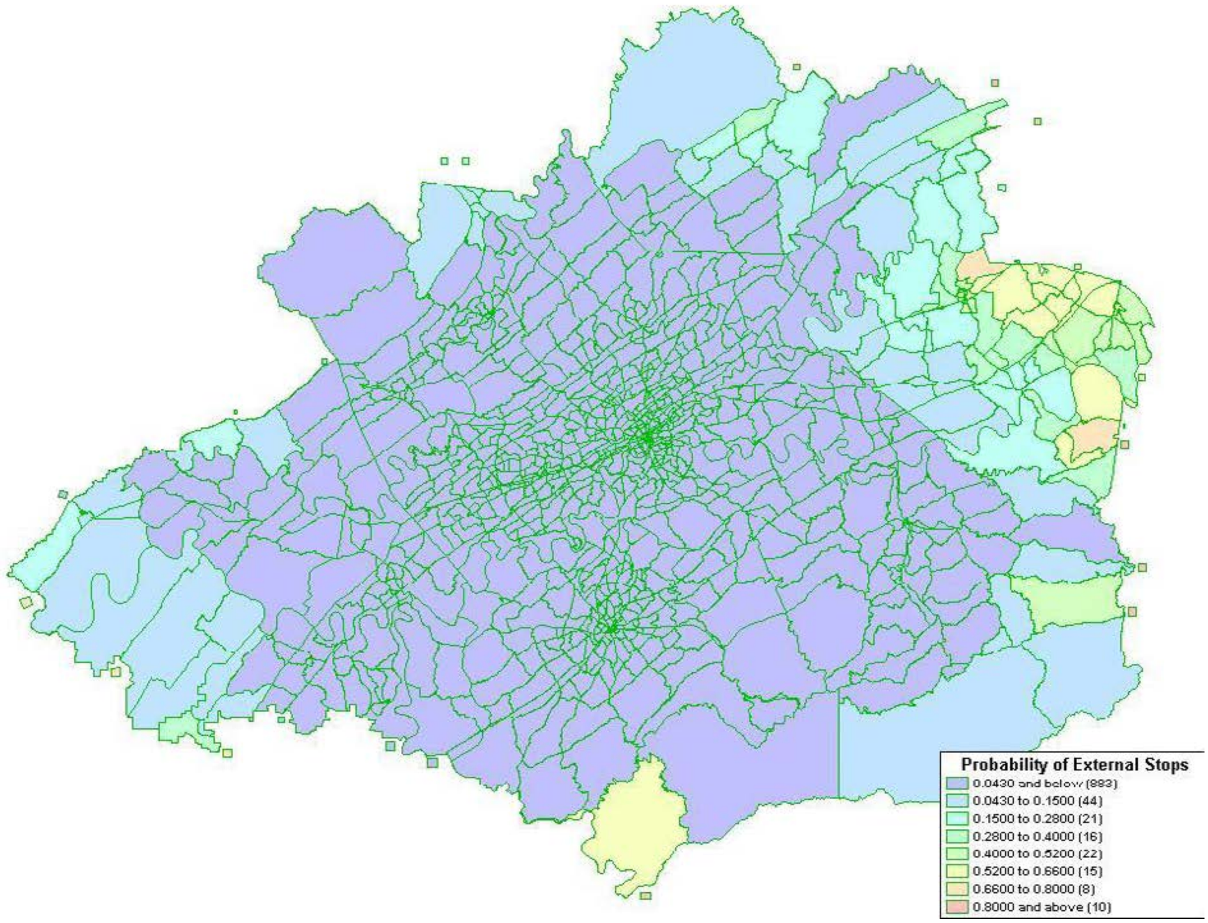

Figure 19. Probability of an External Stop Location

Truck Model

Based on the method recommended in *Quick Response Freight Manual* (1996), a commercial vehicle model was developed for predicting trips for four-tire commercial vehicles, single unit (SU) trucks with six or more tires, and multiple unit (MU) trucks. The model uses a four-step process. These steps are trip generation, distribution, choice of time of day and trip assignment. In addition, the special trip generators of inter-region and inter-modal trucks were added in the model to better replicate the current inter-region and inter-modal truck movements.

The inputs to trip generation are the number of employees and the number of households by Traffic Analysis Zone (TAZ). The daily trip generation rates shown in Table 56 are for trip Origins (O) and Destinations (D). These rates were obtained by adjusting the original generation rates in the *Quick Response Freight Manual*. To replicate the current truck traffic condition in the study area, these rates were further adjusted by factors of 0.10, 0.30 and 0.60 for four-tire commercial vehicles, single unit (SU) trucks, and multiple unit trucks respectively. For example, the final multiple unit truck trip rate per retail employee is 0.0325 which is equal to original rate 0.065 multiplied by 0.50.

The airport was also designated as a special truck trip generator, generating an additional 0.4 multiple unit, 0.1 single unit and 12.5 four tire commercial vehicle trips per employee beyond those predicted by the truck trip generation equations below.

Table 56. Daily Truck Trip Generation Rates

Generator (Employment and Household)	Commercial Vehicle Trip Destinations (or Origins) per Unit per Day		
	Four -Tire Vehicles	Trucks (Single Unit 6+ Tires)	Trucks (Combination)
Agriculture, Mining and Construction	1.11	0.289	0.174
Manufacturing, Transportation, Communications, Utilities & Wholesale Trade	0.938	0.242	0.104
Retail	0.888	0.253	0.065
Office and Services	0.437	0.068	0.009
Households	0.025	0.010	0.004

The productions of External-Internal and Internal-External (EI-IE) truck trips are obtained from the external trip model. The special EI-IE truck trip attractions are generated by inter-regional and inter-modal special generators. Since there is no freight and truck survey available in the study area, it is assumed that the normal EI-IE truck trip attractions are proportional to the truck trip destinations. At the beginning, the truck trip destinations are used as the normal EI-IE truck trip attractions, and then the balancing process scales the total attractions of normal truck trips to match the difference between the total productions of EI-IE truck trips and the total attractions of special EI-IE truck trips. The special EI-IE truck trips are calculated based on the tonnage and EI-IE trip percent shown in Table 57. Some internal truck trips are also generated by special generators and can be calculated in the same way. The final truck trips are summarized in Table 58.

