Activity-Based Model for Highway Pricing Studies at CMAP

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Main Approach to Demonstration of Pricing ABM

This memorandum describes the first version of an activity-based model for pricing studies (Pricing ABM) for CMAP which is based on PB's CT-RAMP platform. The document also describes the data needs, network preparations, software adjustments, and hardware requirements for the model. This document also incorporates multiple discussions between PB and CMAP staff that finalized the methodology and technical approach for model system development. There were three major goals for this project:

- This project was considered a *first phase in the development of a fully-fledged and fully-functional ABM* that will serve the planning needs of CMAP over the long term. For this reason, we wanted to avoid "surrogates" and dead-end intermediate solutions, as well as model simplifications that would require "starting over" in the future. Our intention was to deliver a complete methodological approach and flexible software system that could be extended in the future but would have all primary functions in place.
- The project scope and budget did not allow for the complete development of a regional ABM (design-estimation-implementation-validation-calibration). Thus, certain simplifications and borrowing from existing CT-RAMP ABMs was necessary. Our plan was to *borrow sub-models that proved to be relatively generic across different regions* (population synthesis, long-term models, and activity-generation components of the Coordinated Daily Activity-Travel Pattern) while the *tour-level and trip-level sub-models for destination choice, time-of-day choice, and mode choice were restructured and re-estimated* based on CMAP's 2007 Travel Tracker household travel survey. The restructuring primarily addressed the needs of highway pricing studies.
- The model system will not be immediately used for planning studies at CMAP. Instead, it will serve as a *demonstration tool* for the concept, model structure, and software. The model system was not fully calibrated across all possible dimensions (highway, transit, and non-motorized modes for each time-of-day period). The focus of this project was on producing a reasonable replication of highway and overall targets developed based on the CMAP household travel survey. Additional goals included the demonstration of model sensitivity to various pricing policies and the general viability of the CT-RAMP model structure and software for a region of CMAP's size and complexity.

There are several key decisions that the CMAP staff and PB team made before the approach was finalized. They are summarized in **Table 1**. The bold features correspond to the currently adopted approach and implemented model structure.

Table 1: Summary of Key Decisions

Model feature	**Implications for model results**	**Implications for software and/or hardware**
Full simulation or sample enumeration (e.g. 1/10)	Certain "lumpiness" especially for small projects but acceptable overall for demonstration of main elasticities and comparison across scenarios	10% sample can be implemented on a single dual or quad core processor and it would not require distributing. **Full simulation for the CMAP area required a new computer cluster purchased by CMAP.**
Transferred model components and components developed specifically for CMAP (see flowchart below)	Transferred model components may be somewhat off and require more extensive calibration (see the validation section below for detailed analysis of each sub-model)	
Mode choice model structure on the highway side (must be supported by corresponding sets of skims and multi-class assignments)	Main modes by occupancy (3-4 categories): **1=SOV** **2=HOV/2** **3=HOV/3** **4=HOV/4** (not used since CMAP does not envision specific HOV4 policies; this was combined with HOV/3) Sub-modes by route-type choice: **1=toll / managed lane** **2=non-toll / managed lane** **3=non-toll / general-purpose lane** (the last two non-toll options were combined since no managed lane projects were considered)	Proliferation of highway modes and sub-modes affects runtime (mode choice, assignment, skimming) proportionately; this leads to implementation of traffic assignment for each of the 8 time-of-day periods in parallel; enhancement of the computing cluster to 8 computers is desired in this regard)
Mode choice model structure on the transit side (must be supported by a corresponding sets of skims which were held constant for the pricing demonstrations)	Main modes: **1=Local Bus/Express Bus** **2=LRT/Subway/Metro** **3=Commuter Rail** Access modes (combination of P&R and K&R skims is possible for the first versions): **1=Walk to transit** **2=P&R** **3=K&R**	Proliferation of transit modes and sub-modes affects runtime (mode choice, assignment, skimming) proportionately.

Model feature	Implications for model results	Implications for software and/or hardware
Mode choice model structure for non-motorized and special modes	**Walk and bike modeled as separate modes** or together. Real separation would require a network of bike lanes or LOS estimates. It is not essential for pricing studies unless area pricing schemes are considered.	Placeholders for both non-motorized modes were created in the mode choice structure with currently simplified LOS variables based on highway distance
Population data available at the TAZ level and smaller unit (see table in the Population Synthesis Section)	Quality of population synthesis is a direct function of the controlled data. However, a reasonable level of "freedom" has to be ensured for population synthesis	
Employment data available at the TAZ level (and smaller units)	Detailed employment and other LU data directly affect quality of the Destination Choice procedure (**2-digit NAICS codes provided by CMAP**)	
School (K-12) and university enrollment data	Enrollment data by grade (**K-8, 9-12, major universities, small colleges**) is essential for a good set of school-related models; was provide by CMAP	
Parking choice for auto trips	Essential for parking policies and areas with constrained parking. Requires additional data on parking supply. Parking cost estimates by TAZ (hourly and daily) are needed as well as proportion of free vs. paid parking.	Additional choice model that somewhat affects runtime but not significantly; currently has been added to the model system as a placeholder with some synthetic data on parking rates and capacities by TAZ
Pedestrian environment quality variables	Was successfully incorporated in the mode choice model and proved to be significant in transit mode utilities with a differential effect by origin and destination	
Hourly traffic counts	Needed for final model validation	

Model Structure of the CMAP Pricing CT-RAMP ABM

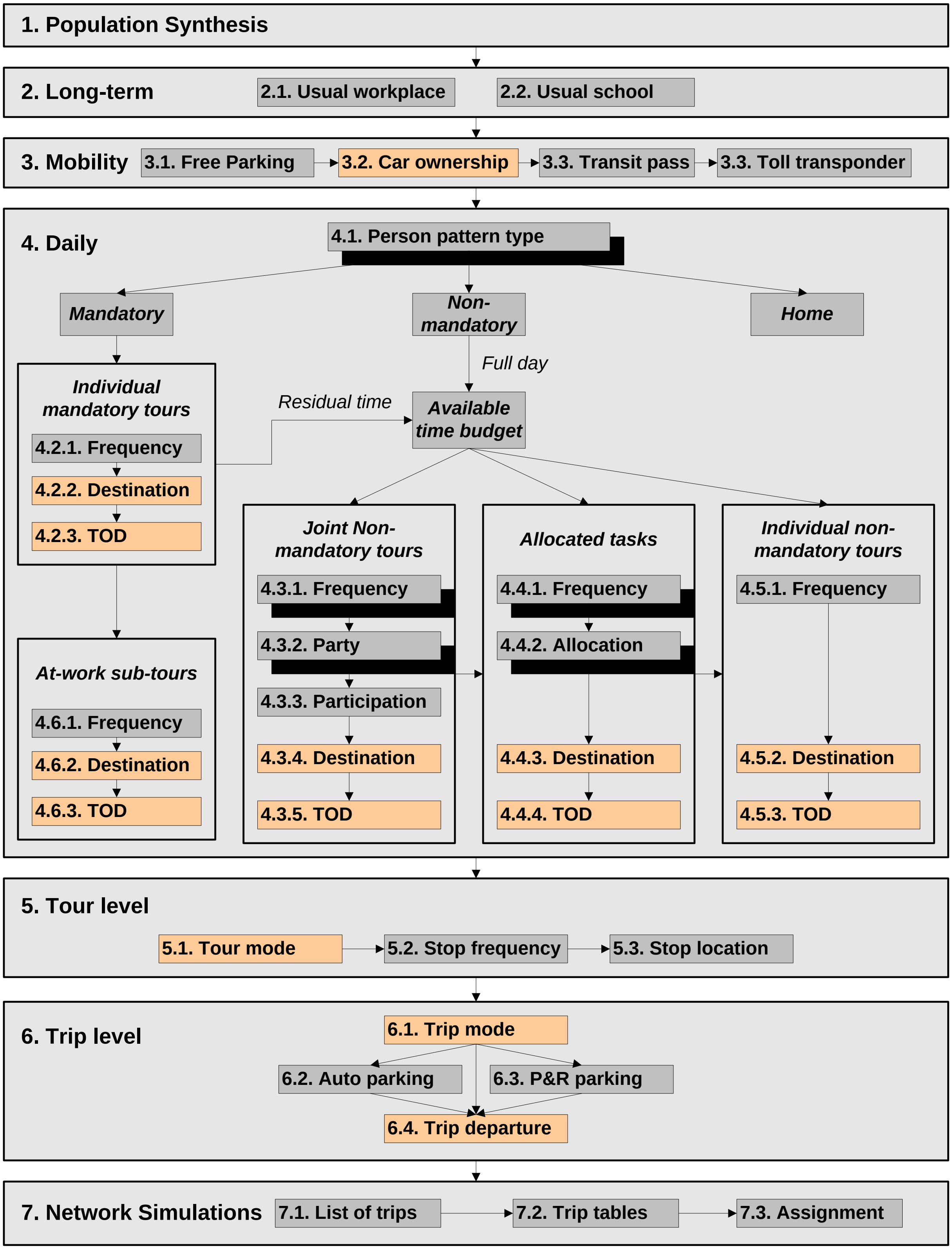
This section describes the structure and implementation of seven different regional Activity-Based Models (ABMs) that share the CT-RAMP conceptual design and software platform. A key feature of the CT-RAMP model is that intra-household interactions are explicitly represented across a wide range of activity and travel dimensions. This important feature allows for greater behavioral realism in representing the response to numerous transportation policies. Modeling intra-household interactions allows for the very real travel constraints and synchronization among household members to influence traveler decisions. This feature of CT-RAMP is particularly relevant for modeling the response to the implementation or expansion of High-Occupancy Vehicle (HOV) and High-Occupancy Toll (HOT) lane facilities as well as other projects and policies that specifically target vehicle occupancy. Another key distinguishing feature of CT-RAMP is that mandatory activities are generated and scheduled before non-mandatory activities are generated. The use of residual (available) time-windows in the generation of non-mandatory activities provides increased sensitivity to travel costs in the consideration of induced travel.

The first ABM of the CT-RAMP family was developed in 2004 for the Mid-Ohio Regional Planning Commission (MORPC) located in Columbus, OH. The Columbus core model structure was adapted for the Tahoe Regional Planning Agency (TRPA) in 2006. The Lake Tahoe ABM included special components to account for the seasonal variability in the Lake Tahoe regional population and travel moving to/from/through the region. The third and fourth ABMs of the CT-RAMP family have been developed in parallel for the Atlanta Regional Commission (ARC) and the San Francisco Bay Area's Metropolitan Transportation Commission (MTC). The ARC model system is now fully calibrated and validated and is being applied to various policies, while the MTC models are undergoing final calibration and will be applied in fall 2010. Three new members of the CT-RAMP family were added in 2008 and 2009, including: San Diego, CA, for the San Diego Association of Governments (SANDAG); Phoenix, AZ, for the Maricopa Association of Governments (MAG); and Jerusalem, Israel, for the Jerusalem Transportation Master Plan Team (JTMT).

Each member of the CT-RAMP family has some distinctive features that were added to the CT-RAMP basic design to better address the regional travel conditions and specifics of the projects of interest. In particular, the last three CT-RAMP implementations (for San Diego, Phoenix/Tucson, and Jerusalem) have many additional advanced features compared to the initial design. The possibility to modify the basic CT-RAMP structure and adding new features is based on the modular OOP software architecture. This feature played an important role in our project since we transferred the CT-RAMP basic structure to Chicago with some modifications and additions to address a wide range of pricing studies.

The standard CT-RAMP structure flowchart is presented in **Figure 1** with the orange-highlighted models specifically redesigned and estimated for based on CMAP's 2007 Travel Tracker household travel survey.

Figure 1: CT-RAMP Structure and Sub-Models Redeveloped for the Chicago Region



Choices that relate to the entire household or a group of household members and assume explicit modeling of intra-household interactions (sub-models 4.1, 4.3.1, 4.3.2, 4.4.1, and 4.4.2) are drop shadowed in **Figure 1**. The other models are assumed to be individual-based for the basic design.

Sub-model set 1: Population synthesis. The model system uses a synthetic household population as base input. Thus, this component comes first in the model chain. The population synthesis procedure creates a list of households, with all household and person attributes based on the input (control) variables defined for each traffic zone. The procedure creates a household distribution in each zone that matches control variables and generates a list of discrete households with additional (uncontrolled) variables by drawing them from the sample data provided by the Census (PUMS or ACS).

Sub-model set 2: Long-term location choices. These sub-models include:

- The usual workplace choice for each worker (sub-model 2.1), taking into account the person occupation.
- The usual school location choice for each student, (sub-model 2.2) taking into account the school type (university, college, high school, elementary school, kindergarten, day care, etc).

Work from home and schooling from home are singled out as special choices alternatives and modeled explicitly.

Sub-model set 3: Mid-term choices of individual mobility attributes. These sub-models predict the following set of household and person attributes:

- Free parking eligibility for workers in the CBD (sub-model 3.1); determines whether workers pay to park if the workplace is in a zone with paid parking.
- Household car ownership (sub-model 3.2)
- Transit pass holding for each person (sub-model 3.3)
- Transponder ownership for use of toll facilities (sub-model 3.3)

Sub-model set 4: Coordinated Daily Activity-Travel Pattern. These sub-models generate and schedule main activities and travel tours for each household member.

The daily activity pattern-type of each household member (model 4.1) is the first travel-related sub-model in the modeling hierarchy. This model classifies daily patterns by three types: 1) mandatory (includes at least one out-of-home mandatory activity), 2) non-mandatory (includes at least one out-of-home non-mandatory activity, but no out-of-home mandatory activities), and 3) home (does not include any out-of-home activity). However, the pattern-type sub-model leaves open the frequency of tours for mandatory and non-mandatory purposes (maintenance, discretionary) since these sub-models are applied later in the model sequence. The pattern choice set contains a non-travel option in which the person can be engaged in an in-home activity only (purposely or because of being sick) or can be out of town. Daily pattern-type choices of the household members are linked in such a way that decisions made by some members are reflected in the decisions made by the other members. It is implemented as a joint choice of pattern-type by all household members that considers all possible combinations as alternatives.

The next set of sub-models (4.2.1-4.2.3) defines the frequency and time-of-day for each mandatory (work and school) activity/tour for each household member (note that locations of usual destinations for mandatory tours have already been determined in long-term choice models). Mandatory tour time-of-day (sub-model 4.2.3) is defined as a combination of departure time from home and arrival time back home for each tour. The scheduling of mandatory activities is generally considered a higher priority decision than any decision regarding non-mandatory activities for either the same person or for the other household members. As a result of the mandatory activity scheduling, "residual time windows" are calculated for each person and their overlaps across household members are estimated. Time window overlaps, which are left in the daily schedule after the mandatory commitment of the household members has been made, constitute the potential for joint and non-mandatory travel. In some CT-RAMP models, work or school tour destinations are assumed to always be the usual workplace or school locations. This is a reasonable assumption for more than 90% of mandatory tours. This essentially eliminates sub-model 4.2.2. In general, this sub-model can be applied to identify cases where a different destination is visited.

The next major model component relates to joint household travel. Joint travel tours are generated and scheduled conditional upon the available time window left for each person after the scheduling of mandatory activities. This model component produces a number of joint tours by travel purpose for the entire household (sub-model 4.3.1), travel party composition in terms of adults and children (sub-model 4.3.2), and then defines the participation of each household member in each joint household tour (sub-model 4.3.3). It is followed by choice of primary destination (sub-model 4.3.4) and time-of-day (sub-model 4.3.5) for each joint tour.

The next stage relates to maintenance tours (shopping and other household-related errands). Maintenance tours are generated by the household (sub-model 4.4.1) and allocated to a single person within the household for implementation (sub-model 4.4.2). Their destination and time-of-day are chosen next for each maintenance tour (sub-models 4.4.3 and 4.4.4). Time-of-day choices for multiple tours are modeled sequentially for each individual in order to ensure consistency of the person daily schedule.

Discretionary tours are modeled entirely at the individual level. The models include tour frequency (sub-model 4.5.1) followed by choice of destination (sub-model 4.5.2) and time-of-day (sub-model 4.5.3) for each tour. Again, time-of-day choices for multiple tours are modeled sequentially for each individual in order to ensure consistency of the person daily schedule.

At-work sub-tours starting and ending at the workplace are modeled next, taking into account the time-window constraints imposed by their parent work tours. The sub-models include frequency of at-work sub-tours (sub-model 4.6.1) followed by primary destination choice (sub-model 4.6.2) and time-of-day choice (sub-model 4.6.3).

Sub-model set 5: Tour-level details. The next set of sub-models relate to the tour-level details on tour mode combination (sub-model 5.1), exact number of intermediate stops on each half-tour and their purpose (sub-model 5.2), and location of stops by order of implementation on each half-tour (sub-model 5.3). This sub-set of models is the least transferrable compared to the other sub-model sets. This is primarily because of the mode choice specifics in each region stemming from the fact that different mode-specific networks play different roles in regional mobility in different metropolitan areas. This model component was completely re-estimated and calibrated for the Chicago region using the recent Travel Tracker household travel inventory from 2007.

Sub-model set 6: Trip-level details. These sub-models add details for each trip including trip mode details conditional upon the tour mode combination (sub-model 6.1), parking location for auto trips (sub-model 6.2), park & ride parking location choice (sub-model 6.3 that has so far been applied for the Jerusalem ABM), and departure time for each trip from/to home, primary destination, or secondary stop within the tour time-of-day window (Sub-model 6.4.). The parking location for auto trips does not necessarily coincide with the trip destination. If parking capacity is constrained and/or parking cost is high, drivers may choose to park remotely and then walk to the destination.

Sub-model set 7: Network simulations. This component encapsulates the interface between the demand model system and network simulation model. The CT-RAMP ABM system first generates a full list of individual trips for the entire regional population with all necessary attributes for a network simulation such as origin, destination, mode, departure time, travel party size, value of time, etc (sub-model 7.1). This format can be utilized directly by a traffic microsimulation or DTA model. If needed, individual trips can be summarized into trip tables by mode and time-of-day as required for conventional static traffic assignments and transit assignments (sub-model 7.2). Finally, trip assignments for auto and transit trips based on route choice in the network equilibrium framework are implemented (sub-model 7.3). This is not a CT-RAMP component per se; assignment (whether static or dynamic) and skim-building were implemented using Emme. CT-RAMP was fully equilibrated with the Emme procedures in a feedback framework.

In the CT-RAMP model chain, sub-models 4-6 are interlinked through various log sum measures and time-space constraints. In addition, the upper-level sub-models 2-3 are fed by various accessibility measures that are sensitive to travel time and land use densities. The entire model system (sub-models 1-7) is integrated with highway and transit network simulation procedures and applied iteratively with special provisions for reaching global demand-supply equilibrium.

Model Requirements for Pricing Projects and Policies

An assessment of modeling requirements must necessarily start with a good understanding of the types of tolling applications under study. In terms of modeling requirements, the potential tolling applications can be classified as follows:

- Traditional projects: new toll roads and new toll bridges,
- Existing freeways or bridge tolling,

- Tolled managed lanes: HOT lanes, express lanes, and truck-only lanes, including dynamically priced lanes,
- Cordon or area pricing: at an inner cordon or at the urban growth boundary,
- Mileage-based road pricing.

There are model requirements that apply to any road pricing study, while others are relevant only for specific applications. Some model requirements are considered essential, while others may be left for advanced stages of the study. **Table 2** lists the modeling requirements corresponding to the typology of tolling applications listed above. At a minimum, the mode choice and assignment models must be sensitive to the toll cost through the use of generalized cost functions and adequate VOT segmentation. A more advanced treatment would include considering the delays at toll plazas and access ramps (if any), further segmentation of VOT, addressing travel time reliability, including pre-route toll versus no toll choice, and equilibrating generalized cost through trip distribution, in addition to mode choice equilibration. There are several examples of U.S. travel demand models in practice (in particular, ABMs applied by the PB team members in New York, San Francisco, and Montreal) that already incorporate at least some of these features, with the exception of travel time reliability.

From a modeling perspective, these applications can be further grouped into two general classes: facility-specific tolling (one or more roads), or cordon/area pricing tolls, which would include mileage-based pricing. The main difference between these two groups is the importance of the trip frequency/trip generation decision. Under cordon/area pricing or ubiquitous mileage-based schemes, it is essential to model the trip suppression effect of the toll. On the other hand, pre-route choice is less important because all possible routes would be tolled, and therefore there would be no free alternative.

Advanced modeling of the long-term effects of these types of schemes necessarily requires integration with a land use model, so that decisions about residential location and commercial land use can be informed by the region-wide changes in the cost of travel. This is particularly important when the policy under consideration seeks to influence land use patterns. The corresponding components of the travel ABM are closely intertwined with components of the land use model; this particular aspect was left open in the current project.

In the framework of the current project, the list of sensitivity tests and corresponding projects/policies for demonstration of the Pricing ABM was suggested by CMAP and included two different toll increase strategies on the existing toll facilities only. The first strategy included raising tolls by a factor of 5 in all time-of-day periods. The second strategy included raising tolls by a factor of 5 in peak periods only (7:00-9:00 AM and 4:00-6:00 PM). All essential features listed in **Table 2** were incorporated. Many of the advanced features were also incorporated while some other ones were reserved for further model improvement efforts. A subset of advanced features included in the current version of CMAP CT-RAMP is summarized in the next sub-section.

Table 2: Summary of Model Features by Type of Pricing Applications

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

Two other equally important aspects of travel model design are the nature of the toll schedule, in particular differences in toll or price across vehicle types and vehicle occupancy, time-of-day, static versus dynamic pricing, and the nature of policies that complement the pricing application, such as improvements to transit service or parking restrictions. The requirements for the most likely tolling options are also listed in **Table 2**. These tolling application options cut across the types of projects listed above. For example, a peak spreading and/or time-of-day choice model would be required if the study is considering variable time-of-day pricing, regardless of whether the application is freeway- or cordon-based.

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

- Congestion pricing necessarily implies that tolls would vary by time-of-day, and possibly by vehicle type; therefore, the model needs to be sensitive to time-of-day travel decisions with a fine level of temporal resolution, whether just within the peak periods (peak spreading model) or across time periods (time-of-day choice model).

- Dynamic pricing requires that tolls be set as a function of congestion levels in a real-time basis. This type of tolling schedule can only be modeled using advanced toll equilibration procedures between the network simulation and the demand model.

- HOT and express lane studies, where the tolls may vary by car occupancy levels, require specific modeling of the occupancy choice, as well as assignment stratification by occupancy levels to restrict unpermitted vehicle types from using the managed lanes. Sensitivity to household size is highly desirable, since opportunities to form carpools as well as the need to do so are greater in large households and among families with children.

- Transit improvements and restrictive parking policies are often studied as policies complementary to road pricing. To do so requires adequate treatment of the transit options and parking costs throughout the model.

The modeling requirements listed in **Table 2** as "essential" for the analysis of truck-only lanes may appear fairly modest, but they reflect the state of the practice. There is a high degree of complexity associated with how the freight transport sector responds to tolls and other road transport level of service attributes, and we are not aware of any operational model with a proven ability to capture these effects. The concurrent CMAP freight project by Cambridge Systematics should be able to supply segmented freight demand trip tables for different types of trucks, commercial vehicles, and time-of-day periods. This should be able to be integrated with the core Pricing ABM and network equilibrium models.

Summary of Implemented Model Features

In this sub-section we provide a concise re-cap of the main model features incorporated in the CMAP Pricing ABM. All these features are supported in the basic CT-RAMP structure described above. The following features are of particular importance:

- *Enhanced temporal resolution*. The time-of-day choice model was implemented with a 30-min resolution to address various congestion pricing schedules and associated peak-spreading effects. Trip departure time choice within the tour window was also modeled. The corresponding highway assignment procedures (in EMME) cover 8 time-of-day periods and run in parallel across 4 computers. The enhanced temporal resolution is also important for future integration with DTA.

- *Carpooling as joint travel arrangement with subsequent impact on mode choice*. Travel generation and mode choice sub-models as well as corresponding assignment procedures fully addressed the specifics of carpooling and joint travel. The model is able to address HOV lanes and HOT lanes with differential eligibility rules or toll discounts by auto occupancy (2 and 3+ persons).

- *Route type choice* (toll vs. non-toll and/or managed lane vs. general-purpose lane) as the lower-level dimension in the mode choice structure.

- *Impact of congestion and pricing on activity & patterns.* The basic CT-RAMP structure includes an advanced system of accessibility measures recently incorporated in the SANDAG and MAG ABMs. This component ensures that congestion and pricing effects propagate through mode choice, time-of-day choice, and destination choice to the upper level models that predict tour frequency and chaining pattern for each tour. The CT-RAMP structure also allows testing of policy scenarios and trends like compressed work schedules and telecommuting.

- *Multi-class traffic assignment and elaborate skimming procedures.* Traffic assignment and skimming procedures were developed in EMME to support the Pricing ABM. User classes addressed vehicle type, car occupancy, willingness to pay tolls, and willingness to use managed lanes. Special provisions can also be made to model dynamically priced lanes if necessary (to the extent possible with conventional static assignment).

- *Individual parameter variation.* The pricing ABM includes the advanced feature of distributed value-of-time (as applied in the pricing version of the SFCTA ABM and the MTC version of CT-RAMP); license plate rationing feature (as applied in the pricing version of New York ABM) can also be added if necessary.

- *Travel time reliability.* The pricing ABM includes advanced optional features to account for travel time reliability factors (to the extent possible with conventional static assignment). In particular, the model can differentiate travelers' responses to time spent in different traffic conditions (free flow, moderate congestion, heavy congestion, and gridlock). This is based on the findings and methods developed in the NCHRP 08-57, SHRP 2 C04, and SHRP 2 L04 projects.

- *Detailed reporting and mapping options for equity analysis and other special types of analysis associated with pricing.* Pricing studies are associated with additional and sometimes quite detailed analysis of winners and losers. The pricing ABM output can fully address these special requirements. The CT-RAMP visualization “dashboard” can be added as a future enhancement.

CT-RAMP ABM Segmentation

Person-Type Segmentation

The CT-RAMP ABM system is implemented in a fully-disaggregate microsimulation framework. A key advantage of using the microsimulation approach is that there are essentially no computational constraints on the number of explanatory variables can be included in a model specification. However, even with this flexibility, the model system includes some segmentation of decision-makers. Segmentation is a way to characterize person roles within a household, and is a useful tool to structure models. For example, each person-type segment can have its own model for certain choices. Note that segments can be created for households as well as persons. There is variation in travel behavior within each segment due to variables like exact age, gender, exact income, education level, etc. However, the internal level of variation within each segment should be lower than the variation between the segments. In other words, the segmentation should encapsulate the most significant differences in travel behavior.

A total of eight segments of person-types, shown in **Table 3**, are used for the CT-RAMP model system. The person-types are mutually exclusive and collectively exhaustive with respect to age, work status, and school status. Every person modeled in the microsimulation process belongs to one and only one segment.

Table 3: Person Types

NUMBER	PERSON-TYPE	AGE	WORK STATUS	SCHOOL STATUS
1	Full-time worker	18+	Full-time*	None
2	Part-time worker	18+	Part-time	None
3	Non-working adult	18 – 64	Unemployed	None
4	Non-working senior	65+	Unemployed	None
5	College student	18+	Any	College +
6	Driving age student	16-17	Any	Pre-college
7	Non-driving student	6 – 15	None	Pre-college
8	Pre-school	0-5	None	None

*Full-time employment is defined as at least 30-35 hours/week depending on the definition used in the Household Travel Survey. Part-time workers work less than 30-35 hours/week but work on a regular basis. In the NHTS 2008 survey, full-time vs. part-time status was a direct question.

Further, workers are further stratified by their occupation. In the current version of the CMAP ABM, there are 12 occupational categories aggregated of the 2-digit NAICS codes. The categories are given in

Table 4. These are used to fully segment zonal terms for work location choice, based on the occupation of the worker.

Table 4: Occupation Types in the CMAP ABM

NUMBER	DESCRIPTION
1	Manufacturing
2	Transportation, utilities, or warehousing
3	Communications/information
4	Retail (retail trade + wholesale trade)
5	Finance and insurance, real estate, rental, or leasing
6	Professional, scientific, or technical services; management of companies or enterprises
7	Educational services
8	Health care or social assistance
9	Arts, entertainment, or recreation
10	Accommodation or food service
11	Government (public administration)
12	Other (agriculture, mining, construction, other services, administrative, support, waste management, or remediation services)

Segmentation of workers by occupation is a very welcome improvement for the workplace location choice model that is of crucial importance in the ABM model system chain. First, segmenting work flows by occupation allows for a more behaviorally realistic structure where the "right" people are sent to the "right" places and not necessarily the closest jobs. In most of the previous ABMs, segmentation by income groups was used in order to somewhat account for heterogeneity in the labor force and job market. In general, average commute distances increase with higher worker incomes and more specialized occupations. In order to support the segmentation of work flows by occupation, both workers (in the population synthesis procedure) and jobs (as defined in the land use data) are segmented in a compatible way.