Table 57. Inter-Region and Inter-Modal Special Trip Generation

PRIMARY SIC	NAICS CODE	TAZID	COMPANY_NAME	Employees	FREIGHT Workers	EI-IE Trip Percent	Internal Trip Percent	Annual Tonnage
421307	48423015	8615	ROANE TRANSPORTATION	50	50	50.00%	50.00%	611500
421304	48423013	8621	WEST TRUCKING INC	70	70	50.00%	50.00%	856100
421312	48423008	5061	PURDY TRUCKING CO	225	225	70.00%	30.00%	2751750
421309	48423017	5058	TOTAL TRANSPORTATION INC	200	200	70.00%	30.00%	2446000
421306	48423016	5038	TRANSPORT SERVICE CO	58	58	50.00%	50.00%	709340
431101	49111001	5052	US POST OFFICE	40	40	50.00%	50.00%	489200
473101	48851011	1658	L & D TRANSPORTATION SVC INC	70	70	50.00%	50.00%	700000
431101	49111001	3014	US POST OFFICE	72	72	50.00%	50.00%	880560
421309	48423017	1646	COLONIAL FREIGHT SYSTEMS INC	110	110	50.00%	50.00%	1345300
873111	48851011	1680	STRATA-GLLC	60	60	50.00%	50.00%	600000
421304	48423013	1647	CRETE CARRIER	180	180	50.00%	50.00%	2201400
458106	48811907	2310	MCGHEE TYSON AIRPORT-TYS	140	140	50.00%	50.00%	34706000
421309	48423015	2304	B P EXPRESS	35	35	50.00%	50.00%	428050
531110	49313007	1697	SAM'S CLUB	170	30	100.00%	0.00%	366900
421309	48423013	1621	YELLOW TRANSPORTATION INC	90	90	50.00%	50.00%	1100700
421306	48423016	1118	HIGHWAY TRANSPORT INC	100	100	50.00%	50.00%	1223000
422509	49311006	1536	KENCO KNOXVILLE	60	60	50.00%	50.00%	733800
421309	48423013	1538	ROADWAY EXPRESS INC	120	120	50.00%	50.00%	1467600
421309	48423017	1538	ESTES EXPRESS LINES	80	80	50.00%	50.00%	978400
421309	48423017	1108	AAA COOPER TRANSPORTATION	100	100	50.00%	50.00%	1223000
421309	48423017	1054	SAIA MOTOR FREIGHT LINE INC	37	37	50.00%	50.00%	452510
421309	48423015	1526	SOUTHEASTERN FREIGHT LINES	62	62	50.00%	50.00%	758260
422510	49311001	1131	SMITH & HAMMAKER OFFICE RECOR	35	35	50.00%	50.00%	428050
421309	48423017	1096	SKYLINE TRANSPORTATION INC	80	80	50.00%	50.00%	978400
421309	48423017	1045	PEMBERTON TRUCK LINES	300	300	70.00%	30.00%	3669000
421304	48423013	1591	G & R TRUCKING CO INC	50	50	50.00%	50.00%	611500
421309	48423017	1067	CON-WAY FREIGHT-SOUTHERN	170	170	50.00%	50.00%	2079100
421309	48423017	1067	GATOR FREIGHTWAYS INC	92	92	50.00%	50.00%	1125160
421309	48423017	1067	FED EX FREIGHT	120	120	50.00%	50.00%	1467600
421309	48423017	1067	TETON MOTOR FREIGHT INC	200	200	70.00%	30.00%	2446000
421309	48423017	1067	USF HOLLAND INC	130	130	50.00%	50.00%	1589900
531110	49313007	1508	SAM'S CLUB	170	30	100.00%	0.00%	366900
421309	48423017	1457	D J & P TRANSPORTATION	50	50	50.00%	50.00%	611500
421309	48423017	1459	WILSON TRUCKING CORP	35	35	50.00%	50.00%	428050
421309	48423017	1459	VOLUNTEER EXPRESS INC	34	34	50.00%	50.00%	415820
478904	48821007	1577	KNOXVILLE LIVESTOCK CTR INC	40	40	50.00%	50.00%	1000000
422506	49311009	1189	G E CO WAREHOUSING & TRNSPRTN	275	275	70.00%	30.00%	3363250
421309	48423017	1189	MOORE FREIGHT SVC	75	75	50.00%	50.00%	917250
431101	49111001	6037	US POST OFFICE	40	40	50.00%	50.00%	489200
421309	48423017	4064	SCHRADER TRUCKING CO INC	75	75	50.00%	50.00%	917250
421309	48423017	4070	FIRST FLEET INC	35	35	50.00%	50.00%	428050
421309	48423017	4019	OLD DOMINION FREIGHT LINE INC	850	850	70.00%	30.00%	10395500

Table 58. Summary of 2006 Truck Trip Generation

Trip Type		Number of Trips	
		Original	Balanced
4-tire Commercial Vehicle	Origin (O)	59,420	59,402
	Destination (D)	59,384	59,402
Internal SU Truck	Origin (O)	34,323	33,837
	Destination (D)	33,350	33,837
Internal MU Truck	Origin (O)	8,059	8,059
	Destination (D)	8,059	8,059
EI-IE SU Truck	Production (P)	6,442	6,442
	Attraction (A)	6,442	6,442
EI-IE MU Truck	Production (P)	37,848	37,848
	Attraction (A)	37,848	37,848

The EI-IE truck trips were classified as a distinct type of trip in order to better replicate the in-balance direction truck flows at different time periods. Before the trip distribution, the trip origins and destinations were balanced for all TAZs and external stations for the following types of trips:

- EI-IE SU truck trips of all TAZs and external stations;
- EI-IE MU truck trips of all TAZs and external stations;
- Internal-to-Internal (II) SU truck trips of all TAZs;
- Internal-to-Internal (II) MU truck trips of all TAZs;
- Internal-to-Internal (II) 4-tire commercial vehicle trips of all TAZs.

The gravity model was employed to distribute zonal trip origins to destinations. The form of the gravity model is expressed as:

$$T_{ij} = O_i \frac{D_j F(t_{ij})}{\sum_j D_j F(t_{ij})}$$

Where T_{ij}= trips between TAZ *i* and TAZ *j*;
O_i = total trip originating at TAZ *i*;
D_j= total trip destined at TAZ *j*;
$F(t_{ij})$ = friction factor between TAZ *i* and TAZ *j;*
t_{ij} = travel time between TAZ *i* and TAZ *j*.

For both internal and EI-IE truck trips, friction factors recommended in *Quick Response Freight Manual* were used as a starting point and then adjusted to replicate the local traffic condition. The recommendation has the following form:

Four-tire commercial vehicles:

$$F_{ij}=10000*e^{-0.20*t_{ij}}$$

Single Unit Trucks:

$$F_{ij}=10000*e^{-0.14*t_{ij}}$$

Multiple Unit Trucks:

$$F_{ij}=10000*e^{-0.12*t_{ij}}$$

The average travel time of all internal trip types are given in Table 59. The travel times are reported both based on the final congested travel times from the model and based on the free-flow paths used to produce the truck trips. The congested travel times also include terminal times; whereas, the free-flow times do not. The four-tire commercial vehicle has the shortest average travel time of 13.78 minutes while the internal MU truck has the longest travel time of 20.61 minutes.

Table 59. Average Truck Travel Times by Trip Type

Trip Type	Average Travel Time (minutes)	Free-flow Time (minutes)
4T commercial Vehicle	13.78	8.53
SU Truck	18.39	13.99
MU Truck	20.61	16.16

The time-of-day assignments were implemented in order to obtain better model results. To facilitate this, the trip tables from trip distribution must be factored to reflect morning peak, midday, and off-peak periods prior to trip assignment. The hourly time-of-day factors recommended in *Quick Response Freight Manual* were aggregated into the periods defined in the following table and applied for the Knoxville Regional Travel Model.

Table 60. Truck Time of Day Factors

Period	4-Tire Com. Vehicle	Internal SU Truck	Internal MU Truck	EI-IE SU Truck		EI-IE MU Truck	
				Departure	Return	Departure	Return
AM Peak – (6-9am)	19.9%	19.5%	15.4%	4.09%	15.41%	3.24%	12.16%
PM Peak – (3-6pm)	23.5%	19.4%	14.4%	12.03%	7.37%	8.97%	5.43%
Off-Peak (rest)	56.60%	61.1%	70.2%	31.15%	29.95%	35.79%	34.41%

As explained in the previous section, trip assignment for the Knoxville model follows time-of-day procedures instead of running a single 24-hour assignment. For each of three time periods, SU truck, MU truck and 4-tire commercial vehicle trip tables were developed and aggregated. Then these aggregated trip tables were assigned onto the network simultaneously with auto trips by using the multi-model multi-class equilibrium assignment method. Total 24-hour link volumes were then obtained by aggregating the truck, and auto loadings by time period.

The Knoxville model utilizes a time-of-day modeling procedure. In this procedure, a 24-hour trip table is broken into tables of AM-Peak, PM-Peak and Off-Peak periods. For each time period, a two-step assignment procedure is implemented. The first step, which is referred to as "priority pre-loading", is to assign the external-to-external trip and the truck trip tables onto the roadway network separately. Then the internal auto trips are assigned onto the network with considerations of these preloading volumes. The assignment method used is user equilibrium assignment.

The Percent Root Mean Square Error (% RMSE) is the traditional and single best overall error statistic used for comparing loadings to counts. It has the following mathematical formulation:

$$\%RMSE = \frac{\sqrt{\sum (Count - Loading)^2 / n}}{Mean\ \mathrm{Count}} \times 100$$

The current RMSE numbers for SU and MU trucks are 0.469 and 0.765 respectively. The combined RMSE for all trucks is 0.575 and the total truck VMT error is +1.02%.

Toll Choice

The Knoxville Regional Travel Model allows the user to forecast traffic and revenue on hypothetical future toll roads in the region. However, since there are no existing toll facilities in the region, this model could only be loosely calibrated for reasonableness. It should therefore be thought of as a rough forecasting tool which would require further enhancements to produce investment-grade forecasts. Despite its limitations, the tool may be useful, primarily for exploring the gross, preliminary feasibility of tolling projects and for sensitivity/risk analyses exploring the range of forecasts resulting from different sensitivity parameter and value of time assumptions.

$$Probability\ of\ Toll\ Eligibility = 1 - \frac{1}{1 + e^{\alpha\left[(Toll\ Travel\ Time - Free\ Travel\ Time) + \frac{60}{Value\ of Time * Wage\ Rate} Toll\right]}}$$

The toll choice model is a simple binary logit model for each vehicle class which divides each vehicle class into two subclasses: toll eligible and toll ineligible. The model is based only on five factors: travel times, tolls, wage rate, value of time and a sensitivity parameter (α). The tolls for autos, single unit and multiple unit trucks are supplied on the network. The value of time (as a fraction of the regional wage rate) is supplied through the user interface. The regional wage rate is calculated from the household income and worker data in the TAZ layer. The sensitivity parameters and default values of time for each vehicle class are displayed below in Table 61.

Table 61. Default Toll Choice Model Parameters

	Value of Time (% of wage rate)	Sensitivity Parameter
Passenger Cars	57.6%	0.453
Four Tire Commercial Vehicles	100.0%	0.424
Single Unit Trucks	277.3%	0.424
Multiple Unit Trucks	335.1%	0.100

Network Assignment

Once vehicle trip tables have been produced for every vehicle class, they are assigned to the model"s roadway network. External automobile trips and single and multiple unit trucks are loaded first, on the assumption that they do not divert do to congestion. Then, local automobile trips are assigned routes through the network on the "user equilibrium" assumption that only minimum congested travel cost routes are used. The new Knoxville regional model makes use of TransCAD 5.0"s origin-based algorithm to solve for the user equilibrium solution to a greater precision (0.0001 relative gap) in less time. More precise or more tightly converged assignment solutions are more stable and have more localized sensitivity.

A generalized travel cost function was used which took into account length as well as travel time, assuming that travelers value 1.45 minutes and one mile equally. Also, the generalized cost for multiple unit trucks penalizes lower functional class facilities. Congested travel speeds and times are estimated within the assignment procedure using the Bureau of Public Roads (BPR) form volume delay function. Three sets of parameters were used and are displayed in Figure 20. Volume Delay FunctionsFigure 20. In calculating volume to capacity ratios, passenger car equivalencies of 1.5, 1.8 and 3.0 were used for four tire commercial vehicles, single unit and multiple unit trucks, respectively.