The SANDAG ABM was the first CT-RAMP model where worker segmentation by 7 occupation categories (which are consistent with the PECAS land use model) was adopted as shown in **Table 5**.

Table 5: Occupation Types in the SANDAG ABM

NUMBER	DESCRIPTION
1	White collar labor
2	Work at home labor
3	Service labor
4	Health labor
5	Retail and food labor
6	Blue collar labor
7	Military labor

In the MAG ABM, the occupation categories included in the NHTS 2008 were used as shown in **Table 6** with their relation to the NAICS codes by which the zonal employment was provided. It should be mentioned that the categories used in the NHTS 2008 are not the best for travel modeling and they should be reconsidered in the future.

Table 6: Occupation Types in the Phoenix NHTS 2008 (adopted for MAG ABM)

NHTS	DESCRIPTION	NAICS	DESCRIPTION
1	Sales or marketing	42	Wholesale Trade
		52	Finance and Insurance
2	Clerical administrative or retail	44	Retail Trade
		45	Retail Trade
		53	Real Estate and Rental and Leasing
		71	Arts, Entertainment, and Recreation
		72	Accommodation and Food Services
		92	Public Administration
3	Production, construction, manufacturing, or transport	11	Agriculture, Forestry, Fishing and Hunting
		21	Mining, Quarrying, and Oil and Gas Extraction
		22	Utilities
		23	Construction
		31	Manufacturing
		32	Manufacturing
		33	Manufacturing
		48	Transportation and Warehousing
		49	Transportation and Warehousing
4	Professional, managerial, or technical	51	Information
		54	Professional, Scientific, and Technical Services
		55	Management of Companies and Enterprises
		56	Administrative and Support and Waste Management and Remediation Services
		61	Educational Services
		62	Health Care and Social Assistance
5	Person care and services	81	Other Services (except Public Administration)

Compared to even the most advanced and recent CT-RAMP ABMs developed for San Diego and Phoenix, the CMAP CT-RAMP ABM takes one step further in terms of detailed representation of journey-to-work flows.

Household-Type Segmentation

The majority of household characteristics are derived from the characteristics of the household members. For example, such important household characteristics as number of workers, number of non-working adults, and number of children (altogether frequently referred to as household composition) are derived from the person-level attributes. However, there are several important attributes that relate to the entire household and can be effectively used for a full or partial segmentation of the ABM sub-models.

Household-type segments are useful for pre-defining certain data items (such as destination choice size terms) so that these data items can be pre-calculated for each segment. Pre-calculation of these data items reduces model complexity and runtime. The household segmentation actually varies for any given model component, but to be complete the basic segmentation is presented here. The segmentation is based on household income as an important determinant of activities and travel behavior, and includes five segments, as shown in **Table 7**.

Table 7: Household Income Groups

TYPE	DESCRIPTION	HOUSEHOLD INCOME (2005 DOLLARS)
1	Very low income	\$0-\$30K
2	Low income	\$30K-\$60K
3	Medium income	\$60K-\$100K
4	High income	\$100K - \$150K
5	Very high income	\$150K+

In addition to household segmentation by income group, after the household car-ownership model has been applied, household segmentation by relative car sufficiency is applied in many models since car sufficiency has a strong impact on the mode preferences and derived accessibility measures used in almost all sub-models of the ABM. Households are segmented by four car sufficiency groups: 1=zero cars, 2=low (cars fewer than workers), 3=balanced (cars equal to workers), 4=high (cars greater than workers) – as shown in **Table 8**.

Table 8: Household Groups by Car Sufficiency

Number of household workers	Number of household cars				
	0	**1**	**2**	**3**	**4+**
0	Zero	High	High	High	High
1	Zero	Balanced	High	High	High
2	Zero	Low	Balanced	High	High
3	Zero	Low	Low	Balanced	High
4+	Zero	Low	Low	Low	Balanced

Activity-Type Segmentation

The CMAP household travel survey contains more than 20 different activity codes. Modeling all of those activity types would add significant complexity to estimating and implementing the model system. Also, the survey sample is too small to support such a level of detail, so these detailed activity types are grouped into more aggregate activity types based on the similarity of the activities. The activity types are used in most model system components, from developing daily activity patterns to predicting tour/trip destinations and modes by purpose. The set of activity types and associated trip purposes applied in the CMAP CT-RAMP ABM (identical to the set applied in the recently developed CT-RAMP ABMs for ARC, MTC, SANDAG, and MAG) is shown in **Table 9**.

Table 9: Activity Types and Associated Trip Purposes

TYPE	PURPOSE	DESCRIPTION	CLASSIFICATION	ELIGIBILITY
1	Work	Working at regular workplace or work-related activities outside the home	Mandatory	Workers and students
2	University	College +	Mandatory	Age 18+
3	High School	Grades 9-12	Mandatory	Age 14-17
4	Grade School	Grades K-8	Mandatory	Age 5-13
5	Day care	All day care types	Mandatory	Age 0-4
6	Escorting	Pick-up/drop-off passengers (auto trips only)	Maintenance	Age 16+
7	Shopping	Shopping away from home	Maintenance	Age 5+ (if joint travel, all persons)
8	Other Maintenance	Personal business/services, and medical appointments	Maintenance	Age 5+ (if joint travel, all persons)
9	Social/Recreation	Recreation, sport, entertainment	Discretionary	Age 5+ (if joint travel, all persons)
10	Visiting relatives and friends	Visiting relatives and friends	Discretionary	Age 5+ (if joint travel, all persons)
11	Eat Out	Eating outside of home	Discretionary	Age 5+ (if joint travel, all persons)
12	Other Discretionary	Volunteer work, religious activities	Discretionary	Age 5+ (if joint travel, all persons)
13	Special event	Sport or cultural event	Discretionary	Age 5+ (if joint travel, all persons)
14	Trip to or from airport	Long-range travel by air	Special type	Age 5+ (if joint travel, all persons)

The activity types are also grouped according to whether the activity is mandatory, maintenance, or discretionary, and eligibility requirements are assigned determining which person-types can be used for generating each activity type. The classification scheme of each activity type reflects the relative importance or natural hierarchy of the activity, where work and school activities are typically the most inflexible in terms of generation, scheduling, and location; whereas discretionary activities are typically the most flexible on each of these dimensions. However, when generating and scheduling activities this hierarchy is not rigid and is informed by both activity type and activity duration.

Each out-of-home location that a person travels to in the simulation is assigned one of these activity types. In the MAG ABM, in addition to activities generated by the core demand models, several important activities, such as special events (as a special type of discretionary activity) and trips to and from airports are supply-driven and assigned to persons. Supply-driven activities have a predetermined location and are generated in a different way compared to demand-driven activities. Activities are either demand-driven (generated by disaggregate core demand models) or supply-driven (generated by aggregate models and assigned to persons).

Temporal Resolution

The model system functions at a temporal resolution of one-half hour. These half-hour increments begin with 3:00 AM and end with 2:59 AM the next day, though the hours between 1:00 AM and 4:59 AM were aggregated to reduce computational burden. Temporal integrity is ensured so that no activities are scheduled with conflicting time windows (overlapping time for the same individual), with the exception of short activities/tours that are completed within a half-hour increment. For example, a person may have a very short tour that begins and ends within the 8:30 AM-8:59 AM period, as well as a second longer tour that begins within this time period, but ends later in the day.

Time periods are typically defined by their midpoint in both estimation (when the travel survey is processed) and application (when the demand model input and output are interpreted and coordinated with the network simulation software). For example, in a model system using half-hour temporal resolution, the 9:15 AM time period would capture activities or travel between 9:00 AM and 9:29 AM.

Tour-level time-of-day period combinations by outbound time interval (departure from home) and inbound interval (arrival back home) are summarized in **Table 10**. In this case, tour duration includes both time spent on participation in the activity and time spent on travel. A similar two-dimensional structure is applied for modeling time-of-day choice for work activity episodes where departure time is replaced with work activity start and arrival back home is replaced with activity end. In this case, duration includes the activity episode only. This structure has been successfully applied in the San Diego and Phoenix CT-RAMP ABMs.

Table 10: Tour-Level Time-of-Day Period Combinations

Tour-level TOD alternative	Departure from home (or activity start) time interval		Arrival back home (or activity end) time interval		Activity & travel duration average value	
1	1	3:00 AM-4:59 AM	1	3:00 AM-4:59 AM	0	0 min[1]
2	1	3:00 AM-4:59 AM	2	5:00 AM-5:29 AM	1	30 min

3	1	3:00 AM-4:59 AM	3	5:30 AM-5:59 AM	2	60 min
…	1	3:00 AM-4:59 AM	…	…	…	…
39	1	3:00 AM-4:59 AM	39	11:30 PM-11:59 PM	38	1,140 min
40	1	3:00 AM-4:59 AM	40	12:00 AM-2:59 AM	39	1,170 min
41	2	5:00 AM-5:29 AM	2	5:00 AM-5:29 AM	0	0 min
42	2	5:00 AM-5:29 AM	3	5:30 AM-5.59 AM	1	30 min
…	…	…	…	…	…	…
818	39	11:30 PM-11:59 PM	39	11:30 PM-11:59 PM	0	0 min
819	39	11:30 PM-11:59 PM	40	12:00 AM-2:59 AM	1	30 min
820	40	12:00 AM-2:59 AM	40	12:00 AM-2:59 AM	0	0 min[1]

[1]For open intervals like the first interval and last interval, average non-zero duration can be imputed for the inter-interval tours based on the observed durations in the household travel survey.

By combining 40 departure intervals with 40 arrival intervals and taking into account that the arrival interval must be later than or equal to the departure interval we arrive at 820 alternatives ((40×(40+1))/2). A tour time-of-day choice model of this structure and level of resolution has been first successfully estimated and applied in the San Diego ABM. This sub-model structure was adopted for the CMAP ABM with all coefficients re-estimated based on the recent Chicago household travel survey. The enhanced level of temporal resolution is essential for pricing studies and specifically for portraying peak spreading effects and congestion pricing impacts.

A critical aspect of the model system is the relationship between the temporal resolution used for scheduling activities and the temporal resolution of the network simulation periods. Although each activity generated by the model system is identified with a start time and end time in half-hour increments, level-of-service matrices are only created for 8 periods for which traffic and transit assignments are actually implemented. Thus, a certain aggregation of modeled trips by time-of-day period has to be implemented. This limitation is purely technical and due to rapid advances in computer power and multiprocessing it will be lifted in the future in one of two possible ways: 1) Static simulations will be implemented for all half-hour periods separately, or 2) Dynamic traffic assignment will be applied for the entire regional network for a 24-hour period.

Technical Aspects of CMAP's Pricing ABM

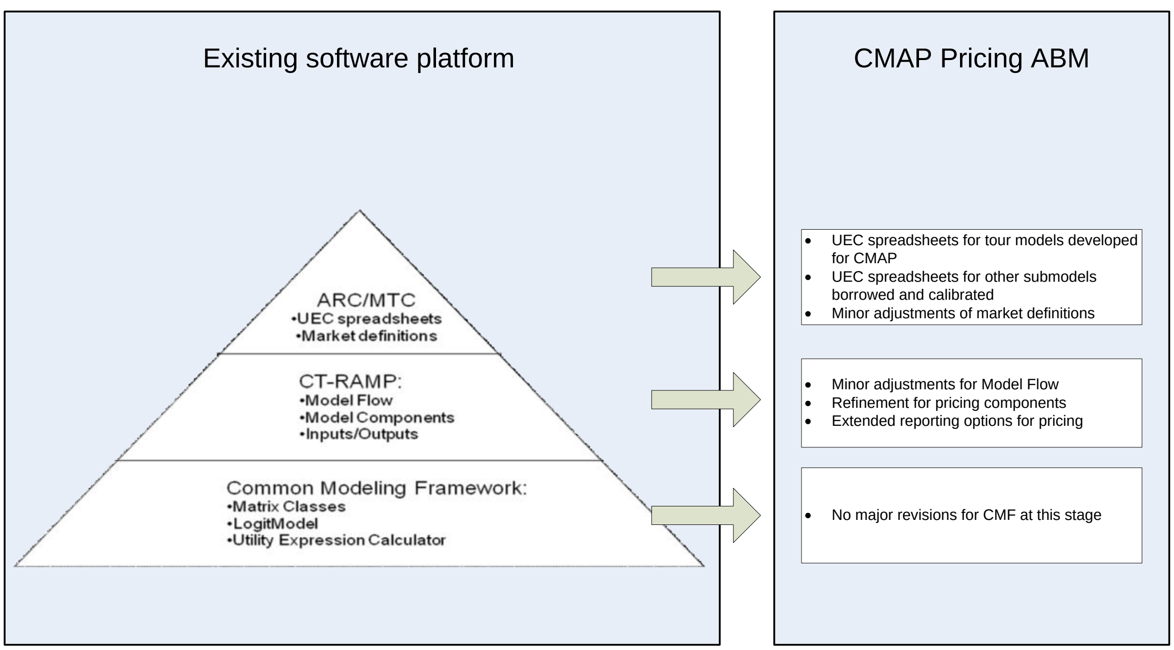
Our approach to create a fully-functional advanced ABM for the CMAP region in a very short time frame was based on two major principles:

- *Focused functionality*. We delivered a fully-functional model, although its immediate applicability is limited to highway pricing studies. However, the model system incorporated all of the innovative features of previous ABM development efforts in order to fully address CMAP's planning and policy work program. The CMAP Pricing ABM is sensitive to a wide variety of pricing forms and projects, including those where aggregate four-step models fail to provide reasonable forecasts. Examples are described in the section on model validation and sensitivity tests below.

- *Modularity and openness*. The model system and software implementation that we utilized for this project has been designed to take advantage of object-oriented programming (OOP) principles and modern software design patterns. This design provides efficiencies in the transfer of the model system from previous implementations to the CMAP Region and allows for the addition of key features in the future.

To achieve these two goals, we implemented the **C**oordinated **T**ravel – **R**egional **A**ctivity-Based **M**odeling **P**latform (CT-RAMP) for the Chicago region, utilizing the existing software platform developed by PB and successfully applied for seven ABMs in practice. We transferred the main CT-RAMP structure to CMAP and made special provisions for model components relevant for highway pricing studies, as shown in **Figure 2** below.

Figure 2: Software Transfer Principles



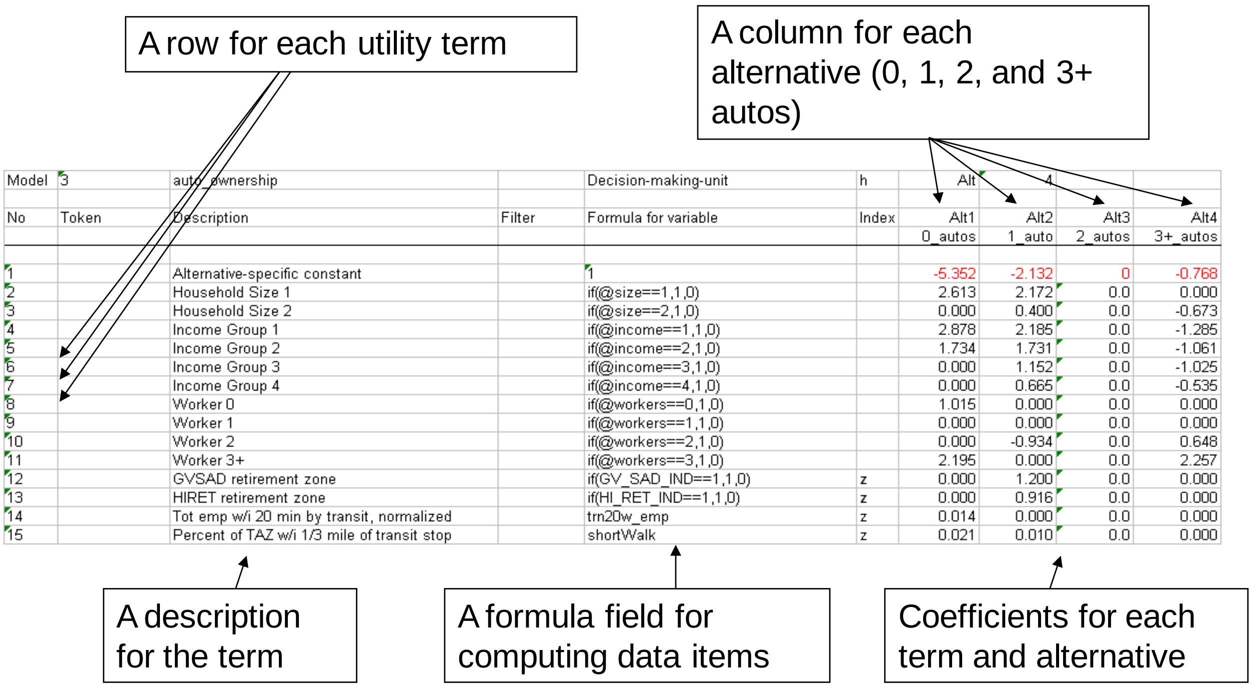
The software developed for the implementation of CT-RAMP consists of three essential components, as shown in the pyramid structure in **Figure 2**. At the bottom of the pyramid is a collection of Java libraries specifically designed for the implementation of disaggregate travel demand models, called the Common Modeling Framework (CMF). The CMF package consists of a library of general classes and methods that are used to construct operational ABMs. This library is open source and is actively supported by PB. It is used by software architects and programmers in the software development process, but is not normally modified by the end user. The CMF contains a number of packages that are essential for the implementation of ABMs, including discrete choice model construction and mathematics, matrix handling, and a powerful utility specification and solver package described in greater detail below.

The CT-RAMP model has been implemented in a separate package, which contains model logic, choice model structure, and model flow, shown as the middle layer of the software design pyramid. CT-RAMP model flow is roughly comparable to a macro script of EMME or TransCAD GISDK script that essentially defines the model system structure. This layer of the pyramid is created by the software architects and programmers and may change or be tailored for specific regional conditions. It is normally not modified by the end user. This software package was co-developed for the Atlanta Regional Commission (ARC) and San Francisco Metropolitan Transportation Commission (MTC) CT-RAMP models, and is utilized by both model systems.

The implementation-specific utility equations and model inputs and outputs are contained in Utility Expression Calculator (UEC) files and minimal supporting software, as shown at the very top of the software pyramid. These Excel-based files open up the models to end users, so that parameters, input files, and certain choice model alternatives can be easily accessed and changed if necessary. An example of a UEC spreadsheet is shown in **Figure 3**. These tend to be the least transferable components of the model system, including mode choice, sub-models for special events, and the variables used for generating synthetic populations. This part of the software pyramid is analogous to control files with parameters (or relevant parts of macro scripts) used in transportation software packages. The top of the pyramid can often be modified by the end-user and can be easily maintained and updated by CMAP staff if necessary. It is this level of the pyramid that has undergone the most change in order to implement CT-RAMP for the Chicago region.

For the current project, the bottom foundation (CMF) was adopted with no change. The middle part (CT-RAMP structure) required only minor adaptation to address specific requirements of pricing studies and associated advanced model features (for example, time-of-day choice with temporal resolution of 30 minutes that was first implemented in the San Diego CT-RAMP ABM and used as a prototype for the time-of-day choice component of the CMAP ABM).

Figure 3: Example Utility Expression Calculator Spreadsheet



Model	3	auto_ownership		Decision-making-unit	h	Alt	4		
No	Token	Description	Filter	Formula for variable	Index	Alt1	Alt2	Alt3	Alt4
						0_autos	1_auto	2_autos	3+_autos
1		Alternative-specific constant		1		-5.352	-2.132	0	-0.768
2		Household Size 1		if(@size==1,1,0)		2.613	2.172	0.0	0.000
3		Household Size 2		if(@size==2,1,0)		0.000	0.400	0.0	-0.673
4		Income Group 1		if(@income==1,1,0)		2.878	2.185	0.0	-1.285
5		Income Group 2		if(@income==2,1,0)		1.734	1.731	0.0	-1.061
6		Income Group 3		if(@income==3,1,0)		0.000	1.152	0.0	-1.025
7		Income Group 4		if(@income==4,1,0)		0.000	0.665	0.0	-0.535
8		Worker 0		if(@workers==0,1,0)		1.015	0.000	0.0	0.000
9		Worker 1		if(@workers==1,1,0)		0.000	0.000	0.0	0.000
10		Worker 2		if(@workers==2,1,0)		0.000	-0.934	0.0	0.648
11		Worker 3+		if(@workers==3,1,0)		2.195	0.000	0.0	2.257
12		GVSAD retirement zone		if(GV_SAD_IND==1,1,0)	z	0.000	1.200	0.0	0.000
13		HIRET retirement zone		if(HI_RET_IND==1,1,0)	z	0.000	0.916	0.0	0.000
14		Tot emp w/i 20 min by transit, normalized		trn20w_emp	z	0.014	0.000	0.0	0.000
15		Percent of TAZ w/i 1/3 mile of transit stop		shortWalk	z	0.021	0.010	0.0	0.000

There are a significant number of additional improvements and new sub-models currently being developed for CT-RAMP ABMS for San Diego Association of Governments (SANDAG), Maricopa Association of Governments (MAG), and Jerusalem Transportation Master Plan Team (JTMT) that can be reserved for future model enhancements. The upper part of the pyramid (model parameters) included all newly estimated models (those that are most important for pricing studies) and minor adaptation (recalibration of alternative-specific constants) for the rest of the models.

To achieve project objectives while providing CMAP with a solid foundation for future enhancements, we addressed the following key issues:

- *Compatibility with the current CMAP database.* Since in the project time frame it was unrealistic to undertake new significant data collection efforts, the pricing ABM was based on existing socio-economic, land use, and network data. The limitations of the existing database were discussed with the CMAP staff and documented in the subsequent section on model validation and recommended further model improvements. New types of data and associated data collection efforts were also recommended to CMAP for future phases of model development.
- *Full CT-RAMP framework*. The CMAP pricing ABM incorporates the full CT-RAMP framework and allows for adding new features depending on the CMAP needs. With respect to the advanced features included in the last generation of CT-RAMP models (SANDAG, MAG, and JTMT) only the features that directly related to pricing studies were included at this time.

- *Inclusion of all advanced features (State of the Art & Practice) for pricing studies* that were realistic within the project time frame. A wide range of possible pricing studies and corresponding model features has been analyzed in detail and tested within the framework of recent large-scale research projects NCHRP 08-57, SHRP 2 C04, and SHRP 2 L04. The advanced microsimulation CT-RAMP framework is specifically beneficial for incorporation of these features. Some of these features are analyzed in the corresponding sections below.
- *Highway calibration focus*. The pricing ABM was calibrated at the necessary level of detail for highway pricing studies including matching mode and time-of-day specific statistics from the expanded CMAP household travel survey. The transit side of the model was calibrated to reasonably replicate main daily regional statistics. Further improvements on the transit side are reserved for future model improvement efforts.
- *Fully redeveloped tour-level models for the region*. The most important tour-level models (tour destination choice, time-of-day choice, and mode choice) were estimated based on the recent CMAP household travel survey. Special attention was paid to differentiation of value-of-time (VOT) by person type, travel purpose, tour complexity, and other dimensions in line with the findings of the NCHRP 08-57 and SHRP 2 C04 projects. Most of the other models were borrowed from the ARC CT-RAMP ABM, and the alternative-specific constants were re-calibrated to match the aggregate targets developed based on the CMAP household travel survey.
- *Compatibility with any level of spatial resolution*. The pricing ABM at the current stage is based on the existing TAZ system (1,944 TAZs). However, the CT-RAMP structure can take advantage of an enhanced spatial resolution. For example, the SANDAG CT-RAMP ABM operates with 32,000 Master Geography Reference Units (MGRAs). This approach offers clear advantages over the simpler parcel-level approach, as it utilizes discrete stop-to-stop transit path calculations as well as accurate non-motorized accessibilities. The CMAP ABM could utilize the MGRA approach, assuming transit stop locations can be identified in the transit network, or the simpler parcel level approach, with no major restructuring of the code. CMAP has already developed a similar zonal system (16,819 smaller zones nested within the TAZ) that can be utilized in future model improvement.
- *Future transit enhancements.* The proposed CT-RAMP structure can fully address a variety of transit studies including FTA New Starts analysis. In order to address transit planning studies, a more detailed model calibration will be required, typically utilizing a transit on-board survey in addition to the CMAP household travel survey. Also, model features may be added, such as station choice for drive-transit, accounting for station parking capacity constraints and/or improved transit assignment capacity-restraint with crowding (as applied recently by PB in the Sydney model). This direction for further improvements is addressed in more detail in the conclusion section.
- *Future integration with DTA*. The pricing ABM is designed and developed for future integration with a regional DTA model. For this reason, we utilized a temporal resolution of 30 minutes. A demonstration of ABM-DTA integration can be considered as an important strategic avenue for model improvement at CMAP.

- *Future integration with models for trucks and commercial vehicles*. In the current version of the pricing ABM, placeholders were created for all freight traffic components in the multi-class assignment where the current truck trip tables from the four-step model were utilized and split between toll and non-toll users. If a more advanced freight model has been developed it can be integrated with the pricing ABM.
- *Future integration with a land use model (LUM)*. PB has vast experience in the development of ABMs that are fully or partially integrated with a land use model. Examples of fully integrated models (where the demand models utilize labor flows from the land use models) include the Oregon and Ohio statewide models. Examples of partially-integrated models (where the demand models utilize zonal data produced by the land use model) include the SANDAG and MAG ABMs. Such enhancements provide increased sensitivity to economic conditions and land use variables and should be considered for long-term inclusion in the CMAP ABM.

Population Synthesis Controlled Variables

The population synthesis procedure embedded in the basic CT-RAMP structure can incorporate any number of household-level and person-level controls. However, in practice, there is always a certain optimal degree of controlling the population structure, especially for future years. With a large number of controls, it is difficult to guarantee consistency between them as well as ensure that the main demographic tendencies are properly portrayed and not suppressed. The only way to ensure a full consistency across a large number of controls is to generate them by a detailed land use or demographic model that is not yet in place at CMAP.

The main controls that can be used in the population synthesis procedure are summarized in

Table 11. The controls chosen for the current version of the CMAP CT-RAMP ABM are shown in bold. All controlled variables have been provided by CMAP at the TAZ and sub-zone level. These controls have been also used to expand the CMAP household travel survey. The survey expansion was necessary to calculate aggregate travel statistics used as the model validation targets (as discussed in the subsequent sections in detail).

Table 11: Controls for Population Synthesis Procedure

Variable	Household-level	Person-level
Household size	Household distribution by size category (1,2,3,4,5+)	Average household size by providing total population
Number of workers	Household distribution by number of workers (0,1,2,3+)	Average number of workers per household by providing total labor force by place of residence
Household income	Household income distribution (by absolute thresholds or percentiles). The following categories were used (consistent with the travel survey): \$0-30K, \$30-60K, \$60-100K, \$100K+	
Housing type	Household distribution by such categories as single-family detached house and apartment in multi-family house	
Person age	**Household distribution by age of the household head** (a proxy for age of other household members); currently the following categories were adopted: U35, 35-64, 65+	Population brackets of which the most important for ABM are 0-5, 6-18, 19-35, 36-64, 64+)
Person type used in advanced ABMs (it is partially correlated with age; any of controls for some of these variables would be useful)		1=Full time worker 2=Part time worker 3=University student 4=Adult non-worker under 65 5=retiree 6=driving age school child 7=pre-driving age school child 8=preschool child
Worker distribution by occupation (may improve ABM significantly but only available from a land use model)		Labor force distribution by occupation categories provided by the land use model
Group Quarters / special populations	**Student living in dorms at universities,** **Military institutions,** **Other**	

The adopted controlled variables were used for expansion of the CMAP household travel survey with the adopted level of geography. The level of geographic aggregation included 16 districts defined as 5 concentric rings (CBD, dense urban, inner suburban, outer suburban, rural, external) and 3 radial sectors (North, West, and South) as was suggested by CMAP.

Tour/Trip Mode Choice Structure

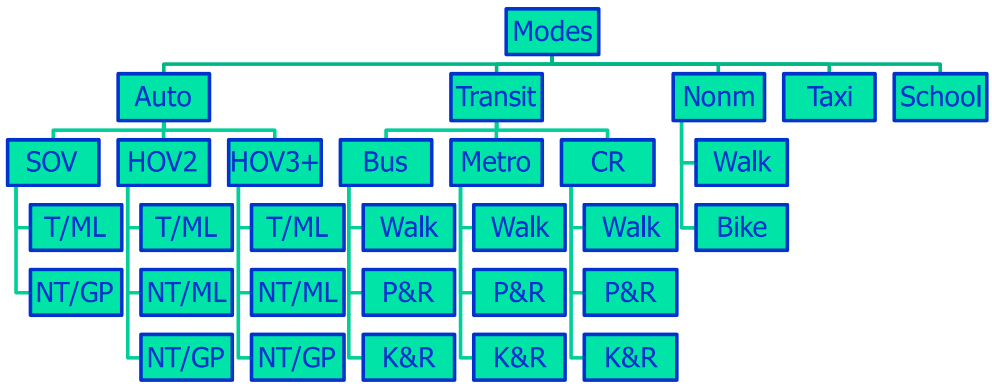
Set of Mode / Occupancy / Route Type Alternatives

The following nested structure was estimated which includes 21 modes at both tour- and trip-level:

- Auto:
  - SOV:
    - Toll route with possible use of managed lanes
    - Non-toll route, general-purpose facilities and lanes
  - HOV2
    - Toll route with possible use of managed lanes
    - Non-toll route, with possible use of managed lanes (HOV2)
    - Non-toll route, general-purpose facilities and lanes
  - HOV3
    - Toll route with possible use of managed lanes
    - Non-toll route, with possible use of managed lanes (HOV2, HOV3)
    - Non-toll route, general-purpose facilities and lanes
- Transit:
  - Bus (express and local, CTA and Pace):
    - Walk/bike access/egress
    - Park & Ride access/egress
    - Kiss & Ride access/egress
  - Metro (CTA rail with all bus services):
    - Walk/bike access/egress
    - Park & Ride access/egress
    - Kiss & Ride access/egress
  - Commuter rail (Metra with CTA rail and all bus services):
    - Walk/bike access/egress
    - Park & Ride access/egress
    - Kiss & Ride access/egress
- Non-motorized:
  - Walk
  - Bike
- School bus (for school trip only):
- Taxi

The corresponding nesting tree is presented in **Figure 4**. The actual configuration of nests might change as the result of statistical analysis and model estimation but the shown structure is the most typical in applied models.

Figure 4: Nested Structure for Mode Choice



One of important features of this structure that was added specifically to address different pricing projects and policies is the lower-level auto sub-nests that correspond to three route types. This all-or-nothing route choice framework embedded in a deterministic traffic assignment has an inherent drawback in portraying the proportion between those who chose a toll route and those who do not. In this regard adding an explicit choice of route type (toll vs. non-toll) as the lower level in the mode choice structure helps compensate for this deficiency. Recently, a similar problem has been recognized with respect to all types of managed lanes (not necessarily tolled). Hence route type choice has been extended to incorporate distinctive route types explicitly. The suggested three route types are explained in **Table 12**.

Table 12: Auto Route Types

Route Type	Path building	SOV	HOV2	HOV3+
Toll with possible use of managed lanes	Non-zero toll required	All links available for SOV	All links available for HOV2	All links available for HOV3
Non-toll using managed lanes	Tolled links excluded, 3 miles of managed lanes required	Not eligible	All non-toll links available for HOV2	All non-toll links available for HOV3

Route Type	Path building	SOV	HOV2	HOV3+
Non-toll using general-purpose lanes only	Tolled links and managed lanes excluded	General-purpose links	General-purpose links	General-purpose links

Observed Modal Split in CMAP's 2007 Travel Tracker Survey

The Travel Tracker household travel survey implemented in the Chicago region in 2007 provides a rich dataset of all daily trips and activities for 14,000 households. Un-weighted number of observed tours by purpose and mode is presented in **Table 13** for the entire region and in **Table 14** for travel to and from the CBD.

Table 13: Modal Split for the Entire Chicago Region (Un-weighted Number of Tours)

Mode	Mode Label	1-Work	2-University	3-School	4-Escorting	5-Shopping	6-Maintenance	7-Eating Out	8-Visiting	9-Discretionary	Total
0	Unknown/Missing	18	3	1	0	20	42	2	1	23	**110**
1	SOV	11001	281	275	2736	3821	3091	821	1079	2841	**25,946**
2	SOV - toll	785	8	1	17	18	57	11	24	36	**957**
3	HOV2	569	37	806	76	1136	905	464	420	1028	**5,441**
4	HOV2 - toll	29	1	0	2	6	9	5	5	10	**67**
5	HOV3	96	4	713	637	241	234	137	133	474	**2,669**
6	HOV3-toll	2	0	0	7	7	7	4	5	3	**35**
7	HOV4+	62	4	523	531	160	122	111	116	373	**2,002**
8	HOV4+ - toll	1	0	0	4	1	1	2	4	4	**17**
9	Bus/walk	338	28	104	10	103	150	15	41	65	**854**
22	Bus/bike	1	0	0	0	0	1	0	0	0	**2**
10	Bus/PNR	18	1	1	0	2	3	0	1	2	**28**
11	Bus/KNR	23	2	13	0	3	5	2	2	4	**54**
12	Metro/walk	480	25	29	4	24	50	7	9	33	**661**
23	Metro/bike	2	0	0	0	0	0	0	0	0	**2**
13	Metro/PNR	114	2	2	0	1	14	1	2	3	**139**
14	Metro/KNR	60	3	6	0	3	7	1	3	5	**88**
15	Rail/walk	283	5	10	0	5	13	4	1	8	**329**
24	Rail/Bike	4	0	0	0	0	0	0	0	0	**4**
16	Rail/PNR	124	4	5	0	2	8	2	3	2	**150**
17	Rail/KNR	491	13	6	2	3	11	4	1	14	**545**
18	Walk	299	24	533	282	421	359	142	228	492	**2,780**
19	Bike	150	5	48	8	43	35	12	25	87	**413**
20	Taxi	95	3	6	0	9	31	5	7	26	**182**
21	School Bus	8	10	1592	1	1	6	0	1	15	**1,634**
	Total	**15,053**	**463**	**4,674**	**4,317**	**6,030**	**5,161**	**1,752**	**2,111**	**5,548**	**45,109**

It is of course clear that many cells in the purpose-mode matrix have a very small number of tours and a full segmentation of the mode choice model is infeasible. At least 30 observations are needed to justify segmentation and estimation of a purpose-mode-specific constant. However, with a partial segmentation across travel purposes, a reasonable choice model proved to be possible.

While transit share for the entire region is not high (around 4%) it is very significant when the tours to and from the CBD are singled out (over 30%). The modal share numbers in this section are preliminary since they are calculated without weights and the survey sample is not perfectly proportional to the actual population. The calibration targets calculated based on the expansion factors are used below in the section on model validation where the mode choice statistics are discussed in detail and compared to the model output.

Table 14: Modal Split for the Tours to and from the CBD (Un-weighted Number of Tours)

	Mode Label	1-Work	2-University	3-School	4-Escorting	5-Shopping	6-Maintenance	7-Eating Out	8-Visiting	9-Discretionary	Total
0	Unknown/Missing	3	0	0	0	0	4	0	0	1	**8**
1	SOV	470	7	1	44	27	48	10	9	28	**644**
2	SOV - toll	42	1	0	0	0	1	1	0	0	**45**
3	HOV2	59	3	5	2	9	31	4	2	20	**135**
4	HOV2 - toll	0	0	0	0	0	1	0	0	0	**1**
5	HOV3	12	0	6	11	2	6	0	0	7	**44**
6	HOV3-toll	0	0	0	0	1	0	0	0	0	**1**
7	HOV4+	6	0	4	1	0	6	1	1	4	**23**
8	HOV4+ - toll	0	0	0	0	0	0	1	0	0	**1**
9	Bus/walk	149	12	0	0	16	23	5	2	13	**220**
22	Bus/bike	0	0	0	0	0	0	0	0	0	**0**
10	Bus/PNR	14	0	0	0	1	0	0	0	1	**16**
11	Bus/KNR	8	0	0	0	0	0	0	0	0	**8**
12	Metro/walk	304	14	4	0	7	22	4	1	12	**368**
23	Metro/bike	1	0	0	0	0	0	0	0	0	**99**
13	Metro/PNR	88	1	0	0	0	7	1	0	2	**1**
14	Metro/KNR	36	1	0	0	0	1	1	0	2	**41**
15	Rail/walk	227	2	0	0	1	7	2	0	3	**242**
24	Rail/Bike	3	0	0	0	0	0	0	0	0	**3**
16	Rail/PNR	98	3	0	0	0	5	0	0	2	**108**
17	Rail/KNR	436	8	1	0	2	7	3	0	9	**466**
18	Walk	57	6	0	0	22	24	8	2	27	**146**
19	Bike	40	1	0	0	0	3	1	0	1	**46**
20	Taxi	75	3	0	0	2	7	3	1	11	**102**
21	School Bus	2	0	3	0	0	2	0	0	1	**8**
	Total	**2,130**	**62**	**24**	**58**	**90**	**205**	**45**	**18**	**144**	**2,776**

Negative Toll Bias

An important effect has been found and statistically confirmed in the recently completed SHRP 2 C04 Project "Improving Our Understanding How Congestion and Pricing Affect Travel Demand" that will be incorporated in the route type choice. There is a significant negative "threshold" bias against paying a toll, regardless of the toll amount. This preference against paying a toll is generally found across travel purposes from both revealed preference and stated preference data, and is supported by research in behavioral economics. The estimated toll "penalty" effect is generally equivalent to 15-20 minutes travel time.

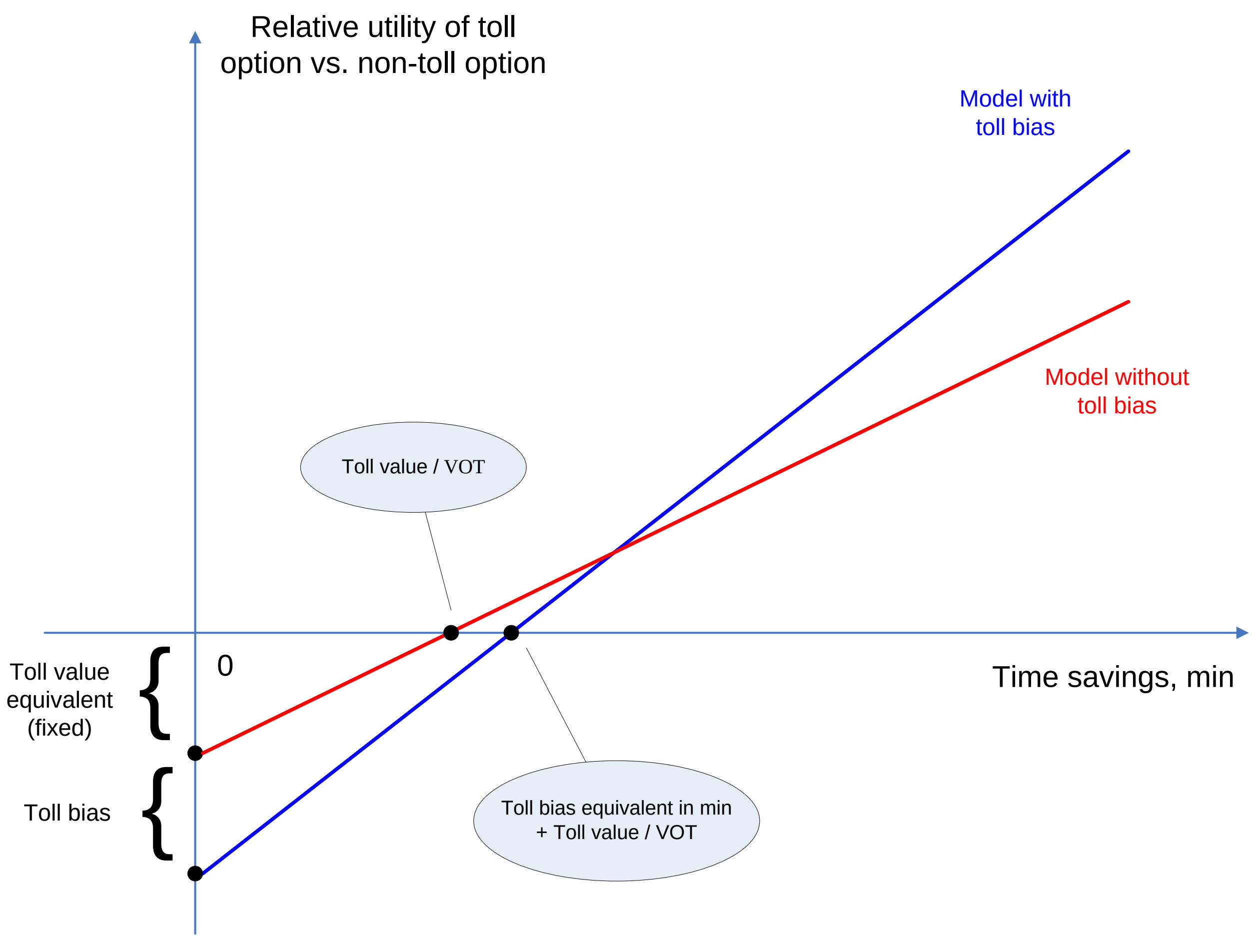
After accounting for differences in price, average travel time and reliability, there appears to be a general reluctance in the population to paying any toll at all to use a highway facility captured by the toll bias. This result is frequently obtained in stated preference (SP) studies, where it is sometimes explained as a "protest response" or "strategic bias" to avoid the introduction of tolls. However, such a bias is also found sometimes in revealed preference (RP), as it is in models estimated for this project. In particular, it was confirmed by the RP data from New York where toll facilities have a long history and explanations like short-term psychological protest or ramp-up cannot be applied. While the relative size of such a bias tends to be smaller when estimated from RP data as compared to SP data, it can still be substantial, and equivalent to as much as 15-20 minutes of travel time.

In other words, travelers would go that far out of their way to avoid paying any toll at all. This type of behavior has also been noted in recent texts in Behavioral Economics, where people are observed to go to seemingly irrational lengths to get something for free as opposed to paying for it.

It is actually logical to have a significant toll bias in combination with a relatively high willingness to pay measured by VOT that was discussed above. These two factors are screened separately in the auto mode utility. In a simplified form where the toll bias is not included, the entire utility gets readjusted that most frequently results in a lower VOT. This is illustrated in **Figure 5**.

We assume that toll values are fixed and analyze the relative utility of toll options vs. non-toll options (both options are assumed available for the user) as a function of travel time savings achieved with toll options. If there is no time savings, the relative utility of the toll option is logically negative. For a model without a toll bias, the associated disutility is equal to the toll value in equivalent units of utility. For a model with a toll bias, the associated disutility is even worse because it includes both the toll equivalent and bias.

Figure 5: Effect of Negative Toll Bias



The point where the difference between toll and non-toll utilities becomes zero corresponds to the 50/50 split between toll and non-toll users. For the model without a toll bias, this point corresponds to the time savings equal to the toll value divided by VOT. For the model with toll bias, this point is shifted and corresponds to the toll value divided by VOT plus toll bias equivalent in minutes. By virtue of the model estimation on the same data set, the model with a toll bias would have a greater slope (and higher VOT).

As seen above, the pricing policy response of a model with a bias and higher VOT can be very different from the response of a simplified model without the bias and adjusted (lower) VOT. A model with bias tends to produce a very conservative traffic & revenue forecast until substantial time savings are guaranteed for toll users. However, when the savings grow, the number of toll users will grow at a higher rate. By contrast, a simplified model will over-predict the number of toll users if the travel time savings are insignificant while under-predicting number of toll users when the travel time savings grow significantly. In a certain sense, the model suggested in the current research would be more “demanding” from the pricing projects to guarantee a “value for the money”.

The resistance to paying a toll appears to present an obstacle to the effective widespread introduction of congestion pricing policies. In many cases, however, a pricing policy can be effective even if only a limited proportion of drivers choose to pay the toll, and, just like VOT, the resistance to paying any toll at all may vary a great deal across the population. In that sense, toll bias becomes another dimension of market discrimination, similar to VOT. What is important is that resistance can be overcome by a guaranteed superior level of service in terms of travel time savings and reliability improvements. In this sense, tolling existing facilities in order to collect revenue but without a substantial level-of-service improvement would always be perceived very negatively by highway users.

Furthermore, one can expect that the resistance to paying a toll will fade over time as road pricing becomes more ubiquitous and more convenient. In the past, drivers had to wait in lines to pay tolls, which in itself could explain a good deal of resistance to tolls. Now, with the increasing implementation of electronic tolling, paying tolls is both faster and less noticeable in terms of the amount of money actually being spent. There are already fully-automatic open-road toll collection technologies in place that completely eliminate delays. The more widespread that this kind of electronic road pricing becomes, the more we can expect anti-toll bias to be reduced, although it may never disappear completely.

In practice, there are different opinions and methods regarding the use of anti-toll threshold terms in forecasting. Sometimes they are avoided in forecasting on the basis that they are not rational in economic terms. Empirically, however, they do appear to be real, so they should be included to obtain the most accurate results, at least for short-term forecasts. In general, this bias would result in a more conservative traffic & revenue forecast if travel time savings are not significant, but it also may result in a more optimistic forecast for pricing projects that improve travel time significantly. For longer term forecasts, it may be appropriate to explore scenarios with reduced or eliminated anti-toll bias/threshold terms. This advanced model component was incorporated in the CMAP mode choice model.

Highway Network Coding Guide and EMME Network Scripts

Vehicle Classes

PB prepared a highway network guide and EMME scripts jointly with CMAP. The multiclass assignment includes the following classes (11+6=17):

- Internal auto trip tables generated by CT-RAMP:
    - SOV – toll / Managed Lane:
        - Low VOT (average across travel purposes and income groups)
        - High VOT (average across travel purposes and income groups)
    - SOV – non-toll General Purpose,
    - HOV2 – toll (and possibly Managed Lane):
        - Low VOT (average across travel purposes and income groups)
        - High VOT (average across travel purposes and income groups)
    - HOV2 – non-toll Managed Lane,
    - HOV2 – non-toll General Purpose,
    - HOV3 – toll (and possibly Managed Lane):
        - Low VOT (average across travel purposes and income groups)
        - High VOT (average across travel purposes and income groups)
    - HOV3 – non-toll Managed Lane
    - HOV3 – non-toll General Purpose,
- Additional non-travel vehicle classes (binary toll/non-toll choice implemented at the pre-assignment stage as part of the network processing in EMME):
    - Commercials,
    - Light trucks,
    - Heavy trucks,
    - External auto traffic (segmented by occupancy and VOT and added to the auto classes).

Highway assignment is implemented for 8 time-of-day periods as it is currently implemented in the existing CMAP four-step model. The fine temporal structure of highway assignments is beneficial for pricing studies and specifically for congestion pricing schemes where peak spreading effects are essential. The period specific assignments are distributed across the computers in the cluster for an efficient implementation.

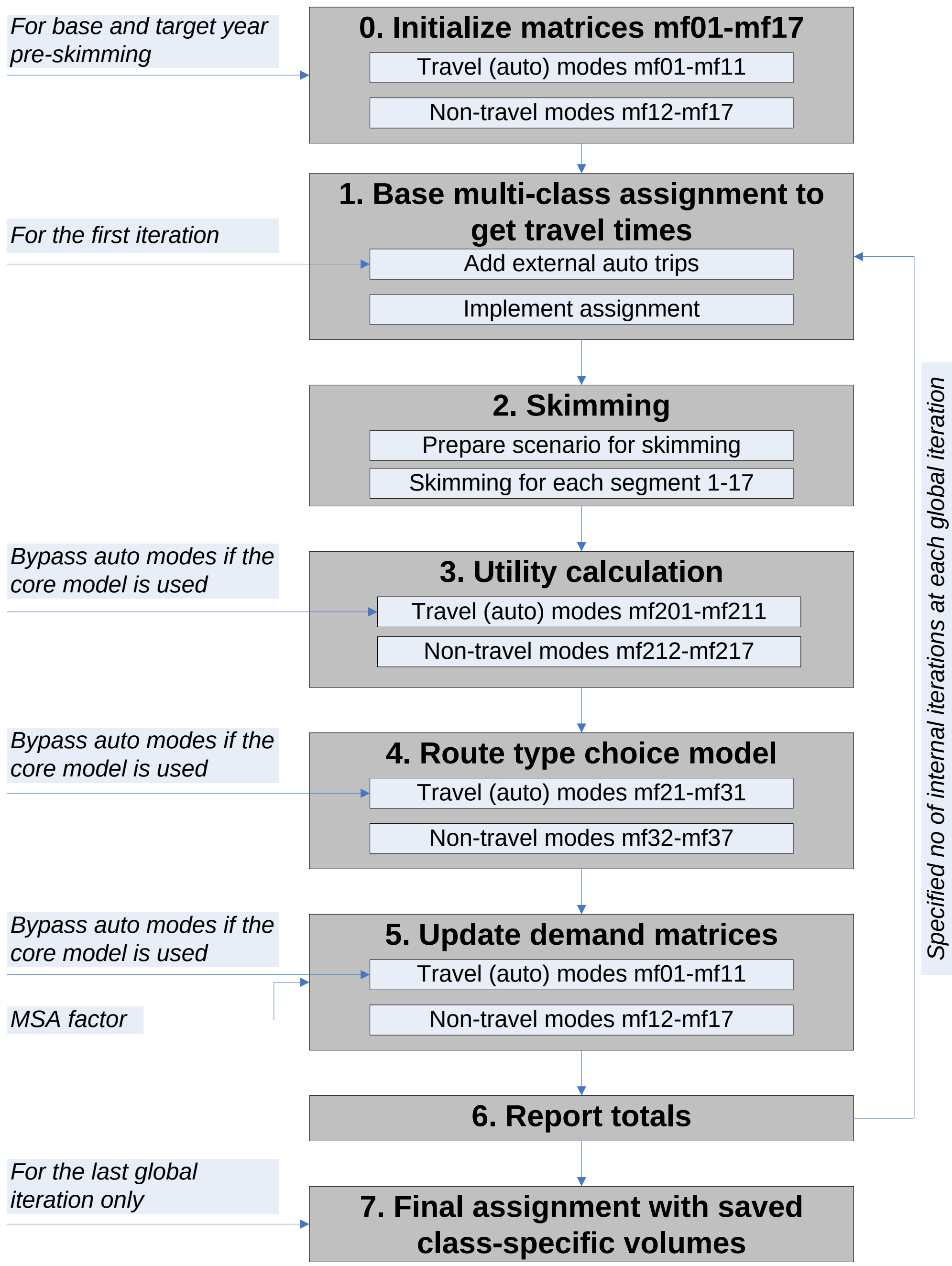
The following main skims are generated for each vehicle class and TOD period:

- Total travel time
- Free-flow travel time (used to calculate delay and reliability proxy)
- Toll (used to define availability of toll choice)
- Total distance (used to calculate vehicle operating cost)
- Distance on managed lane (used to define availability of manage lane choice)

EMME Macro Script for Assignment/ Skimming/ Binary Choice

The developed tool that combines all necessary highway network procedures encapsulated in the EMME macro script (CT_RAMP_SKIM.mac) is presented in **Figure 6**. Binary (trinary) choices for auto modes are applied only at the very first global iteration to create initial sets of skims for toll and non-toll users.

Figure 6: Implemented Highway Network Procedure



The highway skimming and assignment procedures as well as route type choice for non-core traffic components (trucks, commercials, externals, and airport ground access) are done with EMME. The settings are specified in the macros as described below. Note that the runSkimming.bat and runSkimmingInitial.bat call these macros with the appropriate command line arguments that are specific to each global iteration:

1) TOD_tables.mac – creates time-of-day period specific matrices for highway assignment, including the initial version of the auto trip matrices that will be filled by CT-RAMP (to generate starting sets of skims for each period). This macro is run once for each time-of-day period before the first global iteration. The command line argument are:
    a. Time period code, such as “1” for p1
2) extraclass.mac – creates extra attributes for CT_RAMP_skim macro. This macro is only run once for each time-of-day period before the first global iteration when running the initial skimming. It has no command line arguments.
3) CT_RAMP_skim.mac – toll road choice (for non-CT-RAMP user classes) and skimming macro. Implements binary choice between toll and non-toll users and all necessary highway skimming procedures. Can be applied independently to generate starting skims and/or explore pricing scenarios. When applied to support CT-RAMP, auto trip tables mf101-mf106 are generated by CT-RAMP, Truck trip tables mf107-mf110, external autos mf111-mf116 and passenger autos to airports mf121-mf126 are split by this macro (between toll and non-toll users). This macro is run 4 times (internal iterations) for each global iteration (to equilibrate non-core traffic components). The command line arguments are:
    a. 0 = initialize split matrices mf131-mf174 (only for first global iteration), 1 = start with the previous set
    b. MSA factor for averaging matrices (0.0 = no update, 1.0 = full update)
    c. 0 = skip final assignment, 1 = implement final assignment (for last global iteration)
    d. base network scenario for assignment (p1-8)
    e. number of assignment iterations (normally set to 10, 20, 30, 40 by internal iterations)
    f. 0 = include auto split (for initial skims), 1 = exclude (when applied with CT-RAMP)
4) Toll_scenario.mac – creates a new toll (pricing) scenario from a base scenario. This was used to create the toll scenario test cases. The command line arguments are:
    a. Baseline scenario, such as 3
    b. Pricing scenario, such as 1
    c. Toll multiplier, such as 5

Highway Network Coding

The following are the rules for highway network coding that PB specified for CMAP:

- Managed lanes should be coded separately from general purpose lanes with a realistic coding of access points between them and ramps.

- Tolls should be coded as link extra attributes for each vehicle type (@TSOV, @THOV2, …). Special EMME scripts automatically calculate tolls (mileage-based, dynamic, vehicle-type-based discounts, etc.); toll equivalents in minutes are added to VDF based on VOT.

- Class-specific eligibility rules for managed lanes, freeways, TOT Lanes, etc. are specified through link auto mode codes (a=SOV, b=HOV2, c=HOV3, d=HOV4+, e=Commercial, d=Light truck, f=Heavy truck). To simplify coding it can be done in a cumulative network way:

    - SOV (S)
    - HOV2 (SH)
    - HOV3 (SH)
    - HOV4 (SH)
    - Commercial and b-plate trucks (b)
    - Light truck (l)
    - Medium truck (m)
    - Heavy truck (h)

- Toll plazas and booths can be coded explicitly or implicitly to account for additional average delays; an appropriate mix of toll collection methods is assumed; vehicles are not segmented by payment type (cash, card transponder, Automatic Vehicle Identification).