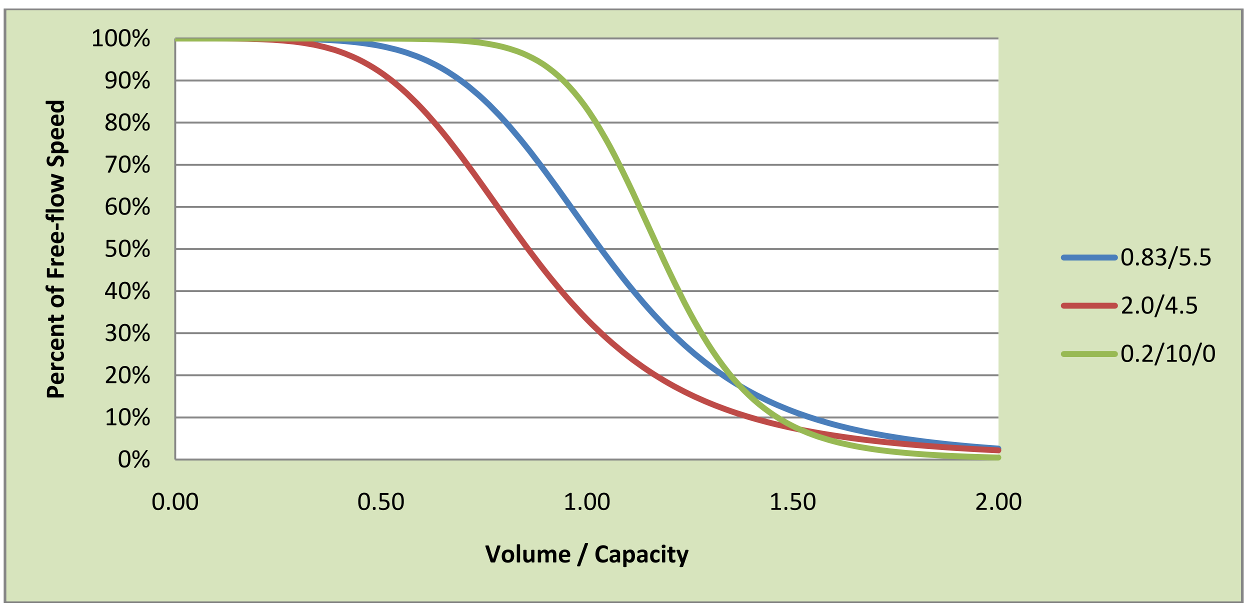

Figure 20. Volume Delay Functions

Total link daily volumes from the base year am, pm and off-peak assignments was validated by comparing the percentage difference between observed traffic count and estimated model volume on the link. The calibration/validation checks were performed based on *Minimum Travel Demand Model Calibration and Validation Guidelines for State of Tennessee.* It recommended conducting the following checks using the criteria suggested by Federal Highway Agency (FHWA),

- Percent difference in value for screenlines and link volumes
- Percent difference in volume by classification
- Correlation coefficient by link volumes
- Root mean square for link volumes

Criteria for acceptable errors between observed and estimated traffic volumes vary by facility type, according to the magnitude of traffic volume usage. For example, higher volume roadways have stricter calibration guidelines than those with lower volumes. Acceptable error ranges used for the calibration/validation efforts in this model are shown in Table 62.

Table 62. Assignment Validation Criteria

Category	Acceptable Error
Total VMT % Error	± 10%
Screenline % Error	± 10%
Freeways	± 7%
Major Arterials	± 10%
Minor Arterials	± 15%
Collectors	± 25%
All Area Types	± 10%
Volume Group 1,000 ~ 2,500 vpd	± 200%
Volume Group 2,500 ~ 5,000 vpd	± 100%
Volume Group 5,000 ~ 10,000 vpd	± 50%
Volume Group 10,000 ~ 25,000 vpd	± 20%
Volume Group 25,000 ~ 50,000 vpd	± 15%
Volume Group > 50,000 vpd	± 10%

Source: FHWA, 1997

In the Knoxville model, the CAL_REP module was developed using the Geographic Information System Developer"s Kit (GIS-DK) script language to report model performance for the:

- network as a whole,
- functional classes,
- volume group ranges,
- designated screenlines,
- designated corridors,
- area types, and
- counties.

Error statistics reported and used for diagnosing the possible sources of model error are:

- percent root mean square errors,
- systemwide average error,
- mean loading errors and percentage errors, and
- total VMT and percentage errors.

The calibration and validation tasks were based on following a decision-tree that begins with finding "global" problems in the model. This beginning approach to correct global problems then moved on the "sub-area" errors, and was completed by focusing on specific link problems. In these approaches, all roadways in the Knoxville model network with daily counts higher than 1,000 vehicles were targeted.

The global problems were first identified by a system-wide average error and a system-wide vehicle miles traveled (VMT). All model components affecting these problems were revisited and corrected where necessary. These efforts included:

- Modification to truck trip generation rates and trip lengths,
- Adjustment of intrazonal time calculation,
- Adjustment of stop sign delay,
- Varied values of length in generalized cost.

The sub-area and individual link problems were then identified and applied with the following corrections:

- Increase in Sevier County hotel room occupancy rate,
- Introduction of the external stop location choice model,
- Relocation of centroid connectors,
- Special trip generator for the airport, and
- Adjustment of volume-delay functions.

For the links where counts are higher than 1,000 vehicles per day, comparisons were made by volume group between modeled and observed traffic counts. Table 63 summarizes the errors by volume-group in comparison to calibration criteria identified in Table 62. In Table 63, "% Error" represents the percentage difference between ground counts ("Average Counts") and model estimates ("Average Loading"). The Percent Root Mean Square Error (% RMSE) is the traditional and single best overall error statistic used for comparing loadings to counts. It has the following mathematical formulation:

$$\%RMSE = \frac{\sqrt{\sum (Count - Loading)^2 / n}}{Mean\ \text{Count}} \times 100$$

A model is in a high degree of accuracy when the system-wide % RMSE of the network gets down in the range of 30%. When evaluating % RMSE for groups of links disaggregated by volume ranges, relatively large errors are acceptable for low volume groups. But, the errors should become smaller as volume increases.

The initial model run returned a RMSE value of 36%. The previous two versions of the model achieved 32.95% and 31.96% RMSE. After model calibration, the system-wide RMSE is 28.13%. On the whole, the model is at -5.22% loading error and -0.46% VMT error. The "Acceptable Range" column shows the acceptable percent error ranges adopted for this model. Comparison of the percent error with the acceptable range indicates that the model far exceeds the calibration minimum criteria for all volume ranges. Also, as volume increases, smaller % RMSE and % errors are observed.