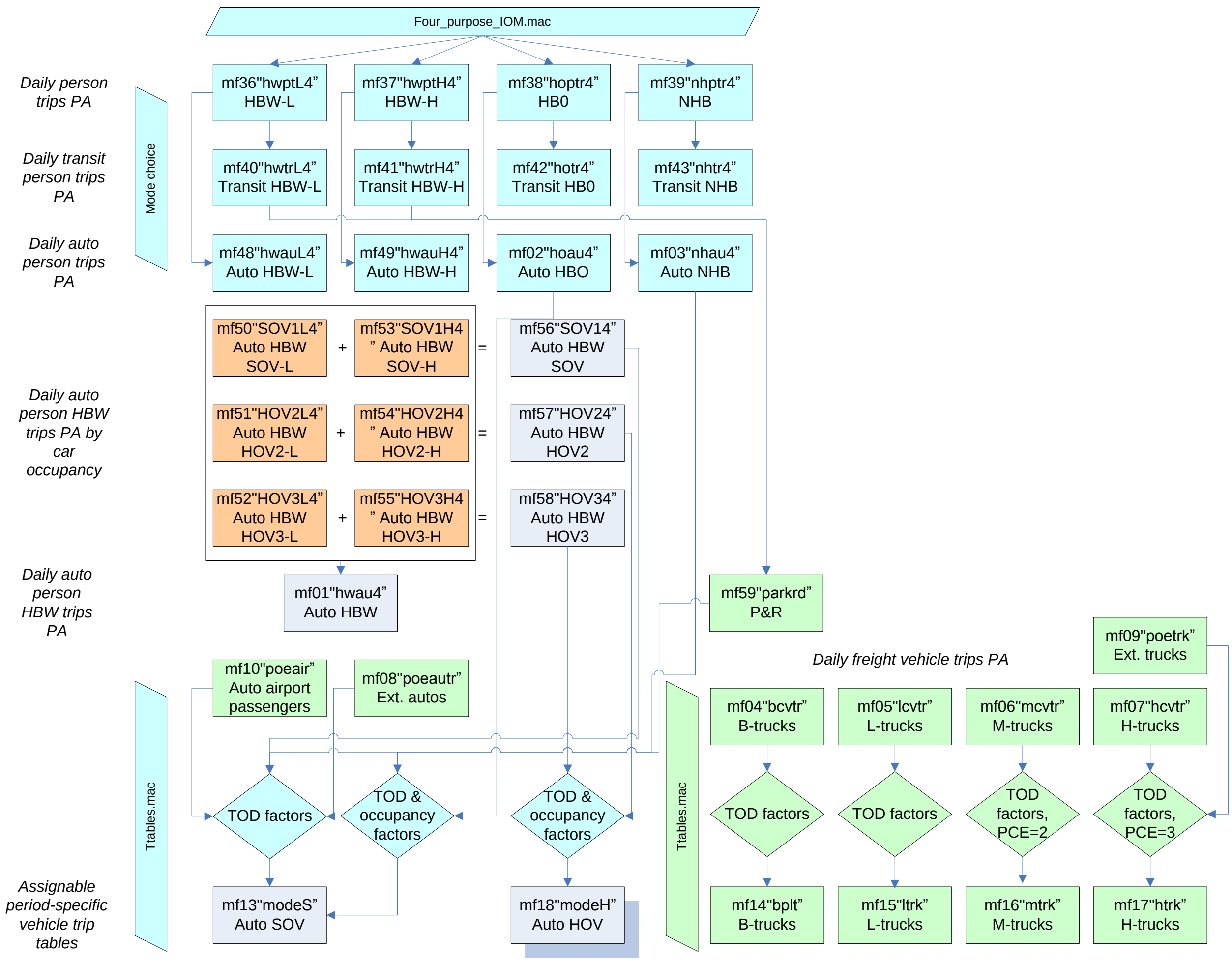
Trip Tables Generated by CMAP's Four-Step Model

The existing four-step model process goes through the following main steps:

1. <Trip generation model>
2. Free.skim.mac
3. Init_HOVsim.databk.mac
4. <Pre-distribution procedures>
5. Four_purpose_IOM.mac
6. <Mode choice model>
7. Iter.master6c.mac
8. Daily.Total.Asmt5I_6c.mac

Trip tables generated by the existing model are presented in **Figure 7**.

Figure 7: Existing Four-Step Model Process and Generated Trip Tables



Input highway trip tables to support the designed CT-RAMP structure are listed in **Table 15**. Auto tables were needed only to generate starting skims for the first global iteration of the CT-RAMP procedure. These tables were overwritten by the core demand model during subsequent global iterations. Truck tables were used as inputs but not changed by CT-RAMP, although, in the process, they were split between toll and non-toll users before the assignment. A full set of highway tables was constructed for each TOD period 1-8.

Table 15: Input TOD-Period-Specific Highway Trip Tables to Support the CT-RAMP Structure

Trip table	Network code	Source	Overwritten by CT-RAMP after 1st global iteration
SOV1, low VOT (mf101)	S	Mf50"SOV1L4" (CMAP) + Mf02"hoau4" (CMAP TOD) * (L-income/1-occupancy factor) + Mf03"nhau4" (CMAP TOD) * (L-income/1-occupancy factor) + P&R (from mf40"hwtrL4")	Yes
SOV1, high VOT (mf102)	S	Mf53"SOV1H4" (CMAP) + Mf02"hoau4" (CMAP TOD) * (H-income/1-occupancy factor) + Mf03"nhau4" (CMAP TOD) * (H-income/1-occupancy factor) + P&R (from mf41"hwtrH4")	Yes
HOV2, low VOT (mf103)	H	Mf51"HOV2L4" (CMAP) + Mf02"hoau4" (CMAP TOD) * (L-income/2-occupancy factor) + Mf03"nhau4" (CMAP TOD) * (L-income/2-occupancy factor)	Yes
HOV2, high VOT (mf104)	H	Mf54"HOV2H4" (CMAP) + Mf02"hoau4" (CMAP TOD) * (H-income/2-occupancy factor) + Mf03"nhau4" (CMAP TOD) * (H-income/2-occupancy factor)	Yes
HOV3+, low VOT (mf105)	H	Mf52"HOV3L4" (CMAP) + Mf02"hoau4" (CMAP TOD) * (L-income/3-occupancy factor) + Mf03"nhau4" (CMAP TOD) * (L-income/3-occupancy factor)	Yes
HOV3+, high VOT (mf106)	H	Mf55"HOV3H4" (CMAP) + Mf02"hoau4" (CMAP TOD) * (H-income/3-occupancy factor) + Mf03"nhau4" (CMAP TOD) * (H-income/3-occupancy factor)	Yes
B-plate trucks (commercials)	T(b)	Mf14"bplt" (CMAP)	No
Light trucks	T(l)	Mf15"ltrk" (CMAP)	No
Medium trucks	T(m)	Mf16"mtrk" (CMAP)	No
Heavy trucks	T(h)	Mf17"htrk" (CMAP)	No

Multi-Class Highway Assignment with Fixed Cost Component

The developed structure of the traffic assignment with class-specific tolls is presented in **Table 16**. The currently adopted structure is simpler with a single toll value across all vehicle types.

Table 16: Structure of Multi-Class Assignment

Class	Mode	Fixed cost				Trip table (demand in auto equivalents)
		Toll		Managed lane		
		Value, $ (100 for non-eligible)	Weight ($ equivalent in min)	Value	Weight (100 for non-choosers)	
1= SOV/toll/managed lane/high VOT	“a”	@TOLLa1	60/VOTa1h	@MLa1=1	0	SOVtmh
2= SOV/toll/managed lane/low VOT	“a”	@TOLLa1	60/VOTa1l	@MLa1=1	0	SOVtml
3= SOV/non-toll/general-purpose lane	“a”	@TOLLa1	100	@MLa1=1	100	SOVng
4= HOV2/toll/managed lane/high VOT	“a”	@TOLLa2	60/VOTa2h	@MLa2=1	0	HOV2tmh/2
5=HOV2/toll/managed lane/low VOT	“a”	@TOLLa2	60/VOTa2l	@MLa2=1	0	HOV2tml/2
6= HOV2/non-toll/managed lane	“a”	@TOLLa2	100	@MLa2=1	0	HOV2nm/2
7= HOV2/non-toll/general purpose lane	“a”	@TOLLa2	100	@MLa2=1	100	HOV2ng/2
8= HOV3+/toll/managed lane/high VOT	“a”	@TOLLa3	60/VOTa3h	@MLa3=1	0	HOV3tmh/3.3
9=HOV3+/toll/managed lane/low VOT	“a”	@TOLLa3	60/VOTa3l	@MLa3=1	0	HOV3tml/3.3
10= HOV3+/non-toll/managed lane	“a”	@TOLLa3	100	@MLa3=1	0	HOV3nm/3.3
11= HOV3+/non-toll/general purpose lane	“a”	@TOLLa3	100	@MLa3=1	100	HOV3ng/3.3
12=Commercials/toll/managed lane	“a”	@TOLLc	60/VOTc	@MLc=1	0	COMMt
13=Commercials/non-toll/general purpose	“a”	@TOLLc	100	@MLc=1	100	COMMn
14=Light trucks/toll/managed lane	“x”	@TOLLlt	60/VOTlt	@MLt=1	0	LTRUCt*2.0
15=Light trucks/non-toll/general purpose	“x”	@TOLLlt	100	@MLt=1	100	LTRUCn*2.0
16=Heavy trucks/toll/managed lane	“y”	@TOLLht	60/VOTht	@MHt=1	0	HTRUCt*3.0
17=Heavy trucks/non-toll/general purpose	“y”	@TOLLht	100	@MHt=1	100	HTRUCn*3.0

Transit Skims in CMAP's ABM

Transit skims are located in the EMME databanks as shown in **Table 17**. There are currently only two TOD sets of skims – peak and off-peak. These two sets are used for modeling mode, TOD, and destination choice with highway skims generated by 8 TOD periods. The correspondence between highway and transit skims is shown in **Table 18**. The current level of detail on the highway side (8 time-of-day periods) is not matched by the level of detail on the transit side (only 2 time-of-day periods). Improvement to the transit side of the model represents one of the major directions for future improvement as discussed below in the conclusion section.

Table 17: Location of Transit Skims in EMME Databank

Variable	Matrix # by transit mode & sub-mode					
	Bus		Metro		Rail	
	Walk	Drive	Walk	Drive	Walk	Drive
In-vehicle time	351 (bus)	361 (bus)	371 (metro)	381 (metro)	391 (rail)	401 (rail)
In-vehicle time (bus)	352 (zero)	362 (zero)	372 (bus)	382 (bus)	392 (bus)	402 (bus)
In-vehicle time (metro)	353 (zero)	363 (zero)	373 (zero)	383 (zero)	393 (metro)	403 (metro)
Wait time	354	364	374	384	394	404
Walk time	355	365	375	385	395	405
Number of transfers (boardings)	356	366	376	386	396	406
Fare, cents	357	367	377	387	397	407
Auto access time	358 (zero)	368	378 (zero)	388	398 (zero)	408
Parking cost, generalized in min	359 (zero)	369	379)zero)	389	399 (zero)	409
Station used	360 (zero)	370	380 (zero)	390	400 (zero)	410

Table 18: Correspondence between Highway and Transit Skims by Time-of-Day Period

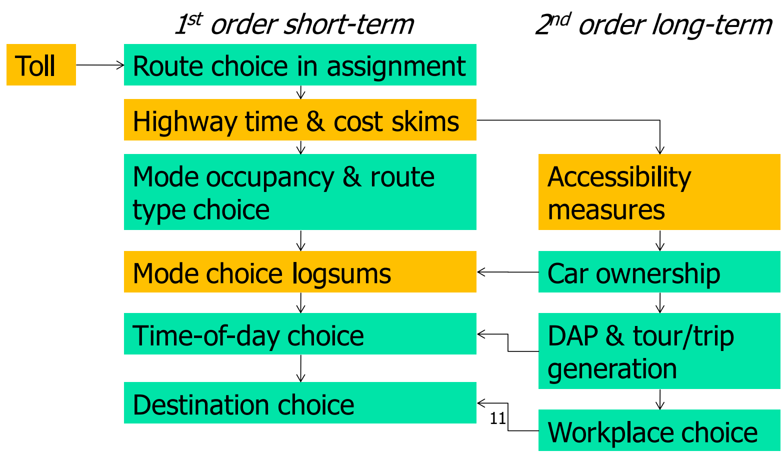
TOD Period	Highway skims	Transit skims
1	8pm-6am	Off-peak
2	6am-7am	Peak
3	7am-9am	Peak
4	9am-10am	Peak
5	10am-2pm	Off-peak
6	2pm-4pm	Off-peak
7	4pm-6pm	Peak transposed
8	6pm-8pm	Peak transposed

Impacts of Pricing on Travel Choices

In the CT-RAMP model system, the introduction of tolls propagates through the sequence of inter-related choice and affects practically all travel dimensions as shown in **Figure 8**. First-order effects include direct impacts of pricing on route choice, mode/occupancy choice, time-of-day choice and destination choice through generalized cost functions included in the route and mode utility expressions.

However, in the CT-RAMP model system there is also a wide range of accessibility-based effects on the upper-level choices of car ownership, daily activity patterns & tour generation, as well as long-term choices of workplace and school. This part of the model system is explained in more details in the subsequent section.

Figure 8: Propagation of Impacts of Pricing on Different Travel Choices



Accessibility Measures in the CT-RAMP Model System

Types of Accessibility Measures

There are multiple accessibility measures used in the CT-RAMP model system. Most of the applied accessibility measures represent simplified destination choice logsums, which is the composite utility of travel across all modes to all potential destinations from an origin zone to all destination zones in different time-of-day periods. These accessibility measures are zonal characteristics that can be stored as a vector indexed by TAZ. Another type of accessibility measure describes the amount of impedance between zones. Accessibilities of this type are stored as TAZ-to-TAZ matrices.

These accessibility measures are primarily needed to ensure that the upper-level models in the ABM hierarchy such as car ownership, daily activity pattern, and (non-mandatory) tour frequency are sensitive to improvements of transportation level-of-service across all modes, as well as changes in land use. Accessibility measures are similar in nature to density measures, but take into account the accessibility between zones as well as the opportunities to engage in various types of activities in those zones. Accessibility measures are needed since it is infeasible to link all choices by full logsums due to the number of potential alternatives across all dimensions (activities, modes, time periods, tour patterns, and daily activity patterns). Accessibility measures reflect the opportunities to implement a travel tour for a certain purpose from a certain origin (residential or workplace). They are used as explanatory variables in the upper level models (daily activity pattern type and tour frequency) and the corresponding coefficients are estimated along with the coefficients for person and household variables.

The applied zonal accessibility measures have the following general form:

$$A_i = \ln\left[\sum_{j=1}^{I} S_j \times \exp\left(TMLS_{ij}\right)\right] \qquad \textbf{Equation 1}$$

where:

$i, j \in I$	=	origin and destination zones,
A_i	=	accessibility measure calculated for each origin zone,
S_j	=	attraction size variable for each potential destination zone,
$TMLS_{ij}$	=	time-of-day and mode choice logsum as the measure of impedance.

The composite travel impedance between zones (the origin-destination (OD) accessibility measure) is calculated as a two-level logsum taken over time-of-day periods and modes:

$$TMLS_{ij} = \mu \ln\left[\sum_{t=1}^{2} \exp\left(MLS_{tij} + \alpha_t\right)\right] \qquad \textbf{Equation 2}$$

where:

$t = 1,2$	=	time-of-day periods (currently peak and off-peak are used),
MLS_{ij}	=	mode choice logsum for a particular time-of-day period,
α_t	=	time-of-day-specific constant,
μ	=	nesting coefficient for mode choice under time-of-day choice.

In this form, the destination choice accessibility measure is essentially a sum of all attractions in the region discounted by the travel impedance. Note that this measure is sensitive to travel improvements in both peak and off-peak periods. The relative impact of each period is regulated by the time-of-day-specific constant that is estimated for each travel segment (or activity type).

Accessibility measures are linearly included in a utility function of an upper-level model. To preserve consistency with random-utility choice theory, the coefficient for any accessibility measure should be between 0 and 1; though it is not as restrictive as in a case of a proper nested logit model.

The general logic of inclusion of accessibility measures in travel models is as follows. For models that generate activity patterns, tours, and trips where specific destinations are not known yet, zonal accessibility measures are applied that describe the accessibility of all potential activity locations from the household or tour origin. For models where the destination is known, OD accessibility measures should be used.

Zonal Size Variables

Zonal size variables estimated for the CMAP CT-RAMP ABM are presented in **Table 19**.

Table 19: Zonal Size Variables as Functions of Population and Employment Types

Explanatory variables		Size variables by activity type							
Variable	**Description**	**p4_esco**	**p5_shop**	**p6_main**	**p7_eati**	**p8_visi**	**p9_disc**	**p10_atwo**	**p11_allnm**
total_HH	Total number of households	1.0000				0.1421	0.3595		0.5016
retail	Retail employment (n44+n45)		4.2810	1.4185	1.2908		0.4387	0.5403	7.4291
n51	Information			0.7091					0.7091
n52	Finance & Insurance							0.1265	
n53	Real Estate Rental Leasing			2.4753					2.4753
n55	Management of Companies & Enterprises							1.3759	
n56	Administrative & Support							0.2357	
n62	Health Care, Social Assistance			1.0618		0.2349			1.2968
n71	Arts, Entertainment, Recreation				0.3224		0.9049		1.2273
n72	Accommodation, Food Services		1.1224		1.0458		0.4422	0.2809	2.6104
n92	Public Administration			0.5356				0.2265	0.5356
total_emp	Total employment							0.1578	

Composite Impedance Measures (Origin-Destination Accessibilities)

A set of various OD accessibility measures is used in the CT-RAMP model system as summarized in **Table 20**. Each impedance measure is associated with a certain aggregate travel purpose (1-4) for which the mode utilities are calculated according to the coefficients in the table. Then, depending on the type of accessibility measure, car sufficiency is taken into account. If a general accessibility measure is calculated which is going to be applied in the model system before the car-ownership model, the mode utilities are averaged across all car-sufficiency groups with the weight that reflects the observed proportion between different car-sufficiency groups in the region. If an accessibility measure is calculated for a specific car-sufficiency group (that means that it is going to be applied after the car-ownership model) the mode utilities for this specific group are used.

Table 20: Origin-Destination Accessibility Measures

Token	Purpose	Car sufficiency			Modes included					Off-peak constant
		Zero cars	Cars fewer than workers	Cars equal to or greater than workers	SOV	HOV	WT	DT	NM	
Work	1=Work	0.05	0.35	0.6	1	1	1	1	1	-0.9
Univ	2=Univ	0.05	0.35	0.6	1	1	1		1	-0.5
Scho	3=Scho	0.05	0.35	0.6	1	1	1		1	-1.2
Auto	4=Other	0.05	0.35	0.6	1					0.5
Tran	4=Other	0.05	0.35	0.6			1			0.5
Nonm	4=Other	0.05	0.35	0.6					1	0.5
Indi_0	4=Other	1			1		1		1	0.5
Indi_1	4=Other		1		1		1		1	0.5
Indi_2	4=Other			1	1		1		1	0.5
Join_0	4=Other	1				1	1		1	0.5
Join_1	4=Other		1			1	1		1	0.5
Join_2	4=Other			1		1	1		1	0.5
Esco_0	4=Other	1				1			1	-0.5
Esco_1	4=Other		1			1			1	-0.5
Esco_2	4=Other			1		1			1	-0.5
Wrkad	1=Work	0.05	0.35	0.6	1	1		1		-0.9
Unvad	2=Univ	0.05	0.35	0.6	1	1		1		-0.5
Schad	3=Scho	0.05	0.35	0.6	1	1		1		-1.2
Wrknad	1=Work	0.05	0.35	0.6			1		1	-0.9
Unvnad	2=Univ	0.05	0.35	0.6			1		1	-0.5
Schnad	3=Scho	0.05	0.35	0.6			1		1	-1.2

Not every mode is included in each logsum. The set of modes is restricted for two reasons. The first reason is that some modes are not observed for some of the trip purposes. For example, Drive to Transit (DT) is relevant for work trips only. The second reason is that certain modes are made unavailable in order to calculate a specific (mode-restricted) type of accessibility needed for a particular behavioral model. For example, mode-specific accessibilities that are used in the car-ownership model are based on a single representative mode each. Accessibilities that describe individual activities should logically exclude HOV. Accessibilities that describe joint activities naturally exclude SOV. Accessibilities that describe auto dependency include only modes that need an auto (SOV, HOV, and DT). Accessibilities that describe auto non-dependency include only modes that do not need an auto (WT and NM).

Finally, to complete the logsum calculation across time-of-day periods, a bias constant for off-peak period is specified (the peak period is used as the reference alternative with zero bias). This constant is set to replicate the observed proportion of trips in the peak period vs. off-peak.

Zonal Accessibility Measures

The set of zonal accessibility measures incorporated in the CT-RAMP ABM is summarized in **Table 21**. The variety of measures stems from the combination of different size variables segmented by the underlying activity type with different impedance measures segmented by trip purpose and person/household type. The impact of various accessibility measures will be discussed in detail in subsequent sections in the context of model estimation results. Such models as car ownership (mobility attributes), work and schooling from home, and coordinated daily activity-travel pattern are very good illustrations for zonal accessibility measures with some components that relate to OD accessibility measures. Such models as usual workplace and school location are based on OD accessibility measures.

Table 21: List of Zonal Accessibility Measures

Measure	Size variable		Impedance measure		Model in which applied
	No	Token	No	Token	
1	12	Whom1	1	Work	Work from home
2	13	Whom2	1	Work	Work from home
3	14	Whom3	1	Work	Work from home
4	15	Whom4	1	Work	Work from home
5	16	Whom5	1	Work	Work from home
6	17	Shom1	3	Scho	Schooling from home
7	18	Shom2	3	Scho	Schooling from home
8	19	Shom3	2	Univ	Schooling from home
9	11	AllNM	4	Auto	Car ownership
10	11	AllNM	5	Tran	Car ownership
11	11	AllNM	6	Nonm	Car ownership
12	11	AllNM	7	Indi_0	Coordinated Daily Activity-Travel Pattern
13	11	AllNM	8	Indi_1	Coordinated Daily Activity-Travel Pattern

Measure	Size variable		Impedance measure		Model in which applied
14	11	AllNM	9	Indi_2	Coordinated Daily Activity-Travel Pattern
15	11	AllNM	10	Join_0	Coordinated Daily Activity-Travel Pattern
16	11	AllNM	11	Join_1	Coordinated Daily Activity-Travel Pattern
17	11	AllNM	12	Join_2	Coordinated Daily Activity-Travel Pattern
18	5	Shop	10	Join_0	Joint tour frequency
19	5	Shop	11	Join_1	Joint tour frequency
20	5	Shop	12	Join_2	Joint tour frequency
21	6	Main	10	Join_0	Joint tour frequency
22	6	Main	11	Join_1	Joint tour frequency
23	6	Main	12	Join_2	Joint tour frequency
24	7	Eati	10	Join_0	Joint tour frequency
25	7	Eati	11	Join_1	Joint tour frequency
26	7	Eati	12	Join_2	Joint tour frequency
27	8	Visi	10	Join_0	Joint tour frequency
28	8	Visi	11	Join_1	Joint tour frequency
29	8	Visi	12	Join_2	Joint tour frequency
30	9	Disc	10	Join_0	Joint tour frequency
31	9	Disc	11	Join_1	Joint tour frequency
32	9	Disc	12	Join_2	Joint tour frequency
33	4	Esco	13	Esco_0	Allocated tour frequency
34	4	Esco	14	Esco_1	Allocated tour frequency
35	4	Esco	15	Esco_2	Allocated tour frequency
36	5	Shop	7	Indi_0	Allocated tour frequency
37	5	Shop	8	Indi_1	Allocated tour frequency
38	5	Shop	9	Indi_2	Allocated tour frequency
39	6	Main	7	Indi_0	Allocated tour frequency
40	6	Main	8	Indi_1	Allocated tour frequency
41	6	Main	9	Indi_2	Allocated tour frequency
42	7	Eati	7	Indi_0	Individual tour frequency
43	7	Eati	8	Indi_1	Individual tour frequency
44	7	Eati	9	Indi_2	Individual tour frequency
45	8	Visi	7	Indi_0	Individual tour frequency
46	8	Visi	8	Indi_1	Individual tour frequency
47	8	Visi	9	Indi_2	Individual tour frequency
48	9	Disc	7	Indi_0	Individual tour frequency
49	9	Disc	8	Indi_1	Individual tour frequency
50	9	Disc	9	Indi_2	Individual tour frequency
51	10	Atwo	7	Indi_0	Individual sub-tour frequency
52	10	Atwo	9	Indi_2	Individual sub-tour frequency

Incorporation of Travel Time Reliability Impact

It is suggested for future model improvement to explore statistically and test in model application a set of perceptional weights associated with different congestion levels (specified in terms of V/C ratios) as shown in **Table 22**. These weights serve as a proxy for travel time variability resulting from congestion. The synthesis has been implemented as part of the SHRP 2 C04 Project "Improving Our Understanding of How Highway Congestion and Pricing Affect Travel Demand".

Table 22: Perceived Highway Time Weights by Congestion levels

Travel time conditions	UK	US	V/C
Free Flow	1.00	1.00	0-0.4
Busy	1.05	1.03	0.4-0.6
Light Congestion	1.11	1.06	0.6-0.8
Heavy Congestion	1.31	1.20	0.9-1.1
Stop Start	1.50	1.38	1.1-1.5
Gridlock	1.89	1.79	1.5+

The adopted structure of highway assignments and mode choice models in the current version of CMAP CT-RAMP allows for natural incorporation of these perceptional weights. We suggest this interesting and promising extension of the developed model for future tests.

CMAP CT-RAMP Disaggregate Estimation

Estimation of Sub-Models and Coding of Utility Expression Calculators

Several sub-models that are the most important for highway pricing including household car ownership, tour-level and trip-level models of destination, mode, and time-of-day choice, have been developed and estimated for the Chicago region based on the CMAP household travel survey from 2007. In the CT-RAMP software system, each estimated model is coded in a Utility Expression Calculator (UEC) format that is directly read by the main software model stream. UEC can be open in Excel and edited by the user without changing the main code. An example of the Car Ownership Choice Model UEC prepared for the CMAP Pricing ABM (the simplest UEC that can be presented in the report) is shown in **Table 23**. In the UEC, rows correspond to the model variables and their transformations. Columns correspond to the choice alternatives (i.e. number of cars owned by the modeled households). UEC Cells contain the estimated utility coefficient for each variable. The filter column serves for speeding up the calculations. It is evaluated first, and if it is equal to 0, the entire utility term is set to 0 obviating the rest of calculations for the given row. All newly prepared UECs were tested with the main CT-RAMP code.

Table 23: Example of Utility Expression Calculator for Car Ownership Choice Model

Model	1	Car_ownership		Decision-making-unit	h	Alt	5			
No	Token	Description	Filter	Formula for variable	Index	Alt1 0_car	Alt2 1_car	Alt3 2_cars	Alt4 3_cars	Alt5 4+_cars
	nest	alternative indices for nest				0	1	1	1	1
	nestCoeff	nesting coefficient				0.57138	0.57138			
1	nonMandatoryTransitAccess	Transit accessibility to all Non-Mandatory Activity locations		transitOffPeakRetail	z					
2	nonMandatoryWalkAccess	Walk accessibility to all Non-Mandatory Activity locations		nonMotorizedRetail	z					
3	hhNonDrivers	Household non-drivers (children less than 16)		@numChildrenUnder16						
4	hhDrivers	Household drivers (age>=16 years)		@drivers						
5	workers	Number of workers in the Household		@workers						
6	workersToDrivers	Ratio of workers (full-time and part-time) to drivers	hhDrivers > 0	workers/hhDrivers						
7	age65to79ToDrivers	Ratio of persons age 65 to 79 to drivers	hhDrivers > 0	@numPersons65To79/hhDrivers						
8	age80PlusToDrivers	Ratio of persons age 80 or more to drivers	hhDrivers > 0	@numPersons80Plus/hhDrivers						
9	hhIncome	Household Income in Dollars		@hhIncome						
10	lowIncome	Household Income $34,999 or less		hhIncome<35000						
11	mediumIncome	Household Income $35,000 to $59,999	hhIncome>=35000	hhIncome<60000						
12	highIncome	Household Income $100,000 or more		hhIncome>=100000						
13	detachedHome	True, if dwelling type is detached home		@detachedHome						
14	altCarSufficiencyDrivers	Car Sufficienct calculated for each alternative wrt Drivers		$alt -1 - hhDrivers						
15	altCarSufficiencyWorkers	Car Sufficienct calculated for each alternative wrt Workers		$alt -1 - workers						
16	workersAutoDependency	Sum of scaled Auto/DT minus WT/Walk MC Logsum across all workers		@workAutoDependency						
17	studentsAutoDependency	Sum of scaled Auto/DT minus WT/Walk MC Logsum across all students (person type 3 and 6)		@schoolAutoDependency						
18		Household drivers dummy -- 1 driver	hhDrivers==1	1		-6.6473	0	-0.8002	-1.9635	-2.6935
19		Household drivers dummy -- 2 drivers	hhDrivers==2	1		-6.6473	-1.1763	0	-0.8656	-1.7266
20		Household drivers dummy -- 3 drivers	hhDrivers==3	1		-6.6473	-1.0223	-0.6162	0	-0.4237
21		Household drivers dummy -- 4 drivers or more	hhDrivers>=4	1		-6.6473	-0.9079	-0.7626	-0.7626	0
22		Household Income: Less than $34,999	lowIncome	1		2.2246	0.6716	0.0000	-0.1485	-0.2760
23		Household Income: $35,000 to $59,999	mediumIncome	1		0.7523	0.3328	0.0000	-0.1485	-0.2760
24		Household Income: $100,000 or More	highIncome	1		-1.3466	-0.1832	0.0000	0.1843	0.2293
25		Detached Home	detachedHome		1	-1.8172	-0.6144	0.0000	0.3707	0.5652
26		Ratio of Kids under 15 yrs to Driving Age HH Members - Zero Cars		hhNonDrivers/hhDrivers		-0.2295	0.0000	0.0000	0.0000	0.0000
27		Ratio of Kids under 15 yrs to Driving Age HH Members - More cars than drivers	altCarSufficiencyDrivers>0	hhNonDrivers/hhDrivers		0.0000	-0.1424	-0.1424	-0.1424	-0.1424
28		Ratio of Workers to Driving Age HH Members - Zero Cars		workersToDrivers		-0.9879	0.0000	0.0000	0.0000	0.0000
29		Ratio of Workers to Driving Age HH Members - Cars Less than drivers	altCarSufficiencyDrivers<0	workersToDrivers		0.0000	-0.5841	-0.5841	-0.5841	-0.5841
30		Ratio of 65 to 79 yrs old to Driving Age HH Members - Zero Cars		age65to79ToDrivers		-0.9433	0.0000	0.0000	0.0000	0.0000
31		Ratio of 65 to 79 yrs old to Driving Age HH Members - Cars Less than drivers	altCarSufficiencyDrivers<0	age65to79ToDrivers		0.0000	-0.2878	-0.2878	-0.2878	-0.2878
32		Ratio of 65 to 79 yrs old to Driving Age HH Members - Cars more than drivers	altCarSufficiencyDrivers>0	age65to79ToDrivers		0.0000	0.6161	0.6161	0.6161	0.6161
33		Ratio of 80+ yrs old to Driving Age HH Members - Zero Cars		age80PlusToDrivers		-0.2405	0.0000	0.0000	0.0000	0.0000
34		Ratio of 80+ yrs old to Driving Age HH Members - Cars more than drivers	altCarSufficiencyDrivers>0	age80PlusToDrivers		0.0000	-0.7854	-0.7854	-0.7854	-0.7854
35		Non-Motorized Accessibility - Zero Car		nonMandatoryWalkAccess		0.4312	0.0000	0.0000	0.0000	0.0000
36		Non-Motorized Accessibility -Cars fewer than drivers	altCarSufficiencyDrivers<0	nonMandatoryWalkAccess		0.0000	0.1057	0.1057	0.1057	0.1057
37		Non-Motorized Accessibility - Cars more than drivers	altCarSufficiencyDrivers>0	nonMandatoryWalkAccess		0.0000	-0.0454	-0.0454	-0.0454	-0.0454
38		Transit Accessibility - Zero Car		nonMandatoryTransitAccess		0.1330	0.0000	0.0000	0.0000	0.0000
39		Transit Accessibility -Cars fewer than drivers by 2+	IF(altCarSufficiencyDrivers<-1,1	nonMandatoryTransitAccess		0.0000	0.0730	0.0730	0.0730	0.0730
40		Transit Accessibility -Cars fewer than drivers by 1	IF(altCarSufficiencyDrivers==-1,	nonMandatoryTransitAccess		0.0000	0.0481	0.0481	0.0481	0.0481
41		Transit Accessibility - Cars more than drivers	altCarSufficiencyDrivers>0	nonMandatoryTransitAccess		0.0000	-0.0162	-0.0162	-0.0162	-0.0162
42		Mandatory Auto Dependence for workers in the household		workersAutoDependency		-1.9565	-0.3932	0.0000	0.1027	0.1027
43		Mandatory Auto Dependence for students in the household		studentsAutoDependency		-0.5114	0.0000	0.0000	0.0000	0.0000
44		Mandatory Auto Dependence for students in the household	altCarSufficiencyWorkers<0	studentsAutoDependency		0.0000	-0.3459	-0.3459	-0.3459	-0.3459
45		Mandatory Auto Dependence for students in the household	altCarSufficiencyWorkers>0	studentsAutoDependency		0.0000	0.0382	0.0382	0.0382	0.0382

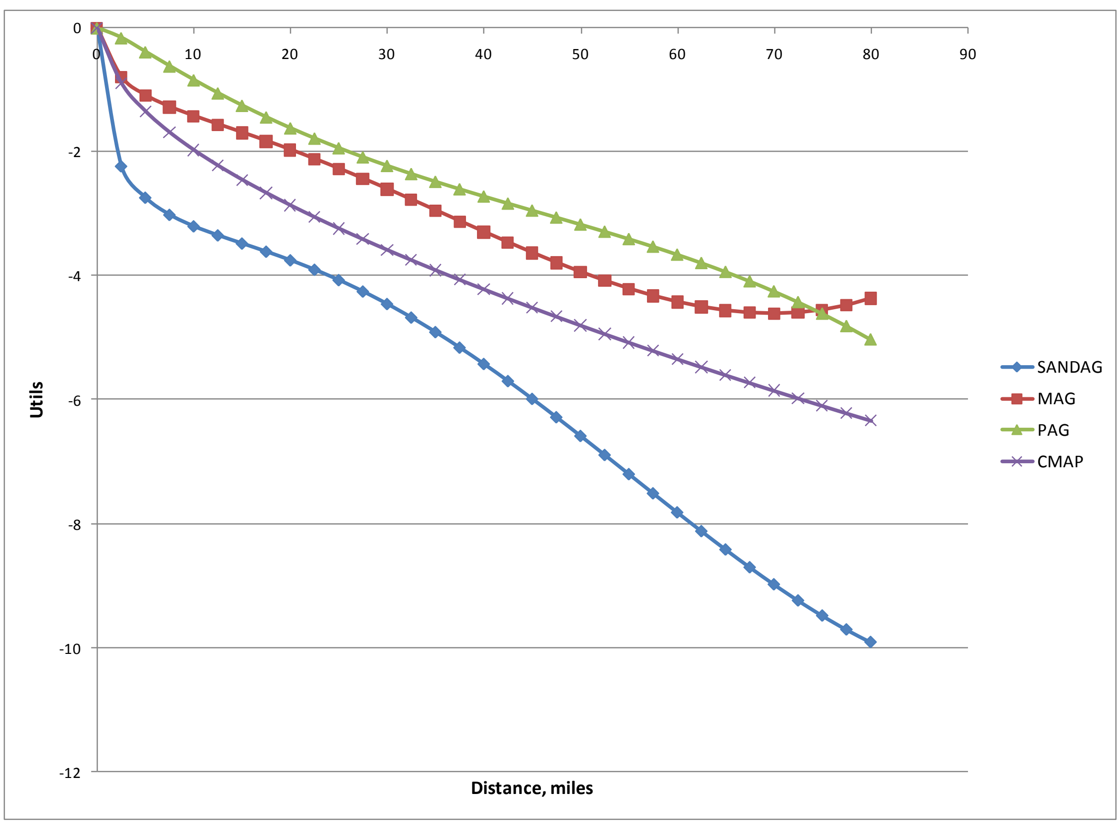
Comparison of Estimated Models with Other Regions

The models estimated for the Chicago region were compared to similar models estimated elsewhere. In general, the comparison has shown that the estimated models and corresponding behavioral effects found in the Chicago region are in line with the previous findings on travel behavior in other regions. However, the exact magnitude of each effect differs from region to region. Thus, it was beneficial to re-estimate these models based on the local data for Chicago rather than directly transfer them from a different region where the CT-RAMP model system was implemented before. Below are several examples of spatial distribution effects incorporated in the usual workplace choice model. The CMAP model components and effects are compared to three other regions where an advanced CT-RAMP model system was implemented recently:

- **SANDAG** (San Diego Association of Governments, San Diego, CA)
- **MAG** (Maricopa Association of Governments, Phoenix, AZ)
- **PAG** (Pima Association of Governments, Tucson, AZ)

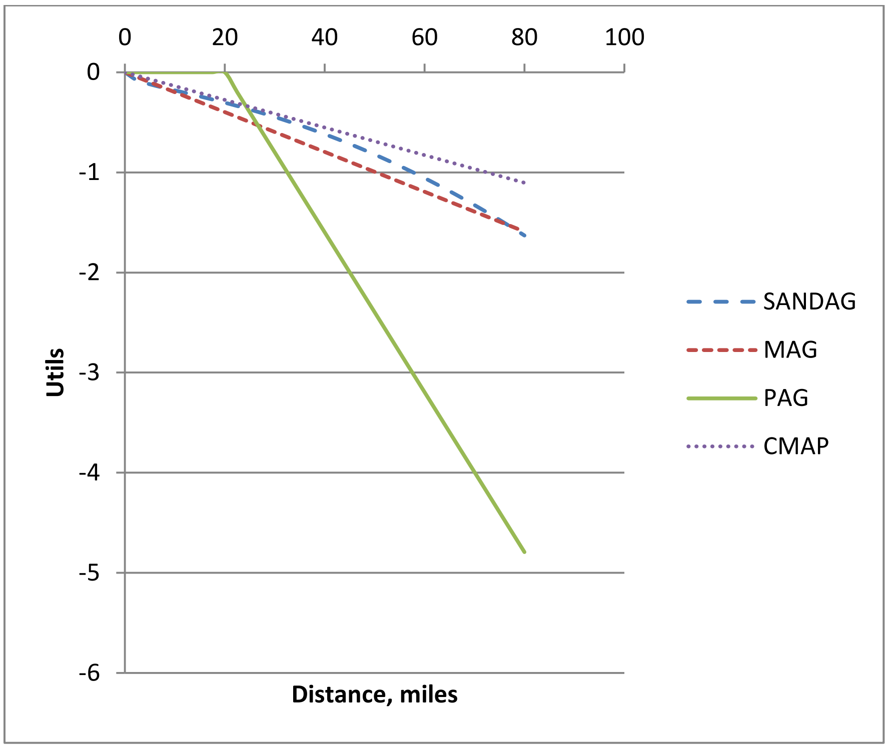
The base distance decay function for the reference worker type (full-time, medium-income, male) is shown in **Figure 9**. It can be seen that in all regions this function is logically monotonically decreasing. The CMAP curve is somewhat in between the SANDAG and MAG areas (two other large metropolitan areas that can serve as a basis for comparison to CMAP).

Figure 9: Base Distance Decay Function for Full-Time, Medium-Income, Male Worker



There are multiple effects applied on top of the base distance-decay function associated with person and household characteristics of the worker. One of important effects is a shorter commuting distance (stronger distance-decay function) for low-income workers compared to the base case of a medium-income worker. Low incomes workers are more versatile in terms of occupation and job specifics. Thus, for them it normally does not make sense to commute a long distance since they can find a similar job closer to their residence. The corresponding curves for different regions are presented in **Figure 10**. In can be seen that this effect in the CMAP region is similar to the other two large metropolitan areas (SANDAG and MAG) but somewhat weaker than can be explained by a generally greater commuting area in the CMAP region.

Figure 10: Base Relative Impact for Low-Income Worker on Distance Decay

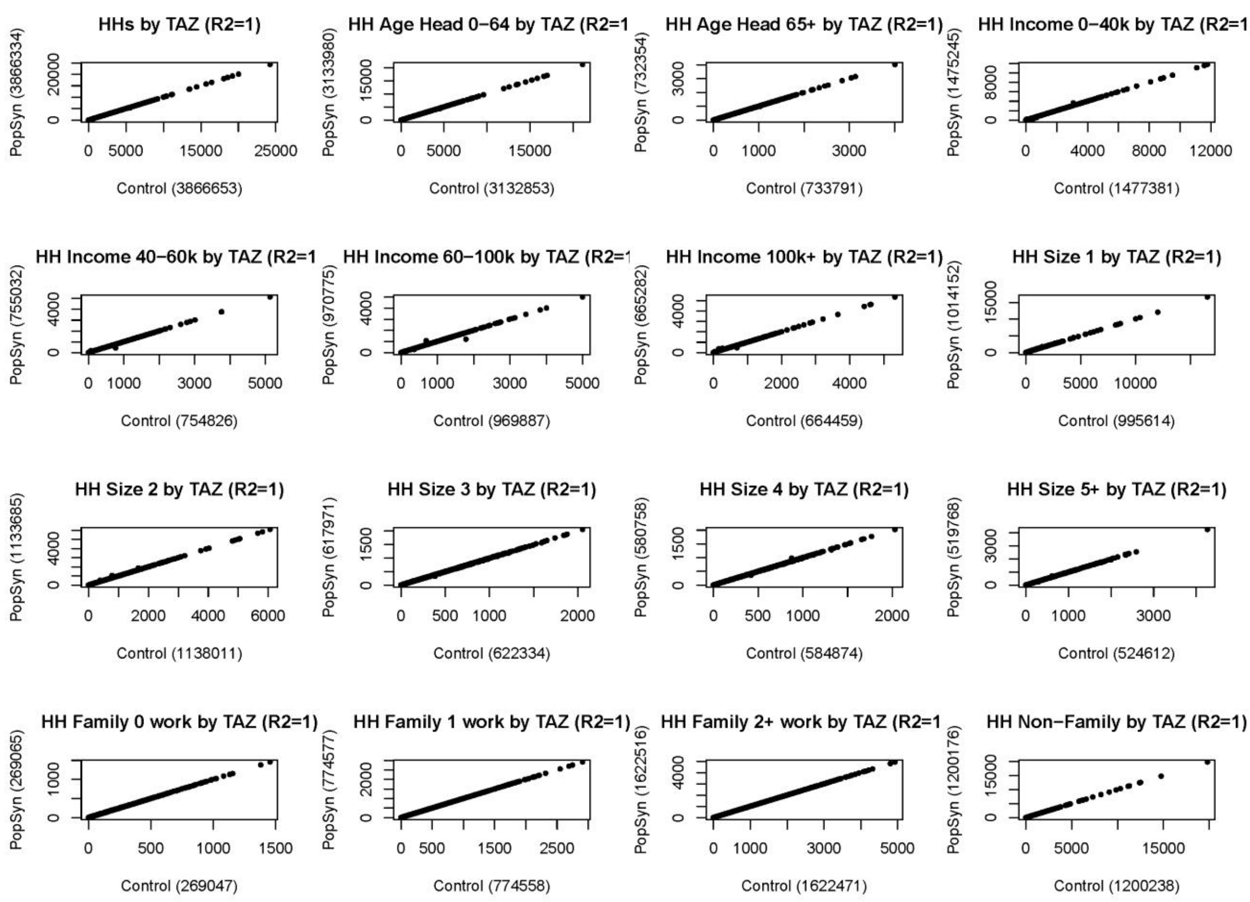


CMAP CT-RAMP Validation and Sensitivity Tests

Validation of the Population Synthesizer

CMAP provided all of the data items required for the Pricing ABM development (for the base year 2010). This included population distribution by 4 household dimensions (size, number of workers, income group, and age of household head). The population data were consolidated with the household travel survey and various consistency checks have been implemented. The problem of having the household distribution by number of workers for family households only has been resolved by restructuring the population sample and balancing procedures to address the household distribution by family and non-family type. The marginal population distributions provided by CMAP have been used to create expansion factors for the household travel survey and for population synthesis. The population synthesizer output shows a very good match to the targets – see **Figure 11**.

Figure 11: Validation Statistics for CMAP Population Synthesizer



Validation of Travel Sub-Models against the Household Travel Survey

The CMAP CT-RAMP model after software system integration was run multiple times to compare all sub-models to aggregate stratified targets developed from the CMAP household travel survey. For this purpose, the survey records were weighted to match the synthetic population proportion, i.e. household distribution by size, number of workers, income group, and age of the household head at the level of 16 super-districts (defined as a product of 5 rings and 3 sectors plus the CBD area as a separate district). The weighting procedure was implemented as an IPF balancing of the individual household weights across more than 20 dimensions in each district separately. The convergence statistics were very good except for one district in the external ring (in Wisconsin) that was not surveyed at all.

The level of validation and scrutiny was very high including separate comparisons by person type, travel purpose, geographic areas, etc. The sub-models that were developed and estimated based on the CMAP household travel survey, which include car ownership choice, workplace location choice, tour mode choice, and tour time-of-day choice, performed very well and required very little or no calibration. Some other sub-models transferred from the ARC CT-RAMP required adjustment of constants to better match the Chicago data. In general, the calibration strategy was not to over-specify the model by adding too many stratified constants but rather to demonstrate performance and sensitivity of the raw model. The calibration process could be continued in future model improvement efforts and practically any match can be achieved for any particular dimension and/or geographic subarea by adding more constants and gradually adjusting them. However, we recommend not to overuse this static calibration but to reserve some residual discrepancies for further model improvement efforts that should include a complete disaggregate re-estimation of all sub-models originally transferred from ARC.

We present below some main validation and calibration results for the main sub-models. The validation results for the household car-ownership model are presented in **Table 24**. The upper section of the table shows car-ownership statistics from the survey. The middle section shows the same statistics from the CT-RAMP run. The lower section demonstrates discrepancies between the model and the survey. Only differences that are greater than either the absolute threshold of 1,000 or relative threshold of 1% are shown. The left-hand side in all sections shows absolute numbers (households) while the right-hand side shows household distribution in percent. It can be shown that without an extensive calibration the car ownership model performed with a reasonable level of accuracy. At the entire-region level all household categories by number of cars (0, 1, 2, 3 and 4+) were replicated with a level of accuracy of 1-2%. Another important validation dimension is associated with relative car-sufficiency (for households with at least 1 car). This dimension, although not explicitly controlled in the choice model by constants, proved to be at a reasonable level of accuracy (5%). It must be mentioned that the developed car-ownership model was able to capture significant geographic variation of urban conditions through the applied set of accessibility measures and special car-dependency indices. In particular, it can be seen that the model reasonably replicated the strong impact of density on percentage of households without cars. This percentage is very high in the CBD (one third of the household), significant in the first ring (one fifth of the households), and is very low (less than 5%) everywhere else. This logical general pattern was properly captured by the model.

Table 24: Validation of Household Car Ownership Model

Survey

Residence		Number of households									Household Distribution							
Ring	Sector	Total	0 cars	1 car	2 cars	3 cars	4+ cars	Cars<Work	Cars=Work	Cars>Work	0 cars	1 car	2 cars	3 cars	4+ cars	Cars<Work	Cars=Work	Cars>Work
1	0	169,098	56,523	84,319	25,310	1,556	1,390	22,087	59,817	30,670	33.4%	49.9%	15.0%	0.9%	0.8%	13.1%	35.4%	18.1%
2	1	420,882	85,096	196,523	111,906	22,456	4,899	57,306	163,524	114,955	20.2%	46.7%	26.6%	5.3%	1.2%	13.6%	38.9%	27.3%
2	2	424,645	57,888	177,297	150,721	30,151	8,587	68,085	170,948	127,725	13.6%	41.8%	35.5%	7.1%	2.0%	16.0%	40.3%	30.1%
2	3	483,714	104,009	200,271	132,535	34,527	12,372	52,691	170,861	156,153	21.5%	41.4%	27.4%	7.1%	2.6%	10.9%	35.3%	32.3%
3	1	164,844	6,778	52,622	79,733	19,860	5,851	9,745	76,823	71,498	4.1%	31.9%	48.4%	12.0%	3.5%	5.9%	46.6%	43.4%
3	2	259,695	9,011	76,274	118,054	41,544	14,812	12,364	113,378	124,943	3.5%	29.4%	45.5%	16.0%	5.7%	4.8%	43.7%	48.1%
3	3	129,755	4,013	38,781	62,934	16,513	7,513	7,027	52,392	66,322	3.1%	29.9%	48.5%	12.7%	5.8%	5.4%	40.4%	51.1%
4	1	347,967	9,456	77,232	166,897	67,211	27,170	8,857	163,419	166,234	2.7%	22.2%	48.0%	19.3%	7.8%	2.5%	47.0%	47.8%
4	2	350,337	5,522	78,941	189,791	50,839	25,244	13,796	188,729	142,289	1.6%	22.5%	54.2%	14.5%	7.2%	3.9%	53.9%	40.6%
4	3	237,582	2,573	58,435	123,685	34,697	18,193	9,992	105,084	119,933	1.1%	24.6%	52.1%	14.6%	7.7%	4.2%	44.2%	50.5%
5	1	56,601	364	14,821	24,360	11,773	5,283	1,779	25,524	28,934	0.6%	26.2%	43.0%	20.8%	9.3%	3.1%	45.1%	51.1%
5	2	79,273	2,906	11,438	40,012	21,109	3,808	0	32,165	44,203	3.7%	14.4%	50.5%	26.6%	4.8%	0.0%	40.6%	55.8%
5	3	16,441	0	2,636	9,177	2,603	2,026	0	6,810	9,631	0.0%	16.0%	55.8%	15.8%	12.3%	0.0%	41.4%	58.6%
6	1	0	0	0	0	0	0	0	0	0	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6	2	258,863	1,682	42,033	154,120	59,491	1,537	0	134,415	122,765	0.6%	16.2%	59.5%	23.0%	0.6%	0.0%	51.9%	47.4%
6	3	287,860	14,176	81,333	119,836	48,448	24,067	8,426	104,375	160,883	4.9%	28.3%	41.6%	16.8%	8.4%	2.9%	36.3%	55.9%
Total		3,687,556	359,997	1,192,956	1,509,074	462,777	162,752	272,156	1,568,264	1,487,139	9.8%	32.4%	40.9%	12.5%	4.4%	7.4%	42.5%	40.3%

Model

Residence		Number of households									Household Distribution							
Ring	Sector	Total	0 cars	1 car	2 cars	3 cars	4+ cars	Cars<Work	Cars=Work	Cars>Work	0 cars	1 car	2 cars	3 cars	4+ cars	Cars<Work	Cars=Work	Cars>Work
1	0	167,715	45,895	83,755	33,185	2,645	2,235	26,135	67,875	27,810	27.4%	49.9%	19.8%	1.6%	1.3%	15.6%	40.5%	16.6%
2	1	423,070	73,240	174,660	133,685	31,020	10,465	62,630	165,000	122,200	17.3%	41.3%	31.6%	7.3%	2.5%	14.8%	39.0%	28.9%
2	2	425,830	63,065	169,405	144,120	36,760	12,480	72,450	152,650	137,665	14.8%	39.8%	33.8%	8.6%	2.9%	17.0%	35.8%	32.3%
2	3	484,070	73,500	198,520	156,430	41,675	13,945	66,220	169,020	175,330	15.2%	41.0%	32.3%	8.6%	2.9%	13.7%	34.9%	36.2%
3	1	164,980	6,025	47,905	76,285	24,720	10,045	18,950	66,455	73,550	3.7%	29.0%	46.2%	15.0%	6.1%	11.5%	40.3%	44.6%
3	2	261,285	9,470	75,580	121,240	39,215	15,780	33,590	109,160	109,065	3.6%	28.9%	46.4%	15.0%	6.0%	12.9%	41.8%	41.7%
3	3	129,485	5,140	37,820	58,930	19,870	7,725	13,960	50,265	60,120	4.0%	29.2%	45.5%	15.3%	6.0%	10.8%	38.8%	46.4%
4	1	347,925	5,685	75,675	176,645	60,430	29,490	36,880	144,510	160,850	1.6%	21.8%	50.8%	17.4%	8.5%	10.6%	41.5%	46.2%
4	2	350,095	8,045	79,635	173,940	58,950	29,525	40,610	150,470	150,970	2.3%	22.7%	49.7%	16.8%	8.4%	11.6%	43.0%	43.1%
4	3	235,450	5,475	53,315	116,150	40,455	20,055	24,425	90,040	115,510	2.3%	22.6%	49.3%	17.2%	8.5%	10.4%	38.2%	49.1%
5	1	55,755	1,750	11,565	25,875	12,235	4,330	5,345	21,100	27,560	3.1%	20.7%	46.4%	21.9%	7.8%	9.6%	37.8%	49.4%
5	2	74,780	735	12,035	36,530	18,790	6,690	7,195	30,765	36,085	1.0%	16.1%	48.8%	25.1%	8.9%	9.6%	41.1%	48.3%
5	3	21,385	180	4,130	9,915	5,270	1,890	2,050	7,920	11,235	0.8%	19.3%	46.4%	24.6%	8.8%	9.6%	37.0%	52.5%
6	1	179,315	4,665	40,085	87,390	36,915	10,260	14,695	67,475	92,480	2.6%	22.4%	48.7%	20.6%	5.7%	8.2%	37.6%	51.6%
6	2	258,680	6,075	58,625	126,045	53,455	14,480	21,350	91,890	139,365	2.3%	22.7%	48.7%	20.7%	5.6%	8.3%	35.5%	53.9%
6	3	286,510	9,390	66,220	137,725	57,115	16,060	22,775	98,875	155,470	3.3%	23.1%	48.1%	19.9%	5.6%	7.9%	34.5%	54.3%
Total		3,866,330	318,335	1,188,930	1,614,090	539,520	205,455	469,260	1,483,470	1,595,265	8.2%	30.8%	41.7%	14.0%	5.3%	12.1%	38.4%	41.3%

Difference (Model-Survey)

								Threshold		1,000							Threshold	1.0%
Residence		Number of households									Household Distribution							
Ring	Sector	Total	0 cars	1 car	2 cars	3 cars	4+ cars	Cars<Work	Cars=Work	Cars>Work	0 cars	1 car	2 cars	3 cars	4+ cars	Cars<Work	Cars=Work	Cars>Work
1	0	-1,383	-10,628		7,875			4,048	8,058	-2,860	-6.1%		4.8%			2.5%	5.1%	-1.6%
2	1	2,188	-11,856	-21,863	21,779	8,564	5,566	5,324		7,245	-2.9%	-5.4%	5.0%	2.0%	1.3%	1.2%		1.6%
2	2	1,185	5,177	-7,892	-6,601	6,609			-18,298	9,940	1.2%	-2.0%	-1.6%	1.5%			-4.4%	2.3%
2	3		-30,509		23,895	7,148		13,529		19,177	-6.3%		4.9%	1.5%		2.8%		3.9%
3	1			-4,717	-3,448	4,860	4,194	9,205	-10,368	2,052		-2.9%	-2.1%	2.9%	2.5%	5.6%	-6.3%	1.2%
3	2	1,590						21,226	-4,218	-15,878						8.1%	-1.9%	-6.4%
3	3				-4,004	3,357		6,933	-2,127	-6,202			-3.0%	2.6%		5.4%	-1.6%	-4.7%
4	1		-3,771		9,748	-6,781		28,023	-18,909	-5,384	-1.1%		2.8%	-1.9%		8.1%	-5.4%	-1.5%
4	2				-15,851	8,111	4,281	26,814	-38,259	8,681			-4.5%	2.3%	1.2%	7.7%	-10.9%	2.5%
4	3	-2,132	2,902	-5,120	-7,535	5,758		14,433	-15,044	-4,423	1.2%	-2.0%	-2.7%	2.6%		6.2%	-6.0%	-1.4%
5	1		1,386	-3,256	1,515			3,566	-4,424	-1,374	2.5%	-5.4%	3.4%			6.4%	-7.3%	-1.7%
5	2	-4,493	-2,171		-3,482	-2,319	2,882	7,195		-8,118	-2.7%		-1.6%	-1.5%	4.1%	9.6%		-7.5%
5	3	4,944		1,494		2,667		2,050	1,110	1,604		3.3%		8.8%		9.6%	-4.4%	-6.0%
6	1	179,315	4,665	40,085	87,390	36,915	10,260	14,695	67,475	92,480	2.6%	22.4%	48.7%	20.6%	5.7%	8.2%	37.6%	51.6%
6	2		4,393	16,592	-28,075	-6,036	12,943	21,350	-42,525	16,600	1.7%	6.4%	-10.8%	-2.3%	5.0%	8.3%	-16.4%	6.5%
6	3	-1,350	-4,786	-15,113	17,889	8,667	-8,007	14,349	-5,500	-5,413	-1.6%	-5.1%	6.4%	3.1%	-2.8%	5.0%	-1.7%	-1.6%
Total		178,774	-41,662	-4,026		76,743		197,104	-84,794		-1.5%	-1.6%		1.4%		4.8%	-4.2%	

The validation results of the workplace location choice model are presented in **Table 25** at the level of 16×16 district to district journey-to-work flows. Although the model accurately replicates the marginals of the journey-to-work table, there are some significant discrepancies in the raw model implementation that resulted in significant underestimation of commuting from the 3rd, 4th, and 5th rings to the CBD while the flow from the 2nd ring to the CBD was overestimated. The analysis of reasons for this discrepancy revealed that the model primarily underestimated transit commuters because of certain limitations in the current transit skimming procedure and crude subdivision of TAZs by transit-access sub-zones that left many outer zones in the 3rd, 4th, and 5th rings with no walk-to-transit access. It was decided not to apply k-factors or other adjustments to the workplace location choice model but rather improve the transit access component in the future (that can be best achieved by adopting smaller spatial units instead of TAZs in transit access calculations, such as was implemented in the San Diego CT-RAMP model).