Table 63. Model Performance by Volume Group

Volume Range	Average Counts	Average Loading	% Error	Acceptable Range	% VMT Error	% RMSE
1,001 to 2,000	1,495	1,706	14.2	±200%	27.1	86.9
2,001 to 3,000	2,434	2,619	7.6	±200%	16.4	73.8
3,001 to 4,000	3,496	2,917	-16.6	±100%	1.1	58.0
4,001 to 5,000	4,454	4,351	-2.3	±100%	-2.0	55.4
5,001 to 6,000	5,520	5,277	-4.4	±50%	4.6	45.0
6,001 to 8,000	6,964	6,682	-4.1	±50%	0.2	37.3
8,001 to 10,000	8,918	7,759	-13.0	±50%	-11.6	35.5
10,001 to 15,000	12,245	11,847	-3.3	±20%	-1.7	33.7
15,001 to 20,000	17,495	15,795	-9.7	±20%	0.2	27.7
20,001 to 25,000	22,049	20,942	-5.0	±20%	2.1	17.1
25,001 to 30,000	27,576	26,227	-4.9	±15%	-0.8	16.6
30,001 to 40,000	33,575	32,089	-4.4	±15%	-5.0	16.9
40,001 to 50,000	44,706	43,609	-2.5	±15%	0.3	12.9
50,001 to 60,000	54,064	51,892	-4.0	±10%	-3.1	7.2
> 60,000	73,336	68,944	-6.0	±10%	-5.2	8.0
All	**12,242**	**11,603**	**-5.2**	**±10%**	**-0.5**	**28.1**

The correlation coefficient estimates the correlation between the actual ground counts and the estimated traffic volumes, and can be obtained using the linear regression method. For a regional model, a correlation coefficient of more than 0.88 was suggested by FHWA. The linear regression results of the Knoxville model are shown in Figure 21. The correlation coefficient is 0.922 and greater than the 0.88 minimum that was suggested by FHWA. The results indicate a good performance of the model at the overall level.

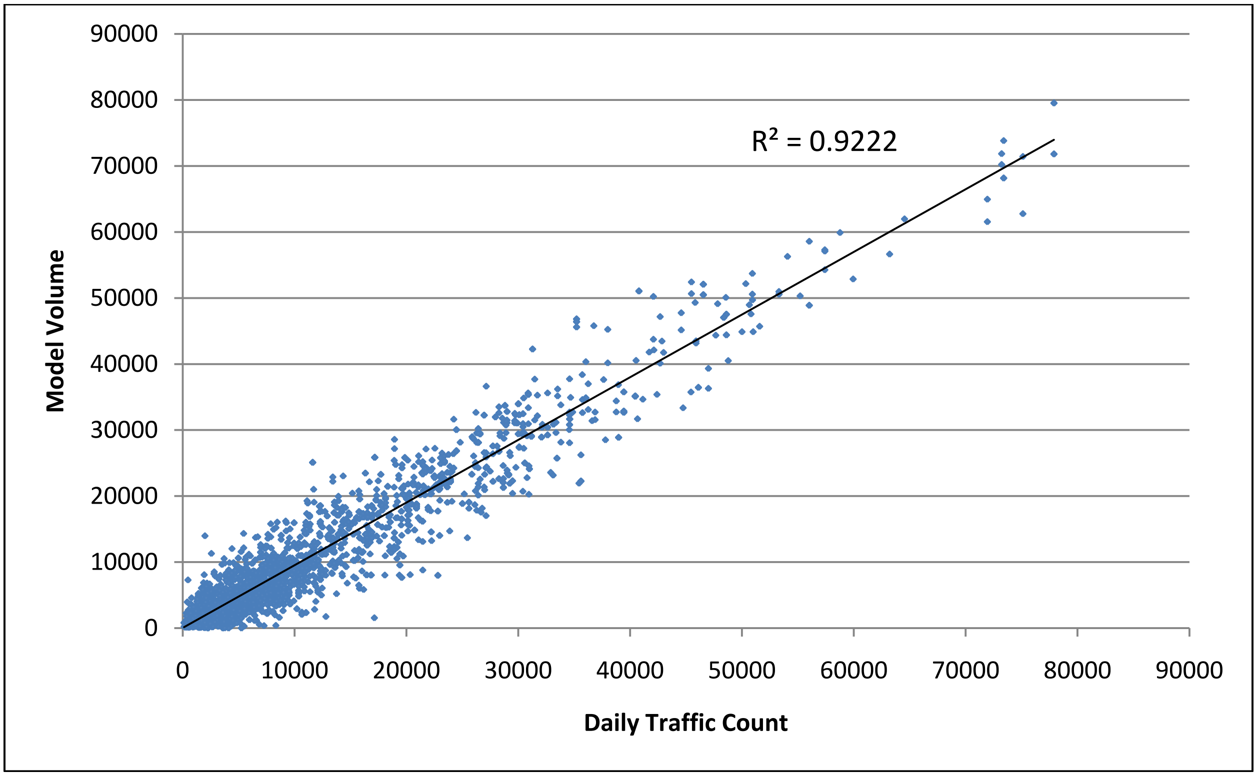

Figure 21. Daily Traffic Count vs. Model Volume

Table 64. Model Performance by Functional Class

Functional Class	Area Type	Average Counts	Average Loading	% Error	Acceptable Range	% VMT Error	% RMSE
Interstates	Urban	38,050	36,131	-5.0	±7%	-4.6	12.5
	Rural	24,387	25,995	6.6	±7%	6.3	10.4
Principal Arterials	Urban	22,972	21,823	-5.0	±10%	-3.6	19.7
	Rural	12,213	12,594	3.1	±10%	13.7	22.2
Minor Arterials	Urban	11,378	10,359	-9.0	±15%	-11.9	35.1
	Rural	8,993	9,873	9.8	±15%	10.1	33.8
Collectors	Urban	7,207	6,699	-7.0	±25%	-9.9	42.5
	Rural Major	3,823	4,372	14.4	±25%	20.2	59.2
	Rural Minor	2,604	2,774	6.5	±25%	6.2	63.5
Local Roads	Urban	4,801	3,994	-16.8		-20.5	53.0
	Rural	2,903	2,350	-19.1		-2.9	56.2

Table 64 and Table 65 provide assignment statistics by road functional classification and for major highway corridors in the study area, respectively. Table 64 also displays the expected general pattern of lower errors on higher volume, higher functional classes and increasing errors on lower volume, lower functional classes. Error statistics summarized in Table 65 also shows the accuracy of the model for 11 major highway corridors.

Table 65. Model Performance on Major Corridors

Major Corridor	Average Counts	Average Loading	% Error	% VMT Error	% RMSE
I-40	44,384	43,568	-1.8	1.8	10.4
I-75	27,402	28,465	3.9	4.0	8.1
I-275	30,351	31,897	5.1	5.2	10.8
I-640	32,149	27,502	-14.5	-17.8	17.0
I-81	19,667	20,104	2.2	4.4	4.2
I-140	21,998	21,185	-3.7	-6.7	13.4
Chapman Hwy	30,379	32,080	5.6	-1.9	19.6
US129	32,342	32,481	0.4	-0.1	9.9
SR66/US321	34,311	30,183	-12.0	-8.5	20.0
Pellissippi Pkwy	21,594	19,401	-10.2	-10.3	10.3
SR62	21,878	20,571	-6.0	-4.6	15.5

Table 66 and Table 67 summarize assignment statistics for area types and counties. Performance by area type is summarized for major employment district, urban, suburban, and rural areas. All area types show errors within the acceptable range. The model does show overloading in rural areas and underloading in urban areas. The overloading in rural areas is likely due in part to the sparseness of the network and coarseness of the zones in these parts of the model. The statistics are presented for all roadway classes including local roads used for access/connectivity in the model. If these local roads were excluded, the model would show even greater accuracy.