Table 25: Validation of Workplace Location Choice Model

Survey

Residence		Workplace ring & sector																
Ring	Sector	1	2	2	2	3	3	3	4	4	4	5	5	5	6	6	6	Total
		0	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	
1	0	153,777	10,863	12,353	9,102	1,383	8,364	883	2,369	877	0	0	0	0	0	0	619	200,591
2	1	156,401	261,198	24,522	16,572	42,934	17,985	2,509	21,752	3,679	1,289	168	183	0	0	0	217	549,408
2	2	157,863	52,620	268,700	29,395	10,423	43,401	1,271	6,238	23,269	8,625	1,010	153	0	0	0	0	602,968
2	3	140,816	23,660	48,964	290,022	5,968	12,672	27,480	2,235	3,714	9,708	0	1,146	0	0	0	5,766	572,151
3	1	25,141	32,519	5,371	4,046	99,791	22,971	212	31,004	6,123	270	295	0	0	0	0	0	227,744
3	2	40,255	17,351	32,714	4,846	15,757	223,217	2,007	9,258	39,178	5,427	0	0	1,150	0	0	142	391,301
3	3	21,425	1,531	10,852	28,644	498	8,036	77,137	778	4,157	17,353	0	1,465	0	0	0	2,148	174,025
4	1	32,003	21,057	9,322	916	45,377	31,319	218	369,352	12,002	153	9,495	1,030	0	0	0	0	532,244
4	2	41,131	12,284	19,963	7,117	16,279	109,202	4,707	28,569	316,495	18,825	202	9,204	515	0	0	777	585,269
4	3	28,825	5,624	15,594	23,443	5,492	18,764	27,414	2,615	26,260	175,904	591	8,015	1,615	0	0	1,241	341,397
5	1	2,829	1,821	887	260	1,127	782	0	34,597	1,669	0	45,429	841	0	0	0	0	90,244
5	2	6,060	752	1,562	2,645	989	6,390	398	3,658	35,632	23,588	83	37,209	151	0	1,984	0	121,101
5	3	122	0	585	2,225	83	585	705	0	1,800	6,694	0	1,827	7,608	0	142	0	22,375
6	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	2	0	0	1	0	0	912	0	0	3,817	41,723	0	2	0	0	362,453	0	408,909
6	3	17,303	1,590	2,347	18,446	620	1,736	7,147	60	410	5,429	0	0	749	0	30	312,745	368,612
Total		823,949	442,871	453,737	437,679	246,722	506,335	152,089	512,484	479,082	314,990	57,274	61,074	11,788	0	364,609	323,655	5,188,338

Model

Residence		Workplace ring & sector																
Ring	Sector	1	2	2	2	3	3	3	4	4	4	5	5	5	6	6	6	Total
		0	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	
1	0	172,270	6,755	8,460	4,790	670	1,620	195	380	145	65	0	5	0	0	0	115	195,470
2	1	171,570	235,970	47,075	7,265	38,275	25,945	385	11,170	780	145	5	5	0	0	0	65	538,655
2	2	153,435	75,995	224,070	25,755	11,600	65,875	2,910	3,765	3,985	1,605	5	25	0	5	0	150	569,180
2	3	187,890	11,960	45,400	247,460	1,280	11,410	34,625	505	1,170	9,515	0	5	30	0	20	16,210	567,480
3	1	10,165	39,110	8,190	355	105,500	33,285	35	34,540	1,925	70	25	10	0	30	0	0	233,240
3	2	25,305	18,855	37,330	3,590	19,345	233,610	2,540	6,710	36,330	4,270	5	125	0	5	15	10	388,045
3	3	23,140	735	9,825	40,280	165	6,915	66,890	30	1,020	19,895	0	5	95	0	155	7,015	176,165
4	1	8,590	21,195	5,300	105	81,780	36,275	10	348,420	22,230	20	7,730	1,160	0	4,340	450	0	537,605
4	2	26,605	8,695	20,905	3,570	13,495	155,400	2,440	17,465	287,960	13,790	55	5,035	85	10	660	0	556,170
4	3	21,680	1,250	16,835	29,820	475	36,550	49,730	65	26,540	144,810	0	3,265	2,520	0	1,155	8,130	342,825
5	1	680	1,325	170	5	5,220	1,380	0	45,925	1,425	0	17,455	295	0	8,095	1,555	0	83,530
5	2	2,825	630	2,765	840	1,590	16,265	950	4,540	57,975	14,825	180	16,165	750	5	2,920	5	123,230
5	3	720	30	335	1,065	30	1,315	2,690	0	2,605	10,705	0	985	7,370	0	3,870	710	32,430
6	1	410	635	55	0	3,340	350	0	32,740	250	0	9,780	10	0	196,700	395	0	244,665
6	2	1,175	220	490	2,335	845	5,055	5,950	7,755	27,145	14,465	4,665	9,200	5,735	1,285	255,015	1,315	342,650
6	3	23,605	555	1,105	29,675	30	105	20,910	15	15	9,085	0	0	550	0	470	282,410	368,530
Total		830,065	423,915	428,310	396,910	283,640	631,355	190,260	514,025	471,500	243,265	39,905	36,295	17,135	210,475	266,680	316,135	5,299,870

Difference (Model-Survey) Threshold 1,000

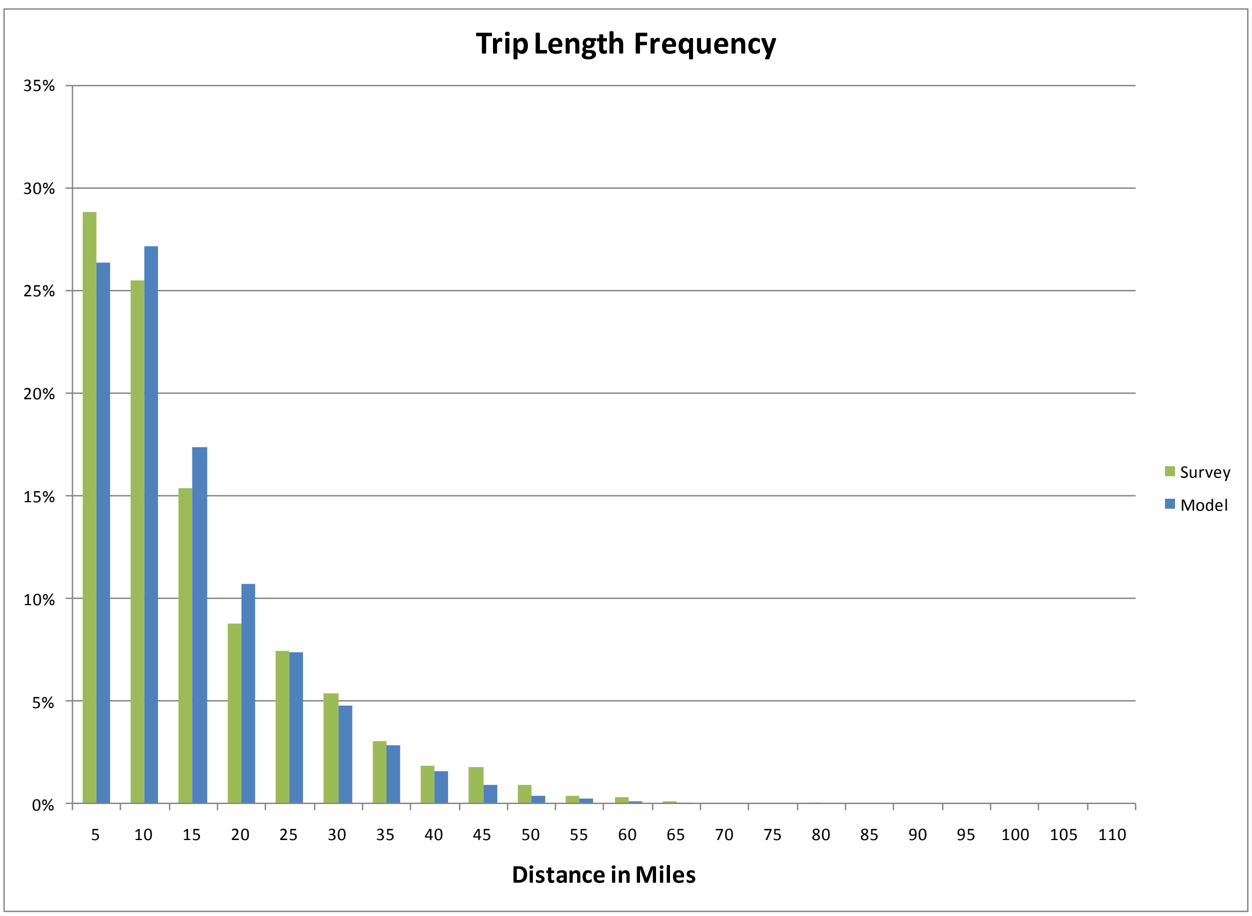
Residence		Workplace ring & sector																
Ring	Sector	1	2	2	2	3	3	3	4	4	4	5	5	5	6	6	6	Total
		0	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	
1	0	18,493	-4,108	-3,893	-4,312		-6,744		-1,989									
2	1			22,553	-9,307	-4,659	7,960	-2,124	-10,582	-2,899	-1,144							
2	2		23,375	-44,630	-3,640	1,177	22,474	1,639	-2,473	-19,284	-7,020	-1,005						
2	3	47,074	-11,700		-42,562	-4,688		7,145	-1,730	-2,544			-1,141				10,444	
3	1	-14,976	6,591	2,819	-3,691		10,314		3,536	-4,198								
3	2	-14,950		4,616	-1,256	3,588			-2,548		-1,157			-1,150				
3	3				11,636		-1,121	-10,247		-3,137	2,542		-1,460				4,867	
4	1	-23,413		-4,022		36,403	4,956			10,228		-1,765			4,340			
4	2	-14,526	-3,589		-3,547	-2,784	46,198	-2,267	-11,104		-5,035		-4,169					
4	3	-7,145	-4,374		6,377	-5,017	17,786	22,316	-2,550		-31,094		-4,750			1,155	6,889	
5	1	-2,149				4,093			11,328			-27,974			8,095	1,555		
5	2	-3,235		1,203	-1,805		9,875			22,343	-8,763		-21,044					
5	3				-1,160			1,985			4,011					3,728		10,055
6	1					3,340			32,740			9,780			196,700			244,665
6	2	1,175			2,335		4,143	5,950	7,755	23,328	-27,258	4,665	9,198	5,735	1,285	-107,438	1,315	-66,259
6	3	6,302	-1,035	-1,242	11,229		-1,631	13,763			3,656							
Total						36,918	125,020	38,171			-71,725	-17,369	-24,779	5,347	210,475	-97,929		

Ratio (Model-Survey)/Max(Model,Survey)
Difference (Model-Survey) Threshold 10%

Residence		Workplace ring & sector																
Ring	Sector	1	2	2	2	3	3	3	4	4	4	5	5	5	6	6	6	Total
		0	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	
1	0	11%	-38%	-32%	-47%		-81%		-84%									
2	1			48%	-56%	-11%	31%	-85%	-49%	-79%	-89%							
2	2		31%	-17%	-12%	10%	34%	56%	-40%	-83%	-81%	-100%						
2	3	25%	-49%		-15%	-79%		21%	-77%	-68%			-100%				64%	
3	1	-60%	17%	34%	-91%		31%		10%	-69%								
3	2	-37%		12%	-26%	19%			-28%		-21%			-100%				
3	3				29%		-14%	-13%		-75%	13%		-100%				69%	
4	1	-73%		-43%		45%	14%			46%		-19%			100%			
4	2	-35%	-29%		-50%	-17%	30%	-48%	-39%		-27%		-45%					
4	3	-25%	-78%		21%	-91%	49%	45%	-98%		-18%		-59%			100%	85%	
5	1	-76%				78%			25%			-62%			100%	100%		
5	2	-53%		44%	-68%		61%			39%	-37%		-57%					
5	3				-52%			74%			37%					96%		31%
6	1					100%			100%			100%			100%			100%
6	2	100%			100%		82%	100%	100%	86%	-65%	100%	100%	100%	100%	-30%	100%	-16%
6	3	27%	-65%	-53%	38%		-94%	66%			40%							
Total						13%	20%	20%			-23%	-30%	-41%	31%	100%	-27%		

Another important validation dimension for the workplace choice as well as for all destination choice components is comparison of the corresponding trip-length distributions (TLDs) produced by the model to the observed TLDs tabulated from the expanded survey. The comparison of the modeled TLD to the observed one is presented in **Figure 12**. Overall, the match is reasonable and it can be easily improved by calibration of the distance-decay function. However, we believe that rather than mechanically adjust the distance-decay function at this stage it would be better to address two particular issues in future model improvement efforts. The first issue relates to an underestimation of the long commuting trips that is correlated with the journey-to-work matrix discrepancies discussed above. We believe that improvement of the transit side of the model may eliminate any need in calibration of the TLD since it will bring more long-distance commuters (primarily by premium transit). The second issues relates to an underestimation of very short commuting cases (under 5 miles). Analysis has shown that it is largely a consequence of mixing together commuters with short distances and those who work from home on a permanent basis (10% in the household travel survey). In the current model structure, workers from home are treated mechanically as intra-TAZ commuters. In the recent advanced versions of CT-RAMP developed for San Diego and Phoenix, a special sub-model for work from home was added that allows for proper treatment of this segment. We recommend including this sub-model in the CMAP CT-RAMP structure in the future so as to resolve the issues in a more consistent way compared to a mechanical adjustment of the distance-decay function.

Figure 12: Validation of Trip Length Distribution for Journey to Work



Validation results for the Coordinated Daily Activity pattern sub-model are presented in **Table 26**. This model required minor calibration since it was originally transferred from the ARC region. In the current state, this sub-model exhibits a very reasonable pattern across 8 major person types and 3 main daily activity pattern types: 1=mandatory day when at least one work or school activity is included, 2=non-mandatory travel day when no mandatory activity is included but at least one out-of-home non-mandatory activity is present, and 3=stay-at-home pattern with no out-of-home activities. For each person type, a distinctive proportion of daily pattern types are properly replicated. This model is relatively easy to calibrate further and eliminate any residual discrepancies for part-time workers, retirees, and preschool children, but it was decided to reserve the final tuning for future model improvements since, for example, the suggested general revision of transit procedures and accessibilities might affect this model as well.

Table 26: Validation of Daily Activity Pattern Model

Survey

Person type	Number of persons				Person distribution		
	Total	Mandatory	Non-mandator	Home	Mandatory	Non-mandatory	Home
1=Full-time worker	4,883,164	3,971,938	627,687	283,538	81.3%	12.9%	5.8%
2=Part-time worker	1,120,090	666,362	310,853	142,875	59.5%	27.8%	12.8%
3=University student	429,610	238,344	145,807	45,460	55.5%	33.9%	10.6%
4=Non-worker U65	1,059,125	5,785	790,790	262,550	0.5%	74.7%	24.8%
5=Retiree	1,230,178	2,659	872,668	354,850	0.2%	70.9%	28.8%
6=School child 16+	383,063	298,332	61,429	23,302	77.9%	16.0%	6.1%
7=School child 5-15	1,824,229	1,309,371	373,565	141,293	71.8%	20.5%	7.7%
8=Preschool child U5	1,063,348	288,149	514,043	261,156	27.1%	48.3%	24.6%
Total	11,992,808	6,780,940	3,696,843	1,515,025	56.5%	30.8%	12.6%

Model

Person type	Number of persons				Person distribution		
	Total	Mandatory	Non-mandator	Home	Mandatory	Non-mandatory	Home
1=Full-time worker	4,090,640	3,350,700	500,700	239,240	81.9%	12.2%	5.8%
2=Part-time worker	903,445	510,050	298,350	95,045	56.5%	33.0%	10.5%
3=University student	380,540	213,175	125,665	41,700	56.0%	33.0%	11.0%
4=Non-worker U65	1,310,540	0	974,445	336,095	0.0%	74.4%	25.6%
5=Retiree	865,960	0	601,120	264,840	0.0%	69.4%	30.6%
6=School child 16+	349,935	274,735	54,255	20,945	78.5%	15.5%	6.0%
7=School child 5-15	1,613,445	1,165,915	323,430	124,100	72.3%	20.0%	7.7%
8=Preschool child U5	934,855	262,995	439,180	232,680	28.1%	47.0%	24.9%
Total	10,449,360	5,777,570	3,317,145	1,354,645	55.3%	31.7%	13.0%

Difference (Model-Survey) Threshold: 1,000 Threshold 1.0%

Person type	Number of persons				Person distribution		
	Total	Mandatory	Non-mandator	Home	Mandatory	Non-mandatory	Home
1=Full-time worker	-792,524						
2=Part-time worker	-216,645	-156,312	-12,503	-47,830	-3.0%	5.3%	-2.2%
3=University student	-49,070						
4=Non-worker U65	251,415						
5=Retiree	-364,218		-271,548	-90,010		-1.5%	1.7%
6=School child 16+	-33,128						
7=School child 5-15	-210,784						
8=Preschool child U5	-128,493	-25,154	-74,863		1.0%	-1.4%	
Total	-1,543,448	-1,003,370			-1.3%		

The discrepancy between the absolute number of observations in the survey and number of person-days in the model run is due to the fact that some households were surveyed during two consecutive days, and, in some cases, both surveyed days were weekdays. The survey expansion factors were developed for households, not for household-days. This does not hamper a comparison between percentage distributions by daily activity pattern for each person type that was used as the basis for model validation and adjustments of constants.

Validation results for the joint travel frequency model are presented in **Table 27**. This model has gone through several rounds of calibrations since it was originally transferred from the ARC region. The comparisons between the survey and the model are included for each household size category and number-of-workers category since these two household characteristics are amongst the strongest determinants of fully joint tour making. All else being equal, large households naturally generate more joint activities while presence of workers (the busiest individual person type) results in less fully joint tours (fully joint tours do not include escorting to school since these tours are not fully joint).

Table 27: Validation of Joint Travel Frequency Model

Survey

Household size	Number of workers	Households	Joint tours by purpose						Joint tour frequency					
			Shopping	Maintenance	Eating out	Visiting	Discretionary	Total	Shopping	Maintenan	Eating out	Visiting	Discretionar	Total
1	0	493,295	0	0	0	0	0	0	0.000	0.000	0.000	0.000	0.000	0.000
1	1	701,753	0	0	0	0	0	0	0.000	0.000	0.000	0.000	0.000	0.000
2	0	262,690	33,923	33,272	12,093	8,912	28,298	116,498	0.129	0.127	0.046	0.034	0.108	0.443
2	1	347,019	27,434	14,285	10,823	5,975	25,903	84,420	0.079	0.041	0.031	0.017	0.075	0.243
2	2+	713,081	29,826	13,927	25,852	9,793	17,363	96,761	0.042	0.020	0.036	0.014	0.024	0.136
3	0	52,959	7,353	3,046	2,760	1,796	9,619	24,574	0.139	0.058	0.052	0.034	0.182	0.464
3	1	229,197	31,716	19,588	8,467	17,146	20,778	97,695	0.138	0.085	0.037	0.075	0.091	0.426
3	2+	454,123	32,921	36,292	11,421	8,822	23,430	112,886	0.072	0.080	0.025	0.019	0.052	0.249
4	0	23,333	5,215	2,631	1,849	3,301	3,417	16,413	0.224	0.113	0.079	0.141	0.146	0.703
4	1	187,106	36,017	22,729	7,348	8,365	29,963	104,422	0.192	0.121	0.039	0.045	0.160	0.558
4	2+	451,156	54,966	30,186	20,778	20,719	54,313	180,962	0.122	0.067	0.046	0.046	0.120	0.401
5+	0	27,305	5,780	1,613	0	315	5,508	13,216	0.212	0.059	0.000	0.012	0.202	0.484
5+	1	219,307	34,799	30,579	8,482	15,183	31,094	120,137	0.159	0.139	0.039	0.069	0.142	0.548
5+	2+	368,048	56,803	36,165	15,611	10,696	47,142	166,417	0.154	0.098	0.042	0.029	0.128	0.452
Total		4,530,372	356,753	244,313	125,484	111,023	296,828	1,134,401	0.079	0.054	0.028	0.025	0.066	0.250

Model

Household size	Number of workers	Households	Joint tours by purpose						Joint tour frequency					
			Shopping	Maintenance	Eating out	Visiting	Discretionary	Total	Shopping	Maintenan	Eating out	Visiting	Discretionar	Total
1	0	498,190	0	0	0	0	0	0	0.000	0.000	0.000	0.000	0.000	0.000
1	1	518,965	0	0	0	0	0	0	0.000	0.000	0.000	0.000	0.000	0.000
2	0	205,945	54,655	16,340	8,940	8,870	9,240	98,045	0.265	0.079	0.043	0.043	0.045	0.476
2	1	342,935	25,255	10,290	9,605	5,365	10,685	61,200	0.074	0.030	0.028	0.016	0.031	0.178
2	2+	585,000	20,250	9,950	18,450	5,750	17,265	71,665	0.035	0.017	0.032	0.010	0.030	0.123
3	0	38,825	12,110	4,165	1,495	2,460	2,550	22,780	0.312	0.107	0.039	0.063	0.066	0.587
3	1	183,150	25,410	13,525	6,845	6,735	13,105	65,620	0.139	0.074	0.037	0.037	0.072	0.358
3	2+	394,225	23,035	14,615	16,365	8,135	24,285	86,435	0.058	0.037	0.042	0.021	0.062	0.219
4	0	22,340	7,420	4,335	750	1,930	2,395	16,830	0.332	0.194	0.034	0.086	0.107	0.753
4	1	152,965	30,915	24,440	5,840	9,635	23,565	94,395	0.202	0.160	0.038	0.063	0.154	0.617
4	2+	403,680	36,340	33,045	19,060	13,395	55,985	157,825	0.090	0.082	0.047	0.033	0.139	0.391
5+	0	26,420	8,445	5,830	805	2,210	3,390	20,680	0.320	0.221	0.030	0.084	0.128	0.783
5+	1	133,610	30,855	28,845	4,655	10,760	28,295	103,410	0.231	0.216	0.035	0.081	0.212	0.774
5+	2+	360,080	46,195	48,755	17,635	23,135	77,100	212,820	0.128	0.135	0.049	0.064	0.214	0.591
Total		3,866,330	320,885	214,135	110,445	98,380	267,860	1,011,705	0.083	0.055	0.029	0.025	0.069	0.262

Ratio (Model-Survey)/max(Model,Survey) **Threshold:** 1,000 **Threshold:** 2%

Household size	Number of workers	Households	Joint tours by purpose						Joint tour frequency					
			Shopping	Maintenance	Eating out	Visiting	Discretionary	Total	Shopping	Maintenan	Eating out	Visiting	Discretionar	Total
1	0	4,895												
1	1	-182,788												
2	0	-56,745	38%	-51%	-26%		-67%	-16%	51%	-37%	-6%		-58%	7%
2	1	-4,084	-8%	-28%	-11%		-59%	-28%	-7%	-27%	-10%		-58%	-27%
2	2+	-128,081	-32%	-29%	-29%	-41%		-26%	-17%	-13%	-13%	-28%		-10%
3	0	-14,134	39%	27%	-46%	27%	-73%	-7%	55%	46%	-26%	46%	-64%	21%
3	1	-46,047	-20%	-31%	-19%	-61%	-37%	-33%	0%	-14%	1%	-51%	-21%	-16%
3	2+	-59,898	-30%	-60%	30%			-23%	-19%	-54%	39%			-12%
4	0		30%	39%	-59%	-42%	-30%	2%	33%	42%	-58%	-39%	-27%	7%
4	1	-34,141	-14%	7%	-21%	13%	-21%	-10%	5%	24%	-3%	29%	-4%	10%
4	2+	-47,476	-34%	9%	-8%	-35%	3%	-13%	-26%	18%	2%	-28%	13%	-3%
5+	0		32%	72%	100%	86%	-38%	36%	34%	73%	100%	86%	-36%	38%
5+	1	-85,697	-11%	-6%	-45%	-29%	-9%	-14%	31%	35%	-10%	14%	33%	29%
5+	2+	-7,968	-19%	26%	11%	54%	39%	22%	-17%	27%	13%	55%	40%	23%
Total		-664,042	-10%	-12%	-12%	-11%	-10%	-11%	5%	3%	3%	4%	5%	4%

In general, a very good match was achieved between the survey and the model with respect to the average joint tour rate per household for each of the 5 non-mandatory travel purposes considered in this sub-model (shopping, other maintenance, eating out, visiting relatives and friends, and other discretionary). It required a slight adjustment of the tour-frequency constants that are currently set for each purpose, but in a generic way (i.e. not specific to each household size and composition). As a result, there are still some structural discrepancies for some travel purposes and household categories. Of course, it would be possible to eliminate these discrepancies by applying a more structural set of adjustment constants but this would be an example of a mechanical over-specification of the choice model. Also, note that fully joint travel of household members cannot occur in a 1-person household, hence there are no joint tour rates in this case in both the survey and model output.

As a future improvement, we suggest fully re-estimating this model with the CMAP household travel survey data that would allow for accounting of the important specifics of the local conditions. Joint household travel is a strong function of urban density and transportation accessibilities; thus the corresponding model parameters estimated for the Atlanta region might be significantly different from the Chicago region (although the model structure itself is quite transferable between regions as the previous 7 applications of CT-RAMP have proven).

Validation results for the individual travel frequency model are presented in **Table 28**. Similar to the joint tour frequency model discussed above, this model also has gone through several rounds of calibrations since it was originally transferred from the ARC region. In a similar way, for the bottom line, a very good match was achieved for the average tour generation rate per person by the 6 non-mandatory travel purposes considered in this sub-model (escorting, shopping, other maintenance, eating out, visiting relatives and friends, and other discretionary). There are some discrepancies at the level of structural details. For this sub-model, analysis is implemented at a high level of detail by 8 person types, 2 daily pattern types (a non-mandatory pattern is logically associated with higher tour rates compared to a mandatory pattern when the person has either work or school activities on the given day), and 2 joint travel participation categories (those who participated in joint activity vs. those who did not with a logical negative impact of joint activity frequency on individual activity frequency due to a substitution effect, as well as because of time constraints).

It should be noted that a combination of all dimensions involved in this analysis results in 192 tour rate cells (8×2×2×6) where some segments were quite thin in the survey resulting in lumpiness in the targets themselves. Again, as with the previously discussed joint tour frequency model, it would be possible to improve the structural match by proliferation of the adjustment constants. However, this over-specification strategy was rejected. Instead, a full re-estimation of this model with the CMAP household travel survey is suggested as part of future model improvements. It should also be noted that the CMAP household travel survey (2007) is in many respects better than the ARC household travel survey (2001), and it includes more person and household variables that can be used to explain travel behavior. Another important angle of view that can be provided with the CMAP household travel survey is the impact of urban density and transportation accessibility on individual travel frequency. The Atlanta region is much more uniform and less transit-rich compared to the Chicago region; thus the full spectrum of these impacts could not be reflected in the ARC model system. In this regard, application of a wider set of accessibility measures (as applied in the SANDAG and MAG CT-RAMP ABMs) is very important for the future improvements of all sub-models of the CMAP CT-RAMP ABM. This is reflected in our general conclusions and recommendations.

Table 28: Validation of Individual Travel Frequency Model

Survey

Person Type	Daily Activity Pattern	Joint tour participation	Persons	Number of Non-Mandatory Tours							Observed Non-Mandatory Tour Rate per Person						
				Escort	Shop	Maint	Eating	Visit	Discr	Total	Escort	Shop	Maint	Eating	Visit	Discr	Total
1=Full-time worker	2=Non-Mandatory	0=no	366,597	146,079	136,558	149,207	40,629	59,730	73,471	605,674	0.398	0.373	0.407	0.111	0.163	0.200	1.652
		1=yes	261,090	56,481	138,482	100,706	42,945	49,933	83,478	472,025	0.216	0.530	0.386	0.164	0.191	0.320	1.808
	1=Mandatory	0=no	3,598,575	195,563	210,901	137,202	53,528	78,800	181,037	857,031	0.054	0.059	0.038	0.015	0.022	0.050	0.238
		1=yes	373,363	27,641	116,996	75,672	79,327	35,043	116,009	450,688	0.074	0.313	0.203	0.212	0.094	0.311	1.207
2=Part-time worker	2=Non-Mandatory	0=no	192,069	88,737	82,598	65,027	10,919	26,699	51,609	325,589	0.462	0.430	0.339	0.057	0.139	0.269	1.695
		1=yes	118,784	46,592	68,531	52,670	22,207	14,748	51,647	256,395	0.392	0.577	0.443	0.187	0.124	0.435	2.158
	1=Mandatory	0=no	596,778	71,269	95,188	76,395	15,894	27,281	40,308	326,335	0.119	0.160	0.128	0.027	0.046	0.068	0.547
		1=yes	69,584	16,349	27,433	20,113	10,701	5,351	23,328	103,275	0.235	0.394	0.289	0.154	0.077	0.335	1.484
3=University student	2=Non-Mandatory	0=no	94,040	30,505	22,233	30,066	17,926	22,076	21,956	144,762	0.324	0.236	0.320	0.191	0.235	0.233	1.539
		1=yes	51,767	10,205	22,445	12,901	10,181	5,544	32,057	93,333	0.197	0.434	0.249	0.197	0.107	0.619	1.803
	1=Mandatory	0=no	224,891	15,253	9,193	13,767	1,985	9,717	16,860	66,775	0.068	0.041	0.061	0.009	0.043	0.075	0.297
		1=yes	13,453	2,794	3,260	3,286	1,304	1,973	4,921	17,538	0.208	0.242	0.244	0.097	0.147	0.366	1.304
4-Non-worker	2=Non-Mandatory	0=no	462,819	253,070	153,841	170,081	24,740	75,072	108,583	785,387	0.547	0.332	0.367	0.053	0.162	0.235	1.697
		1=yes	327,971	120,762	222,088	128,097	33,467	51,495	116,078	671,987	0.368	0.677	0.391	0.102	0.157	0.354	2.049
	1=Mandatory	0=no	5,256	650	88	223	0	0	615	1,576	0.124	0.017	0.042	0.000	0.000	0.117	0.300
		1=yes	529	86	15	86	0	0	428	615	0.163	0.028	0.163	0.000	0.000	0.809	1.163
5=Retiree	2=Non-Mandatory	0=no	589,914	91,026	263,840	222,310	48,302	79,391	174,976	879,845	0.154	0.447	0.377	0.082	0.135	0.297	1.491
		1=yes	282,754	13,608	122,740	121,987	45,594	30,731	97,510	432,170	0.048	0.434	0.431	0.161	0.109	0.345	1.528
	1=Mandatory	0=no	1,866	210	0	25	0	0	519	754	0.113	0.000	0.013	0.000	0.000	0.278	0.404
		1=yes	792	0	47	0	58	47	688	840	0.000	0.059	0.000	0.073	0.059	0.869	1.061
6=Driving age school child	2=Non-Mandatory	0=no	39,400	3,267	7,773	9,227	2,061	14,449	22,657	59,434	0.083	0.197	0.234	0.052	0.367	0.575	1.508
		1=yes	22,029	3,728	10,043	8,633	1,268	3,057	11,576	38,305	0.169	0.456	0.392	0.058	0.139	0.525	1.739
	1=Mandatory	0=no	269,916	10,401	7,760	8,787	2,486	14,451	31,206	75,091	0.039	0.029	0.033	0.009	0.054	0.116	0.278
		1=yes	28,416	553	8,656	6,197	3,788	5,429	12,514	37,137	0.019	0.305	0.218	0.133	0.191	0.440	1.307
7=Pre-driving age school child	2=Non-Mandatory	0=no	136,552	25,819	10,211	16,665	3,229	40,818	74,659	171,401	0.189	0.075	0.122	0.024	0.299	0.547	1.255
		1=yes	237,013	11,803	90,939	65,951	33,831	38,495	103,839	344,858	0.050	0.384	0.278	0.143	0.162	0.438	1.455
	1=Mandatory	0=no	1,122,265	26,708	9,165	20,171	4,248	30,451	104,737	195,480	0.024	0.008	0.018	0.004	0.027	0.093	0.174
		1=yes	187,106	3,769	42,467	37,153	23,020	22,604	87,944	216,957	0.020	0.227	0.199	0.123	0.121	0.470	1.160
8=Preschool child	2=Non-Mandatory	0=no	159,443	107,289	4,972	17,743	472	29,269	54,254	213,999	0.673	0.031	0.111	0.003	0.184	0.340	1.342
		1=yes	354,601	64,027	158,981	93,264	40,241	81,074	115,330	552,917	0.181	0.448	0.263	0.113	0.229	0.325	1.559
	1=Mandatory	0=no	239,213	16,746	2,305	2,569	0	3,988	7,758	33,366	0.070	0.010	0.011	0.000	0.017	0.032	0.139
		1=yes	48,937	11,499	14,241	10,010	8,351	8,855	19,191	72,147	0.235	0.291	0.205	0.171	0.181	0.392	1.474
Total			10,477,783	1,472,489	2,063,990	1,676,191	582,702	866,571	1,841,743	8,503,686	0.141	0.197	0.160	0.056	0.083	0.176	0.812

Model

Person Type	Daily Activity Pattern	Joint tour participation	Persons	Number of Non-Mandatory Tours							Observed Non-Mandatory Tour Rate per Person						
				Escort	Shop	Maint	Eating	Visit	Discr	Total	Escort	Shop	Maint	Eating	Visit	Discr	Total
1=Full-time worker	2=Non-Mandatory	0=no	342,635	131,590	117,455	124,880	34,800	52,075	63,600	524,400	0.384	0.343	0.364	0.102	0.152	0.186	1.530
		1=yes	158,065	34,610	75,015	56,760	25,075	29,745	47,355	268,560	0.219	0.475	0.359	0.159	0.188	0.300	1.699
	1=Mandatory	0=no	2,859,430	156,210	176,315	115,345	57,745	64,900	153,760	724,275	0.055	0.062	0.040	0.020	0.023	0.054	0.253
		1=yes	491,270	37,820	139,490	94,390	94,010	44,835	134,755	545,300	0.077	0.284	0.192	0.191	0.091	0.274	1.110
2=Part-time worker	2=Non-Mandatory	0=no	194,030	87,795	78,300	61,505	10,435	24,720	49,120	311,875	0.452	0.404	0.317	0.054	0.127	0.253	1.607
		1=yes	104,320	38,120	50,530	39,445	16,670	12,295	38,445	195,505	0.365	0.484	0.378	0.160	0.118	0.369	1.874
	1=Mandatory	0=no	422,675	50,505	65,480	52,020	11,140	18,735	28,440	226,320	0.119	0.155	0.123	0.026	0.044	0.067	0.535
		1=yes	87,375	19,345	27,860	21,370	11,720	5,800	23,910	110,005	0.221	0.319	0.245	0.134	0.066	0.274	1.259
3=University student	2=Non-Mandatory	0=no	81,230	29,200	21,235	28,795	16,160	20,365	23,170	138,925	0.359	0.261	0.354	0.199	0.251	0.285	1.710
		1=yes	44,435	9,075	16,675	10,980	8,570	5,115	22,265	72,680	0.204	0.375	0.247	0.193	0.115	0.501	1.636
	1=Mandatory	0=no	182,995	11,935	8,045	10,910	2,000	7,520	13,125	53,535	0.065	0.044	0.060	0.011	0.041	0.072	0.293
		1=yes	30,180	6,330	6,675	7,275	3,010	4,670	9,630	37,590	0.210	0.221	0.241	0.100	0.155	0.319	1.246
4-Non-worker	2=Non-Mandatory	0=no	623,400	321,215	185,670	201,225	30,675	88,925	129,400	957,110	0.515	0.298	0.323	0.049	0.143	0.208	1.535
		1=yes	351,045	118,625	173,415	114,525	32,075	50,715	102,250	591,605	0.338	0.494	0.326	0.091	0.144	0.291	1.685
	1=Mandatory	0=no	0	0	0	0	0	0	0	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		1=yes	0	0	0	0	0	0	0	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5=Retiree	2=Non-Mandatory	0=no	418,370	62,445	176,085	148,350	33,080	52,960	117,365	590,285	0.149	0.421	0.355	0.079	0.127	0.281	1.411
		1=yes	182,750	8,410	66,410	71,225	27,875	19,750	58,100	251,770	0.046	0.363	0.390	0.153	0.108	0.318	1.378
	1=Mandatory	0=no	0	0	0	0	0	0	0	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		1=yes	0	0	0	0	0	0	0	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
6=Driving age school child	2=Non-Mandatory	0=no	28,095	2,540	6,405	6,680	1,280	9,180	14,310	40,395	0.090	0.228	0.238	0.046	0.327	0.509	1.438
		1=yes	26,160	4,450	10,380	9,125	1,295	3,345	10,960	39,555	0.170	0.397	0.349	0.050	0.128	0.419	1.512
	1=Mandatory	0=no	216,170	8,945	9,245	9,065	3,015	12,975	27,645	70,890	0.041	0.043	0.042	0.014	0.060	0.128	0.328
		1=yes	58,565	875	13,975	9,820	5,720	9,455	19,205	59,050	0.015	0.239	0.168	0.098	0.161	0.328	1.008
7=Pre-driving age school child	2=Non-Mandatory	0=no	152,945	27,675	15,900	18,970	4,855	41,930	76,530	185,860	0.181	0.104	0.124	0.032	0.274	0.500	1.215
		1=yes	170,485	7,460	52,775	36,880	19,215	22,970	60,630	199,930	0.044	0.310	0.216	0.113	0.135	0.356	1.173
	1=Mandatory	0=no	804,255	21,140	18,915	20,990	9,255	25,875	94,310	190,485	0.026	0.024	0.026	0.012	0.032	0.117	0.237
		1=yes	361,660	6,060	65,145	55,410	35,195	36,000	129,760	327,570	0.017	0.180	0.153	0.097	0.100	0.359	0.906
8=Preschool child	2=Non-Mandatory	0=no	187,105	121,120	12,115	20,760	3,125	33,800	60,215	251,135	0.647	0.065	0.111	0.017	0.181	0.322	1.342
		1=yes	252,075	45,290	95,865	61,600	27,700	53,860	75,840	360,155	0.180	0.380	0.244	0.110	0.214	0.301	1.429
	1=Mandatory	0=no	182,555	12,905	3,865	3,060	4,795	3,295	7,700	35,620	0.071	0.021	0.017	0.026	0.018	0.042	0.195
		1=yes	80,440	19,120	21,405	15,330	13,000	13,565	28,675	111,095	0.238	0.266	0.191	0.162	0.169	0.356	1.381
Total			9,094,715	1,400,810	1,710,645	1,426,690	543,490	769,375	1,620,470	7,471,480	0.154	0.188	0.157	0.060	0.085	0.178	0.822

Ratio (Model-Survey)/max(Model,Survey)

Threshold 10,000 Threshold 0%

Person Type	Daily Activity Pattern	Joint tour participation	Persons	Number of Non-Mandatory Tours							Observed Non-Mandatory Tour Rate per Person						
				Escort	Shop	Maint	Eating	Visit	Discr	Total	Escort	Shop	Maint	Eating	Visit	Discr	Total
1=Full-time worker	2=Non-Mandatory	0=no	-6.5%	-9.9%	-14.0%	-16.3%				-13.4%	-3.6%	-8.0%	-10.5%	-8.4%	-6.7%	-7.4%	-7.4%
		1=yes	-39.5%	-38.7%	-45.8%	-43.6%	-41.6%	-40.4%	-43.3%	-43.1%	1.2%	-10.5%	-6.9%	-3.6%	-1.6%	-6.3%	-6.0%
	1=Mandatory	0=no	-20.5%	-20.1%	-16.4%	-15.9%		-17.6%	-15.1%	-15.5%	0.5%	5.0%	5.5%	26.3%	3.5%	6.4%	6.0%
		1=yes	24.0%	26.9%	16.1%	19.8%	15.6%		13.9%	17.4%	3.8%	-9.4%	-5.2%	-9.9%	-2.8%	-11.7%	-8.0%
2=Part-time worker	2=Non-Mandatory	0=no								-4.2%	-2.1%	-6.2%	-6.4%	-5.4%	-8.3%	-5.8%	-5.2%
		1=yes	-12.2%		-26.3%	-25.1%			-25.6%	-23.7%	-6.8%	-16.0%	-14.7%	-14.5%	-5.1%	-15.2%	-13.2%
	1=Mandatory	0=no	-29.2%	-29.1%	-31.2%	-31.9%			-29.4%	-30.6%	0.1%	-2.9%	-3.9%	-1.0%	-3.0%	-0.4%	-2.1%
		1=yes	20.4%								-5.8%	-19.1%	-15.4%	-12.8%	-13.7%	-18.4%	-15.2%
3=University student	2=Non-Mandatory	0=no	-13.6%								9.8%	9.6%	9.8%	4.2%	6.4%	18.1%	10.0%
		1=yes								-22.1%	3.5%	-13.4%	-0.8%	-1.9%	7.0%	-19.1%	-9.3%
	1=Mandatory	0=no	-18.6%							-19.8%	-3.8%	7.0%	-2.6%	19.2%	-4.9%	-4.3%	-1.5%
		1=yes	55.4%							53.3%	1.0%	-8.7%	-1.3%	2.8%	5.2%	-12.8%	-4.5%
4-Non-worker	2=Non-Mandatory	0=no	25.8%	21.2%	17.1%	15.5%		15.6%	16.1%	17.9%	-5.8%	-10.4%	-12.2%	-7.9%	-12.1%	-11.5%	-9.5%
		1=yes	6.6%		-21.9%	-10.6%			-11.9%	-12.0%	-8.2%	-27.0%	-16.5%	-10.5%	-8.0%	-17.7%	-17.7%
	1=Mandatory	0=no									-100.0%	-100.0%	-100.0%			-100.0%	-100.0%
		1=yes									-100.0%	-100.0%	-100.0%			-100.0%	-100.0%
5=Retiree	2=Non-Mandatory	0=no	-29.1%	-31.4%	-33.3%	-33.3%	-31.5%	-33.3%	-32.9%	-32.9%	-3.3%	-5.9%	-5.9%	-3.4%	-5.9%	-5.4%	-5.4%
		1=yes	-35.4%		-45.9%	-41.6%	-38.9%	-35.7%	-40.4%	-41.7%	-4.4%	-16.3%	-9.7%	-5.4%	-0.6%	-7.8%	-9.9%
	1=Mandatory	0=no									-100.0%		-100.0%			-100.0%	-100.0%
		1=yes										-100.0%		-100.0%	-100.0%	-100.0%	-100.0%
6=Driving age school child	2=Non-Mandatory	0=no	-28.7%							-32.0%	8.3%	13.5%	1.5%	-12.9%	-10.9%	-11.4%	-4.7%
		1=yes									0.5%	-13.0%	-11.0%	-14.0%	-7.9%	-20.3%	-13.0%
	1=Mandatory	0=no	-19.9%								6.9%	32.8%	22.4%	34.0%	10.8%	9.6%	15.2%
		1=yes	51.5%							37.1%	-23.2%	-21.7%	-23.1%	-26.7%	-15.5%	-25.5%	-22.8%
7=Pre-driving age school child	2=Non-Mandatory	0=no	10.7%							7.8%	-4.3%	28.1%	1.6%	25.5%	-8.3%	-8.5%	-3.2%
		1=yes	-28.1%		-42.0%	-44.1%	-43.2%	-40.3%	-41.6%	-42.0%	-12.1%	-19.3%	-22.3%	-21.0%	-17.0%	-18.8%	-19.4%
	1=Mandatory	0=no	-28.3%						-10.0%		9.5%	65.3%	31.1%	67.1%	15.7%	20.4%	26.5%
		1=yes	48.3%		34.8%	32.9%	34.6%	37.2%	32.2%	33.8%	-16.8%	-20.6%	-22.8%	-20.9%	-17.6%	-23.7%	-21.9%
8=Preschool child	2=Non-Mandatory	0=no	14.8%	11.4%						14.8%	-3.8%	51.8%	-0.3%	82.3%	-1.6%	-5.4%	0.0%
		1=yes	-28.9%	-29.3%	-39.7%	-34.0%	-31.2%	-33.6%	-34.2%	-34.9%	-0.5%	-15.2%	-7.1%	-3.2%	-6.5%	-7.5%	-8.4%
	1=Mandatory	0=no	-23.7%								1.0%	54.5%	35.9%	100.0%	7.6%	23.1%	28.5%
		1=yes	39.2%							35.1%	1.1%	-8.6%	-6.8%	-5.3%	-6.8%	-9.1%	-6.3%
Total			-13.2%	-4.9%	-17.1%	-14.9%	-6.7%	-11.2%	-12.0%	-12.1%	8.8%	-4.5%	-1.9%	6.9%	2.2%	1.3%	1.2%

Validation results for the tour mode choice model are presented in **Table 29** for the entire region and in **Table 30** for the most important geographic segment that represents tours to and from the CBD (not including intra-CBD tours that represent yet another unique segment). This model required several rounds of calibrations for the to-and-from-CBD segment, although, it was estimated with the CMAP survey data. However, following the best practice of disaggregate estimation of behavioral models, this model did not include any geographic constants. This means that the significant differences in modal split (particularly transit share) observed by geographic segments in the Chicago region have to be fully explained by physical measures of level of service by different modes, including actual availability of each mode, its accessibility, convenience, comfort, and other attributes.

Table 29 shows that a reasonable match was achieved (from the very beginning) with respect to the entire-region statistics by mode for each of the 10 travel purposes (work, university, school, escorting, shopping, other maintenance, eating out, visiting relatives and friends, other discretionary, and at-work). The analysis included 14 main modes, including 6 auto modes with an explicit modeling of 3 auto occupancy categories (SOV, HOV/2, HOV/3+) and 2 route type alternatives (Non-toll vs. toll).

However, at the desired level of spatial segmentation, and in particular for such an important segment as tours to and from the CBD, some discrepancies were revealed that proved to be difficult to eliminate at the current stage of the project. The most important issue seen in **Table 30** is that the model currently underestimates commuting to and from the CBD by transit modes in general and premium transit modes in particular. A mechanical adjustment of mode-specific constants to match the observed share of transit for tours to and from the CBD (about 45%) would result in very large values for geographic-specific constants for transit modes that would result in model over-specification.

As mentioned above in the discussion on the journey-to-work table, a thorough analysis revealed some problems with the transit network procedures as well as the supporting split of TAZs by 3 transit-access subzones (short walk, long walk, and no access). As a result of these procedures, a large number of TAZ located in the 3rd, 4th, and 5th rings of the metropolitan area proved to have a high proportion of no-access cases that cannot be changed by model calibration. A further mechanical adjustment of mode-specific constants would enforce the model to compensate for the deficiencies of the network procedures by making an unreasonably large share of transit users in the transit-access sub-zones. For this reason, we decided to adopt the current version of the model that generates a lower proportion of transit tours to and from CBD (35% instead of 45%) but is characterized by reasonable minimal mode-specific constants for this segment.

We believe that the best solution for the mode choice problems will be an overall major revisiting of the transit procedures as well as transferring the entire model structure and restructuring network procedures to a smaller geographic unit than the TAZ. CMAP has prepared most of the socio-economic, land use, and employment variables at the level of 16,819 subzones (based on PLSS quarter-sections). We strongly recommended taking full advantage of this finer level of spatial resolution, as was implemented in the San Diego CT-RAMP model. A finer level of spatial resolution leads to better modeling of transit access, non-motorized accessibilities, and location choice.

Table 29: Validation of Tour Mode Choice Model (Entire Region)

Survey

Tour Mode

Purpose	Total	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
1 Work	4,600,922	2,855,137	170,887	460,166	23,986	200,272	5,308	127,885	81,080	146,093	268,743	12,173	219,354	23,761	6,078
2 University	229,806	99,504	3,214	31,774	23	6,605	-	20,299	6,519	23,522	17,975	1,330	16,679	1,762	602
3 School	1,868,481	53,930	-	256,337	671	514,058	91	288,514	21,223	55,854	14,639	10,889	2,984	1,200	648,090
4 Escorting	1,429,186	-	-	640,505	1,175	610,757	1,130	161,721	3,887	6,768	2,536	-	682	-	25
5 Shopping	1,530,264	802,352	803	325,575	1,304	166,805	1,168	163,771	12,469	34,973	12,189	1,358	3,374	4,104	19
6 Maintenance	1,276,856	609,753	13,683	264,369	2,548	135,871	3,271	135,194	14,793	54,453	18,891	4,057	8,437	10,559	976
7 Eatout	376,135	139,749	1,256	93,849	1,137	79,164	2,518	39,550	10,291	4,493	1,211	448	1,076	1,394	-
8 Visiting	543,974	199,593	7,085	139,458	1,118	91,346	1,689	72,173	9,886	12,922	4,065	1,043	773	2,735	87
9 Discretionary	1,354,864	483,338	3,464	302,717	2,089	308,340	3,569	162,082	29,762	29,202	10,629	2,600	5,417	7,638	4,016
10 At-Work	515,744	280,051	2,967	37,570	261	4,126	-	175,917	2,451	1,448	1,817	224	821	7,473	617
Total	13,726,232	5,523,406	203,358	2,552,320	34,312	2,117,345	18,745	1,347,106	192,360	369,728	352,696	34,122	259,597	60,625	660,511

Tour Mode Distribution

Purpose	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
1 Work	62.1%	3.7%	10.0%	0.5%	4.4%	0.1%	2.8%	1.8%	3.2%	5.8%	0.3%	4.8%	0.5%	0.1%
2 University	43.3%	1.4%	13.8%	0.0%	2.9%	0.0%	8.8%	2.8%	10.2%	7.8%	0.6%	7.3%	0.8%	0.3%
3 School	2.9%	0.0%	13.7%	0.0%	27.5%	0.0%	15.4%	1.1%	3.0%	0.8%	0.6%	0.2%	0.1%	34.7%
4 Escorting	0.0%	0.0%	44.8%	0.1%	42.7%	0.1%	11.3%	0.3%	0.5%	0.2%	0.0%	0.0%	0.0%	0.0%
5 Shopping	52.4%	0.1%	21.3%	0.1%	10.9%	0.1%	10.7%	0.8%	2.3%	0.8%	0.1%	0.2%	0.3%	0.0%
6 Maintenance	47.8%	1.1%	20.7%	0.2%	10.6%	0.3%	10.6%	1.2%	4.3%	1.5%	0.3%	0.7%	0.8%	0.1%
7 Eatout	37.2%	0.3%	25.0%	0.3%	21.0%	0.7%	10.5%	2.7%	1.2%	0.3%	0.1%	0.3%	0.4%	0.0%
8 Visiting	36.7%	1.3%	25.6%	0.2%	16.8%	0.3%	13.3%	1.8%	2.4%	0.7%	0.2%	0.1%	0.5%	0.0%
9 Discretionary	35.7%	0.3%	22.3%	0.2%	22.8%	0.3%	12.0%	2.2%	2.2%	0.8%	0.2%	0.4%	0.6%	0.3%
10 At-Work	54.3%	0.6%	7.3%	0.1%	0.8%	0.0%	34.1%	0.5%	0.3%	0.4%	0.0%	0.2%	1.4%	0.1%
Total	40.2%	1.5%	18.6%	0.2%	15.4%	0.1%	9.8%	1.4%	2.7%	2.6%	0.2%	1.9%	0.4%	4.8%

Model

Tour Mode

Purpose	Total	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
1 Work	4,122,160	2,530,910	107,810	546,890	60,990	142,995	22,615	118,705	167,840	75,255	139,755	10,015	124,315	74,065	-
2 University	141,545	78,845	1,995	15,540	1,145	2,000	365	5,235	9,020	10,885	5,805	1,615	5,835	3,260	-
3 School	1,714,725	38,455	-	424,010	-	237,020	-	151,595	11,545	40,155	6,410	1,935	875	2,320	800,405
4 Escorting	1,400,810	-	-	691,380	9,685	576,745	10,270	89,220	14,470	7,795	1,180	55	10	-	-
5 Shopping	2,031,440	987,970	1,595	437,205	280	303,890	4,785	190,975	62,280	25,120	7,200	2,400	1,960	5,780	-
6 Maintenance	1,640,755	755,180	8,070	324,140	1,180	260,110	12,360	151,250	50,460	38,620	11,910	5,020	3,750	18,705	-
7 Eatout	653,820	251,685	825	173,240	1,320	163,450	6,260	25,230	19,335	4,810	1,645	375	1,075	4,570	-
8 Visiting	867,690	328,940	10,900	217,035	2,255	192,395	2,605	54,910	30,605	13,045	7,390	735	630	6,245	-
9 Discretionary	1,888,110	688,260	10,215	442,745	3,130	513,675	4,255	109,705	65,835	14,640	6,870	1,445	6,975	20,360	-
10 At-Work	1,548,095	1,001,945	8,620	82,985	3,640	1,780	295	382,360	26,600	1,110	670	-	-	38,090	-
Total	16,009,150	6,662,190	150,030	3,355,170	83,625	2,394,060	63,810	1,279,185	457,990	231,435	188,835	23,595	145,425	173,395	800,405

Tour Mode Distribution

Purpose	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
1 Work	61.4%	2.6%	13.3%	1.5%	3.5%	0.5%	2.9%	4.1%	1.8%	3.4%	0.2%	3.0%	1.8%	0.0%
2 University	55.7%	1.4%	11.0%	0.8%	1.4%	0.3%	3.7%	6.4%	7.7%	4.1%	1.1%	4.1%	2.3%	0.0%
3 School	2.2%	0.0%	24.7%	0.0%	13.8%	0.0%	8.8%	0.7%	2.3%	0.4%	0.1%	0.1%	0.1%	46.7%
4 Escorting	0.0%	0.0%	49.4%	0.7%	41.2%	0.7%	6.4%	1.0%	0.6%	0.1%	0.0%	0.0%	0.0%	0.0%
5 Shopping	48.6%	0.1%	21.5%	0.0%	15.0%	0.2%	9.4%	3.1%	1.2%	0.4%	0.1%	0.1%	0.3%	0.0%
6 Maintenance	46.0%	0.5%	19.8%	0.1%	15.9%	0.8%	9.2%	3.1%	2.4%	0.7%	0.3%	0.2%	1.1%	0.0%
7 Eatout	38.5%	0.1%	26.5%	0.2%	25.0%	1.0%	3.9%	3.0%	0.7%	0.3%	0.1%	0.2%	0.7%	0.0%
8 Visiting	37.9%	1.3%	25.0%	0.3%	22.2%	0.3%	6.3%	3.5%	1.5%	0.9%	0.1%	0.1%	0.7%	0.0%
9 Discretionary	36.5%	0.5%	23.4%	0.2%	27.2%	0.2%	5.8%	3.5%	0.8%	0.4%	0.1%	0.4%	1.1%	0.0%
10 At-Work	64.7%	0.6%	5.4%	0.2%	0.1%	0.0%	24.7%	1.7%	0.1%	0.0%	0.0%	0.0%	2.5%	0.0%
Total	41.6%	0.9%	21.0%	0.5%	15.0%	0.4%	8.0%	2.9%	1.4%	1.2%	0.1%	0.9%	1.1%	5.0%

Difference (Model-Survey)

Threshold 1,000

Tour Mode

Purpose	Total	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
1 Work	-478,762	-324,227	-63,077	86,724	37,004	-57,277	17,307	-9,180	86,760	-70,838	-128,988	-2,158	-95,039	50,304	-6,078
2 University	-88,261	-20,659	-1,219	-16,234	1,122	-4,605		-15,064	2,501	-12,637	-12,170		-10,844	1,498	
3 School	-153,756	-15,475		167,673		-277,038		-136,919	-9,678	-15,699	-8,229	-8,954	-2,109	1,120	152,315
4 Escorting	-28,376			50,875	8,510	-34,012	9,140	-72,501	10,583	1,027	-1,356				
5 Shopping	501,176	185,618		111,630	-1,024	137,085	3,617	27,204	49,811	-9,853	-4,989	1,042	-1,414	1,676	
6 Maintenance	363,899	145,427	-5,613	59,771	-1,368	124,239	9,089	16,056	35,667	-15,833	-6,981		-4,687	8,146	
7 Eatout	277,685	111,936		79,391		84,286	3,742	-14,320	9,044					3,176	
8 Visiting	323,716	129,347	3,815	77,577	1,137	101,049		-17,263	20,719		3,325			3,510	
9 Discretionary	533,246	204,922	6,751	140,028	1,041	205,335		-52,377	36,073	-14,562	-3,759	-1,155	1,558	12,722	-4,016
10 At-Work	1,032,351	721,894	5,653	45,415	3,379	-2,346		206,443	24,149		-1,147			30,617	
Total	2,282,918	1,138,784	-53,328	802,850	49,313	276,715	45,065	-67,921	265,630	-138,293	-163,861	-10,527	-114,172	112,770	139,894