Table 66. Model Performance by Area Type

Area Type	Average Counts	Average Loading	% Error	Acceptable Range	% VMT Error	% RMSE
Major Employment District	14,127	13,612	-3.6	±10%	-7.7	30.6
Urban Areas	13,005	11,968	-8.0	±10%	-7.7	27.3
Suburban Areas	12,421	11,609	-6.5	±10%	-3.0	24.5
Rural Areas	9,205	9,518	3.4	±10%	6.5	28.5

Table 67. Model Performance by County

County	Average Counts	Average Loading	% Error	% VMT Error	% RMSE
Anderson	11,675	11,410	-2.3	4.82	31.6
Blount	9,005	8,290	-7.9	-6.44	28.5
Jefferson	3,491	5,218	49.5	18.63	66.4
Knox	9,786	11,791	20.5	-4.62	33.5
Loudon	13,315	12,385	-7.0	7.44	27.6
Roane	11,597	12,130	4.6	10.48	20.8
Sevier	10,976	11,140	1.5	0.37	28.6
Union	12,649	11,756	-7.1	17.70	29.7

Nine screenlines were used to evaluate the performance of the model, as well. The screenlines included the four previously used for validation of earlier versions of the model, including the Knox-Blount County border, the Knox County boundary, the Blount County boundary and the combined Knox and Blount counties boundary. Five additional screenlines were also included in this calibration effort and are displayed in Figure 22.

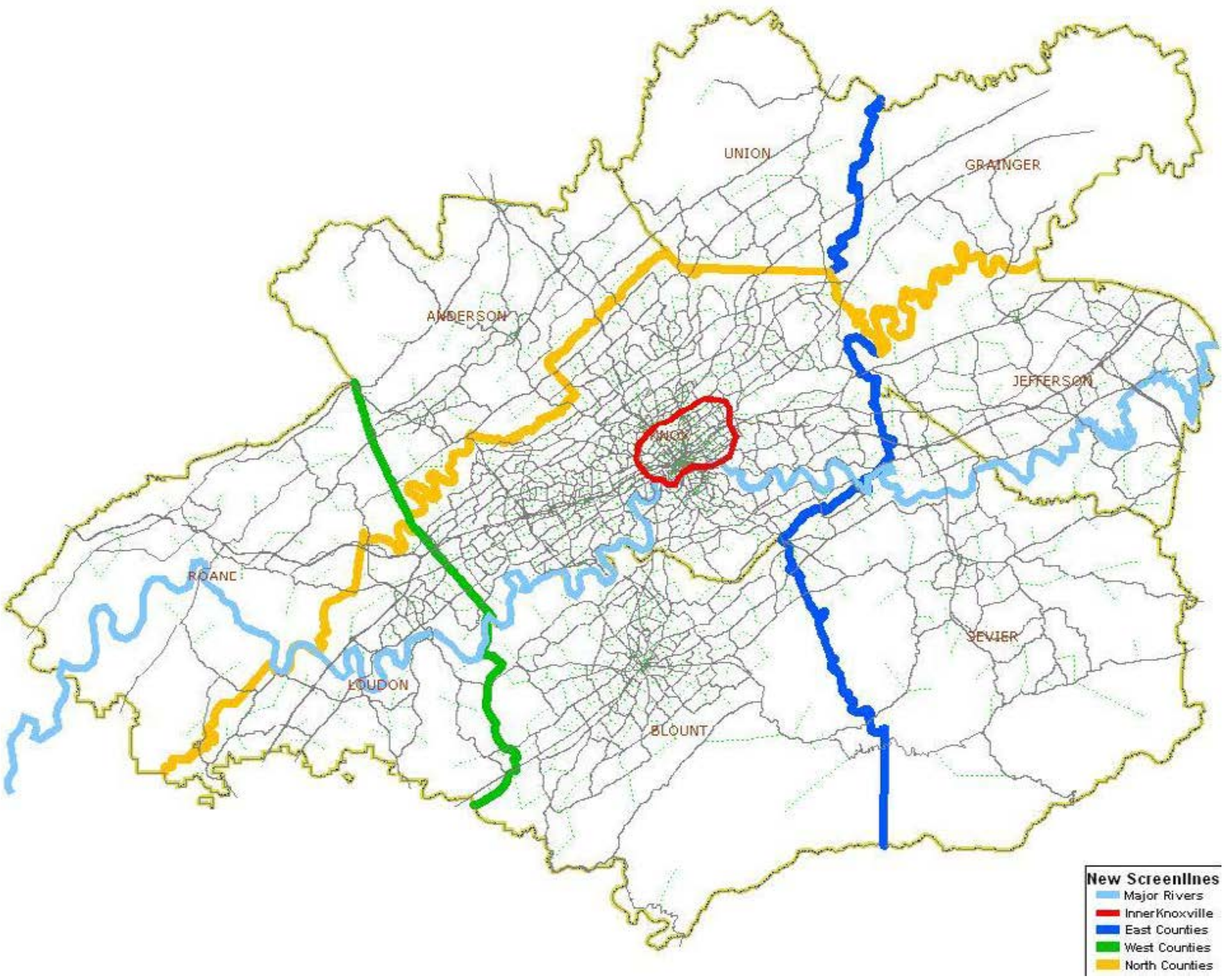

Figure 22. New Screenlines

Table 68. Model Performance on Screenlines

Screenline	Average Counts	Average Loading	% Error	Acceptable Range	% RMSE
Knox - Blount Border	22,957	21,814	-5.0	±10%	6.2
Knox & Blount Boundary	12,469	13,655	9.5	±10%	24.0
Knox Co Boundary	17,316	18,111	4.6	±10%	18.2
Blount Co Boundary	10,362	10,826	4.5	±10%	17.1
Rivers	17,084	18,062	5.7	±10%	19.5
Inner Knoxville	19,391	18,712	-3.5	±10%	22.8
East Counties	10,928	10,900	-0.3	±10%	31.5
West Counties	18,816	20,072	6.7	±10%	19.0
North Counties	11,397	12,576	10.4	±10%	19.6

Table 68 reports the screenline errors, all of which are within the generally acceptable range except for the North Counties screenline separating Roane, Anderson, Union and Grainger counties from the remainder of the model area. Most of the screenline errors show that the model is performing quite well and accurately reproducing intra-regional movements. The North Counties screenline crossings was slightly over 10%. It is worth considering, however, that the calibration criteria being applied here were established for urban models, but are being applied to a truly regional model. The volumes on major screenlines in urban models are generally higher in volume and therefore, lower percent errors can be expected. The North Counties screenline, as well as several other screenlines in the Knoxville model, include many low volume rural roads on which larger percent errors are generally accepted. Considering this and given the overall accuracy of the model as attested to by all the other criteria, the Knoxville Regional Travel Model can be considered well-calibrated despite the North Counties screenline error exceeding 10%.

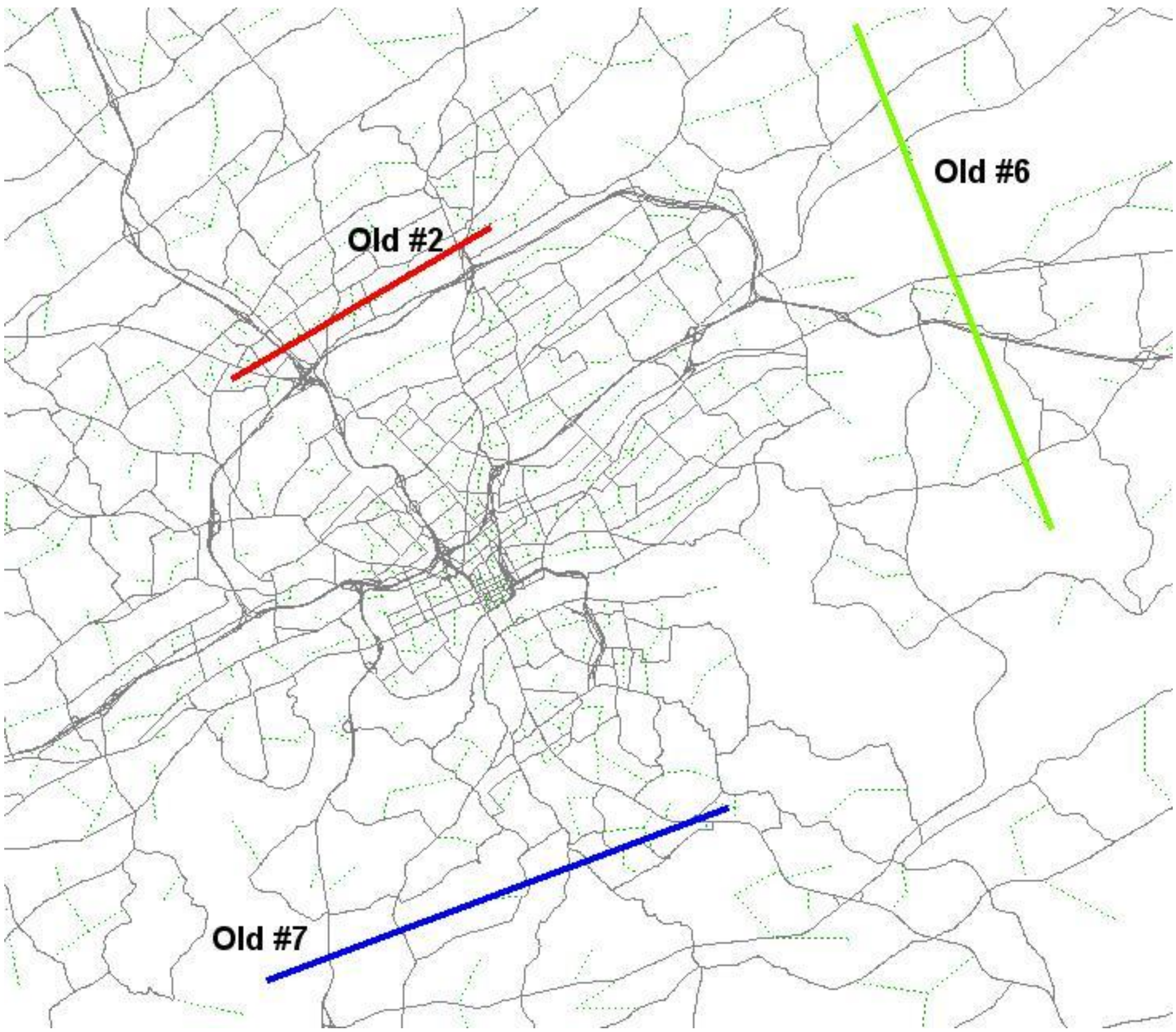

Figure 23. Calibration Cutlines from the Old MINUTP Model

Calibration statistics were also calculated on several cutlines defined for the old MINUTP model at the request of TDOT. These cutlines, shown in Figure 23, provide an indication of the model‟s performance with shorter distance, more urban travel in the more central part of Knox County as compared with the regional screenlines. The model performs acceptable on all three cutlines, with loading errors less than +/-10%.

Table 69. Model Performance on Cutlines

Cutline	Average Counts	Average Loading	% Error	Acceptable Range	% RMSE
Old #2	19,087	19,305	1.1	±10%	12.6
Old #6	21,888	20,035	-8.5	±10%	13.8
Old #7	21,519	20,562	-4.4	±10%	9.9

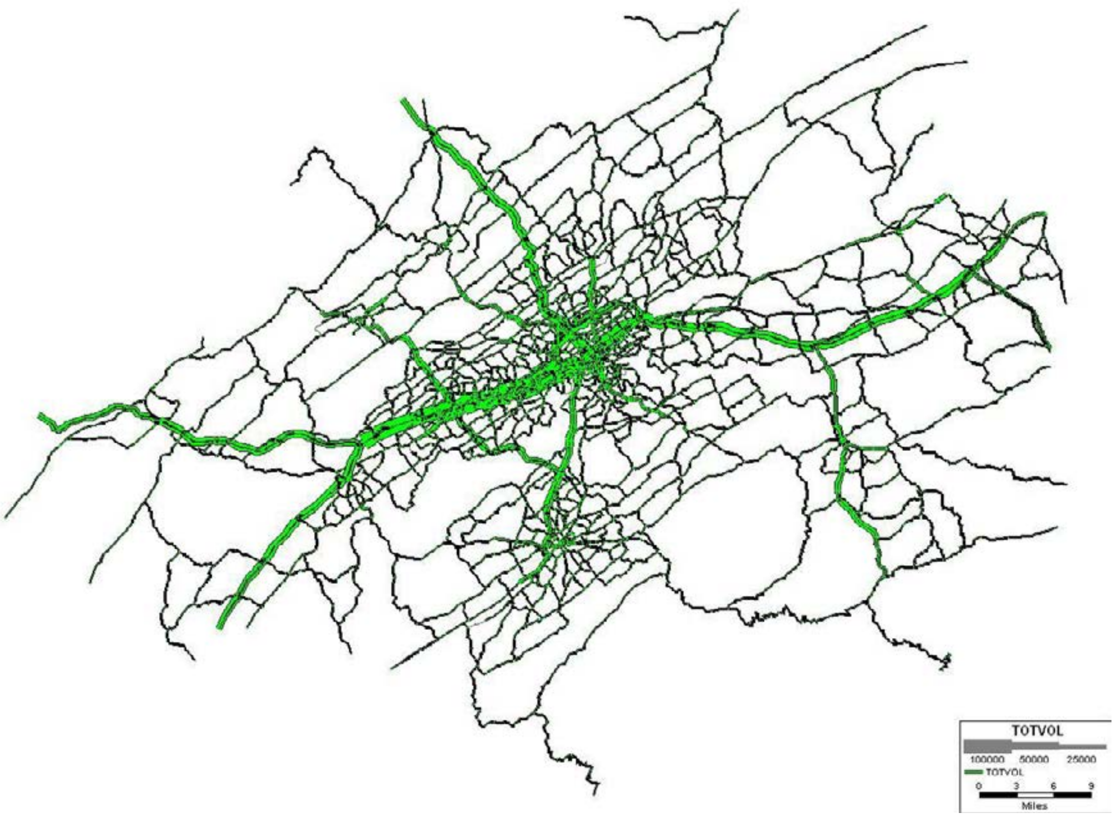

Figure 24. Knoxville Loaded Regional Network

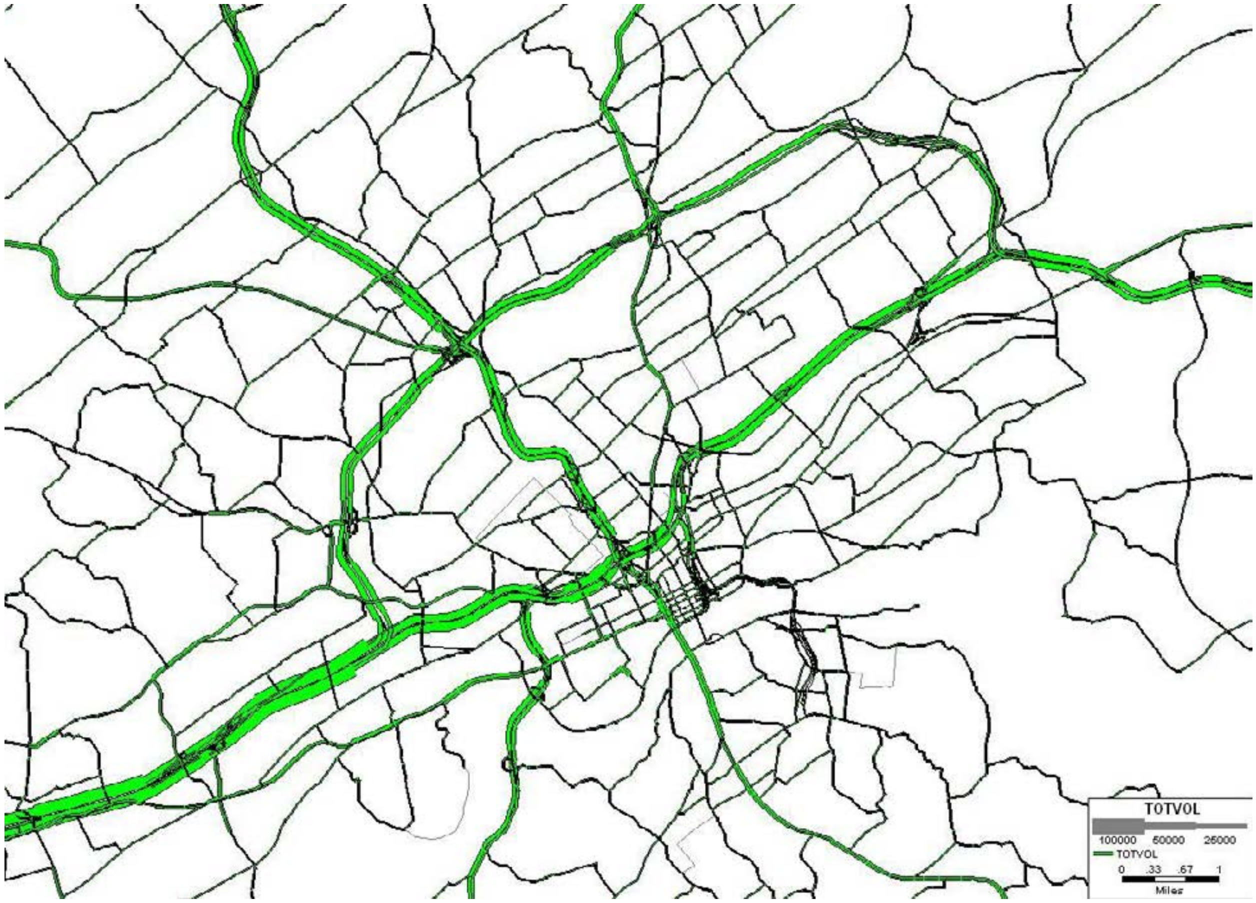

Figure 25. Knoxville Loaded Network (central area detail)

Although previous versions of the Knoxville Regional Travel Model were able to be acceptably calibrated, the new, updated model offers even more accurate performance versus base year counts. The previous version of the model, calibrated to the same 2006 base year and counts resulted in a global RMSE of 32.95% compared to the 28.13% achieved by this model. This represents a 14.6% improvement in the overall accuracy of the model"s loadings versus observed counts. The correlation coefficient and other statistics also reflect this improvement. Moreover, the new model made use of only three volume delay curves and fewer than five centroid connectors were adjusted. On the whole, it is fair to say that the new model achieved its improved accuracy with less calibration adjustments than its predecessors required. Moreover, it is worth recalling that the model also offers a 33% improvement versus its predecessor reproducing the origin-destination patterns observed from the household surveys. It seems reasonable, therefore, to assume the improved loadings are largely a result of improved origin-destination patterns. Although the model still produces notable errors versus observed data, given the improved loadings, origin-destination patterns and the few calibration adjustments, some increased confidence in the model"s forecasts is likely warranted.