Threshold Threshold Threshold 1.0%

Tour Mode Distribution

Purpose	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
1 Work		-1.1%	3.3%					2.3%	-1.3%	-2.5%		-1.8%	1.3%	
2 University	12.4%		-2.8%		-1.5%		-5.1%	3.5%	-2.5%	-3.7%		-3.1%	1.5%	
3 School			11.0%		-13.7%		-6.6%							12.0%
4 Escorting			4.5%		-1.6%		-4.9%							
5 Shopping	-3.8%				4.1%		-1.3%	2.3%	-1.0%					
6 Maintenance	-1.7%				5.2%		-1.4%	1.9%	-1.9%					
7 Eatout	1.3%		1.5%		4.0%		-6.7%							
8 Visiting	1.2%				5.4%		-6.9%	1.7%						
9 Discretionary			1.1%		4.4%		-6.2%	1.3%	-1.4%					
10 At-Work	10.4%		-1.9%				-9.4%	1.2%					1.0%	
Total	1.4%		2.4%				-1.8%	1.5%	-1.2%	-1.4%				

Table 30: Validation of Tour Mode Choice Model (Tours to and from CBD)

Survey

Purpose	Total	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
		Tour Mode													
1 Work	759,354	200,640	11,322	50,166	502	18,257	190	6,111	18,566	46,709	187,348	5,467	196,537	13,679	3,859
2 University	58,504	11,439	760	1,224	-	268	-	1,227	4,360	11,208	10,799	1,264	15,580	375	-
3 School	71,527	503	-	8,124	-	33,522	-	4,617	-	6,002	7,888	1,325	971	459	8,115
4 Escorting	50,184	-	-	28,473	94	15,706	119	4,467	-	1,325	-	-	-	-	-
5 Shopping	39,472	8,337	327	7,341	-	4,652	13	7,470	3,064	2,924	3,716	189	1,438	-	-
6 Maintenance	92,661	22,144	911	20,961	143	9,922	1,264	2,855	2,214	8,685	12,896	2,205	6,117	2,007	336
7 Eatout	19,739	8,178	-	4,412	113	1,036	13	1,276	1,728	1,578	763	-	465	177	-
8 Visiting	22,788	5,581	-	3,799	-	3,587	305	1,024	-	4,257	3,741	-	51	443	-
9 Discretionary	62,102	16,347	-	11,085	-	11,464	911	5,474	1,605	3,471	4,043	198	4,409	2,661	434
10 At-Work	27,483	13,717	-	3,413	-	218	-	7,782	-	358	850	-	821	325	-
Total	1,203,814	286,887	13,320	138,997	852	98,633	2,817	42,302	31,538	86,516	232,043	10,647	226,388	20,126	12,745

Purpose	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
	Tour Mode Distribution													
1 Work	26.4%	1.5%	6.6%	0.1%	2.4%	0.0%	0.8%	2.4%	6.2%	24.7%	0.7%	25.9%	1.8%	0.5%
2 University	19.6%	1.3%	2.1%	0.0%	0.5%	0.0%	2.1%	7.5%	19.2%	18.5%	2.2%	26.6%	0.6%	0.0%
3 School	0.7%	0.0%	11.4%	0.0%	46.9%	0.0%	6.5%	0.0%	8.4%	11.0%	1.9%	1.4%	0.6%	11.3%
4 Escorting	0.0%	0.0%	56.7%	0.2%	31.3%	0.2%	8.9%	0.0%	2.6%	0.0%	0.0%	0.0%	0.0%	0.0%
5 Shopping	21.1%	0.8%	18.6%	0.0%	11.8%	0.0%	18.9%	7.8%	7.4%	9.4%	0.5%	3.6%	0.0%	0.0%
6 Maintenance	23.9%	1.0%	22.6%	0.2%	10.7%	1.4%	3.1%	2.4%	9.4%	13.9%	2.4%	6.6%	2.2%	0.4%
7 Eatout	41.4%	0.0%	22.4%	0.6%	5.2%	0.1%	6.5%	8.8%	8.0%	3.9%	0.0%	2.4%	0.9%	0.0%
8 Visiting	24.5%	0.0%	16.7%	0.0%	15.7%	1.3%	4.5%	0.0%	18.7%	16.4%	0.0%	0.2%	1.9%	0.0%
9 Discretionary	26.3%	0.0%	17.8%	0.0%	18.5%	1.5%	8.8%	2.6%	5.6%	6.5%	0.3%	7.1%	4.3%	0.7%
10 At-Work	49.9%	0.0%	12.4%	0.0%	0.8%	0.0%	28.3%	0.0%	1.3%	3.1%	0.0%	3.0%	1.2%	0.0%
Total	23.8%	1.1%	11.5%	0.1%	8.2%	0.2%	3.5%	2.6%	7.2%	19.3%	0.9%	18.8%	1.7%	1.1%

Model

Purpose	Total	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
		Tour Mode													
1 Work	537,365	166,065	6,465	38,010	240	13,465	140	4,215	14,655	37,500	121,350	4,080	121,390	9,790	-
2 University	27,860	6,905	255	685	55	225	10	270	2,665	6,450	3,970	585	5,575	210	-
3 School	53,695	405	-	5,895	-	24,255	-	3,895	615	4,895	5,005	1,075	840	400	6,415
4 Escorting	39,760	-	-	21,945	55	11,745	65	4,050	500	1,140	255	-	5	-	-
5 Shopping	73,300	17,415	220	13,635	80	8,665	-	13,410	6,695	6,095	4,725	275	1,715	370	-
6 Maintenance	85,195	23,120	1,080	21,670	-	9,725	345	3,320	2,835	10,635	6,120	1,525	3,025	1,795	-
7 Eatout	35,690	15,260	20	7,285	210	1,395	20	2,800	2,930	3,235	1,250	60	950	275	-
8 Visiting	45,410	11,395	620	7,085	330	6,600	390	2,245	1,695	8,440	5,705	30	60	815	-
9 Discretionary	79,005	21,700	410	13,370	365	13,600	1,255	7,965	2,155	4,545	4,070	215	6,170	3,185	-
10 At-Work	26,855	16,870	470	3,010	320	280	95	2,710	2,320	170	345	-	-	265	-
Total	1,004,135	279,135	9,540	132,590	1,655	89,955	2,320	44,880	37,065	83,105	152,795	7,845	139,730	17,105	6,415

Purpose	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
	Tour Mode Distribution													
1 Work	30.9%	1.2%	7.1%	0.0%	2.5%	0.0%	0.8%	2.7%	7.0%	22.6%	0.8%	22.6%	1.8%	0.0%
2 University	24.8%	0.9%	2.5%	0.2%	0.8%	0.0%	1.0%	9.6%	23.2%	14.2%	2.1%	20.0%	0.8%	0.0%
3 School	0.8%	0.0%	11.0%	0.0%	45.2%	0.0%	7.3%	1.1%	9.1%	9.3%	2.0%	1.6%	0.7%	11.9%
4 Escorting	0.0%	0.0%	55.2%	0.1%	29.5%	0.2%	10.2%	1.3%	2.9%	0.6%	0.0%	0.0%	0.0%	0.0%
5 Shopping	23.8%	0.3%	18.6%	0.1%	11.8%	0.0%	18.3%	9.1%	8.3%	6.4%	0.4%	2.3%	0.5%	0.0%
6 Maintenance	27.1%	1.3%	25.4%	0.0%	11.4%	0.4%	3.9%	3.3%	12.5%	7.2%	1.8%	3.6%	2.1%	0.0%
7 Eatout	42.8%	0.1%	20.4%	0.6%	3.9%	0.1%	7.8%	8.2%	9.1%	3.5%	0.2%	2.7%	0.8%	0.0%
8 Visiting	25.1%	1.4%	15.6%	0.7%	14.5%	0.9%	4.9%	3.7%	18.6%	12.6%	0.1%	0.1%	1.8%	0.0%
9 Discretionary	27.5%	0.5%	16.9%	0.5%	17.2%	1.6%	10.1%	2.7%	5.8%	5.2%	0.3%	7.8%	4.0%	0.0%
10 At-Work	62.8%	1.8%	11.2%	1.2%	1.0%	0.4%	10.1%	8.6%	0.6%	1.3%	0.0%	0.0%	1.0%	0.0%
Total	27.8%	1.0%	13.2%	0.2%	9.0%	0.2%	4.5%	3.7%	8.3%	15.2%	0.8%	13.9%	1.7%	0.6%

Difference (Model-Survey)

Threshold 1,000 Threshold Threshold Threshold 1.0%

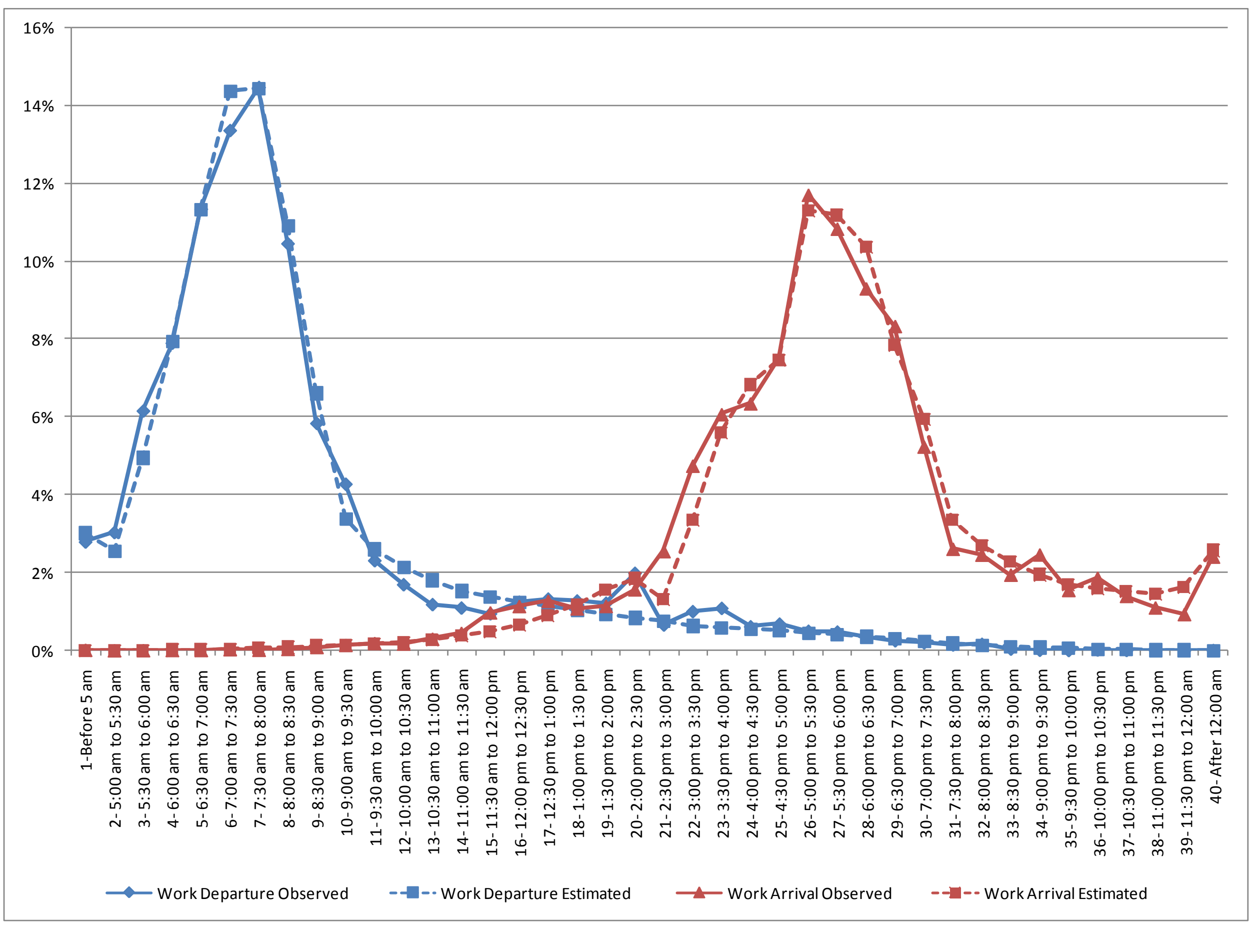
Purpose	Total	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
		Tour Mode													
1 Work	-221,989	-34,575	-4,857	-12,156		-4,792		-1,896	-3,911	-9,209	-65,998	-1,387	-75,147	-3,889	-3,859
2 University	-30,644	-4,534							-1,695	-4,758	-6,829		-10,005		
3 School	-17,832			-2,229		-9,267				-1,107	-2,883				-1,700
4 Escorting	-10,424			-6,528		-3,961									
5 Shopping	33,828	9,078		6,294		4,013		5,940	3,631	3,171	1,009				
6 Maintenance	-7,466									1,950	-6,776		-3,092		
7 Eatout	15,951	7,082		2,873				1,524	1,202	1,657					
8 Visiting	22,622	5,814		3,286		3,013		1,221	1,695	4,183	1,964				
9 Discretionary	16,903	5,353		2,285		2,136		2,491		1,074			1,761		
10 At-Work		3,153						-5,072	2,320						
Total	-199,679	-7,752	-3,780	-6,407		-8,678		2,578	5,527	-3,411	-79,248	-2,802	-86,658	-3,021	-6,330

Purpose	SOVNT	SOVTL	HOV2NT	HOV2TL	HOV3NT	HOV3TL	WALK	BIKE	WK LOCAL	WK PRE	DRIVE LOCA	DRIVE PRE	TAXI	SCHBUS
	Tour Mode Distribution													
1 Work	4.5%									-2.1%		-3.3%		
2 University	5.2%							2.1%	4.0%	-4.2%		-6.6%		
3 School					-1.7%					-1.7%				
4 Escorting			-1.5%		-1.8%									
5 Shopping	2.6%							1.4%		-3.0%				
6 Maintenance									3.1%	-6.7%		-3.1%		
7 Eatout	1.3%		-1.9%				1.4%		1.1%					
8 Visiting			-1.1%		-1.2%			3.7%		-3.9%				
9 Discretionary	1.1%				-1.2%		1.3%							
10 At-Work	12.9%						-18.2%	8.6%						
Total	4.0%		1.7%					1.1%	1.1%	-4.1%		-4.9%		

Validation results for the tour time-of-day choice model are presented in **Figure 13** for work tours and in **Figure 14** for school tours (as examples of travel purposes with the most prominent peaking characteristics). These models have been estimated based on the CMAP household travel survey and applied with the enhanced level of temporal resolution of 30 minutes that was adopted in the recent advanced versions of CT-RAMP developed for SANDAG and MAG. The tour time-of-day choice model simultaneously treats such dimensions as departure time from home, arrival back home, and total tour duration that includes the underlying primary activity duration, travel time to and from the primary destination, and time associated with stops for secondary activities on the way to and from the primary destination. Congestion and pricing effects are incorporated in the time-of-day choice model through bi-directional period-specific mode choice logsums. For 8 simulated highway network periods, 45 bi-directional combinations of departure and arrival times were formed. Time-of-day choice models did not require any calibration since the rich behavioral structure of these models is capable of capturing peak profiles with a high level of accuracy.

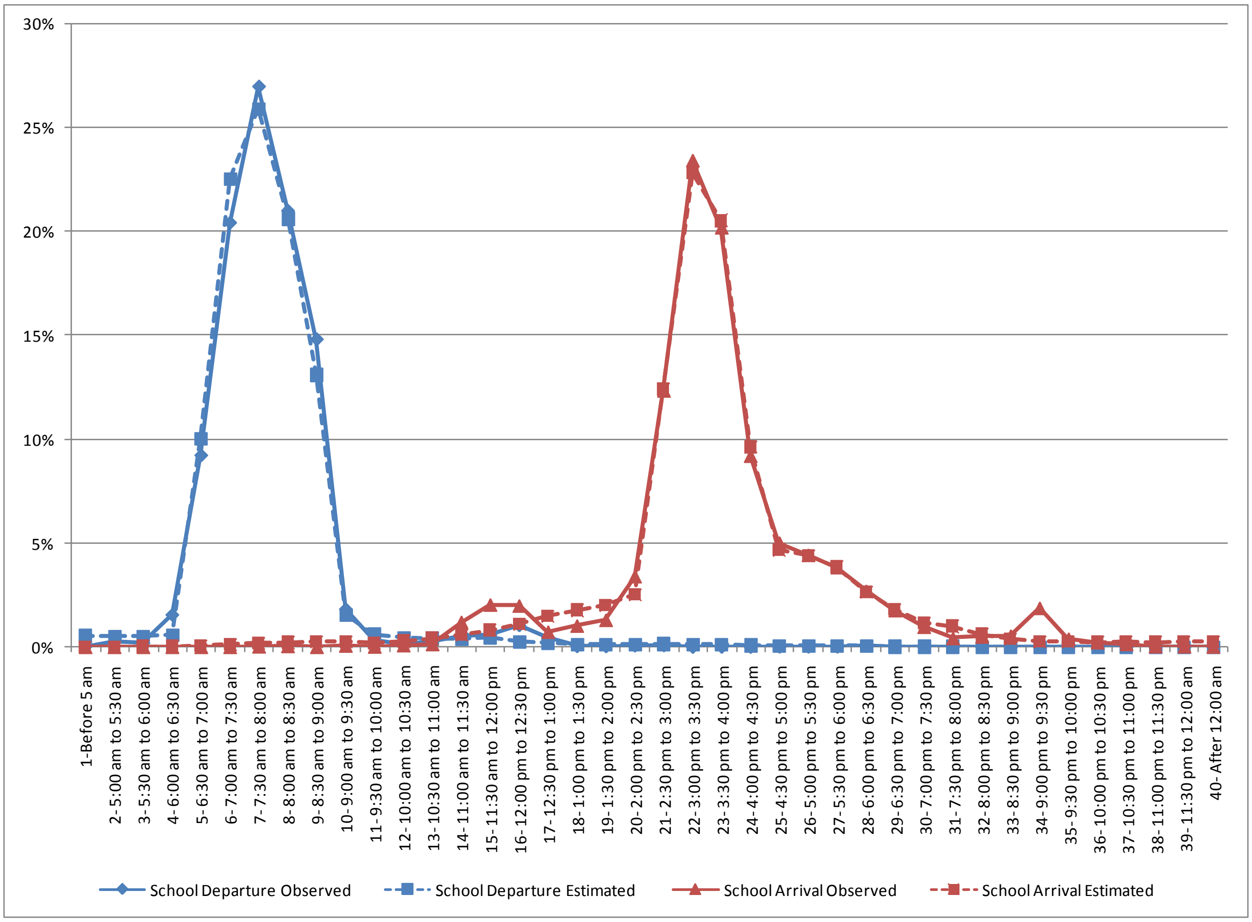
Validation results for tour departure-from-home time and arrival-back-home time for work tours are presented in **Figure 13**. Both outbound and inbound commuting peak patterns were replicated remarkably well.

Figure 13: Validation of Time-of-Day Choice Model (Work Tours)



Validation results for tour departure-from-home time and arrival-back-home time for school tours are presented in **Figure 14**. Both outbound and inbound commuting peak patterns were replicated very well.

Figure 14: Validation of Time-of-Day Choice Model (School Tours)



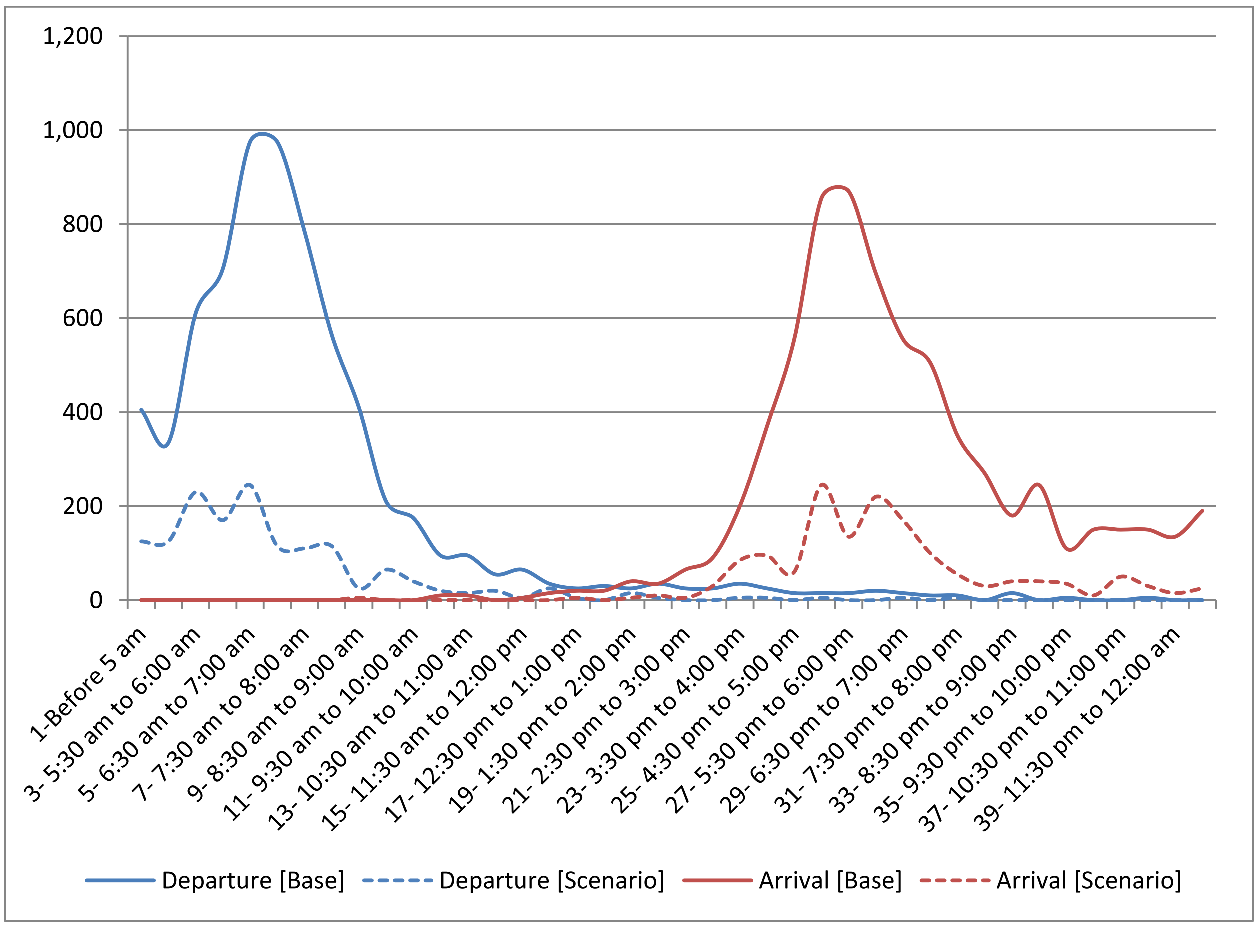
Sensitivity Tests for Highway Pricing Scenarios

CMAP defined two hypothetical regional pricing scenarios to test the sensitivity of the CT-RAMP model and evaluate elasticity of different model components with respect to highway tolls. The first scenario assumed increasing all tolls currently applied in the region by a factor of 5 in all time-of-day periods. This test was primarily intended to evaluate sensitivity of mode choice and highway route type choice (toll vs. non-toll). The second scenario assumed increasing tolls in the peak periods (7:00am-9:00am and 4:00pm-6:00pm) by a factor of 5 while tolls in the other periods were kept at the base level. This test was primarily intended to demonstrate sensitivity of time-of-day choice.

Both scenarios were compared to the base year scenario across various dimensions and the results are presented here in detail. The CMAP staff and PB team discussed the results of the sensitivity tests at the last conference call and concluded that the CT-RAMP model exhibited very reasonable sensitivity and logical response to the scenarios across all main dimensions affected by highway pricing (primarily mode choice, route type choice, and time-of-day choice). Below are some of the most interesting and convincing findings presented in a graphical form where the pricing scenarios are compared to the base scenario in terms of the number of commuters to and from the CBD using toll facilities.

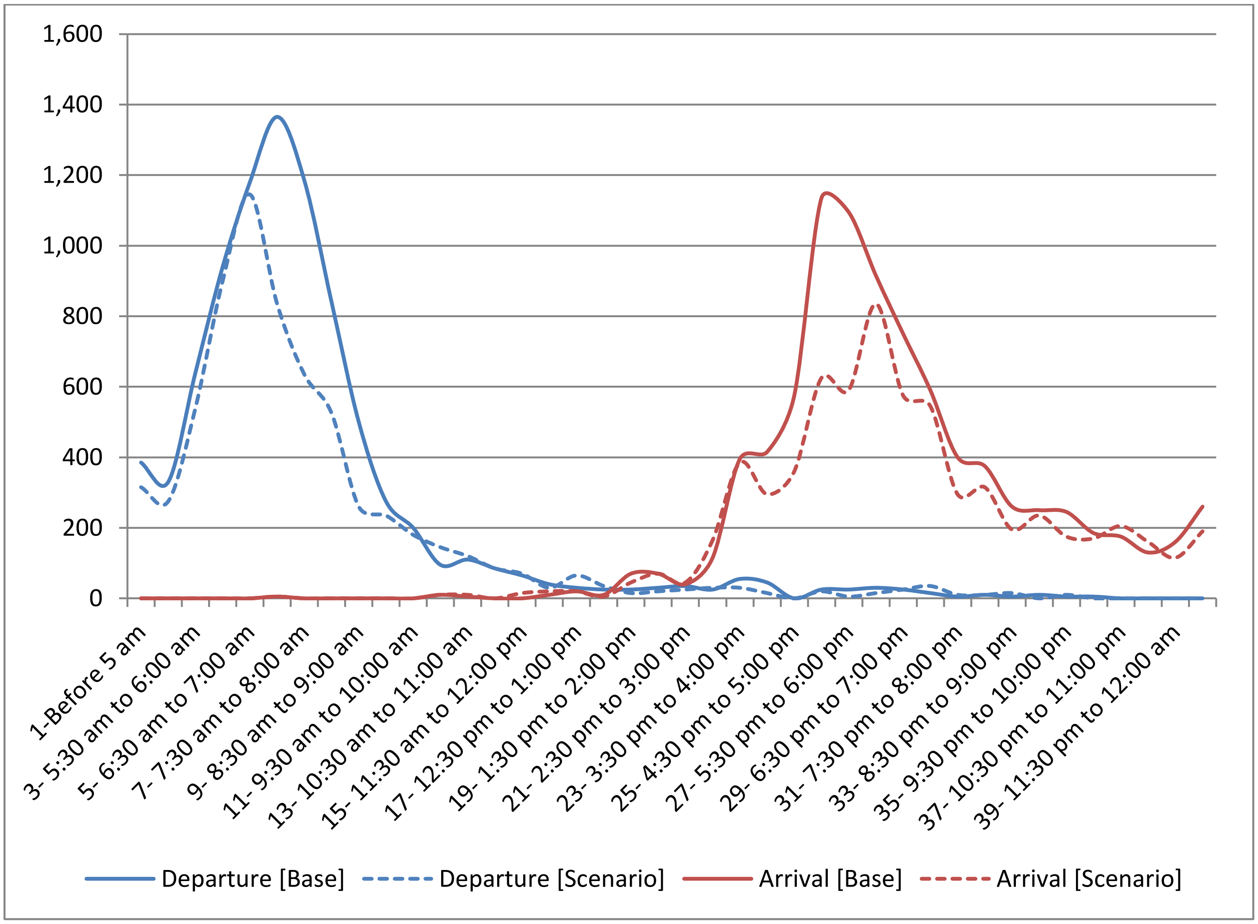
Thie first graph below (**Figure 15**) illustrates the impact of tolls raised by a factor of 5 in all time-of-day periods. Logoically, it resulted in a very significant reduction in the number of commuters to and from the CBD that use toll facilities. The most significant reduction in absolute terms occur in the peak periods but in relative terms, there is a more or less uniform reduction in the number of toll users by 60-70% in all time-of-day periods.

Figure 15: Impact of Global Pricing Increase



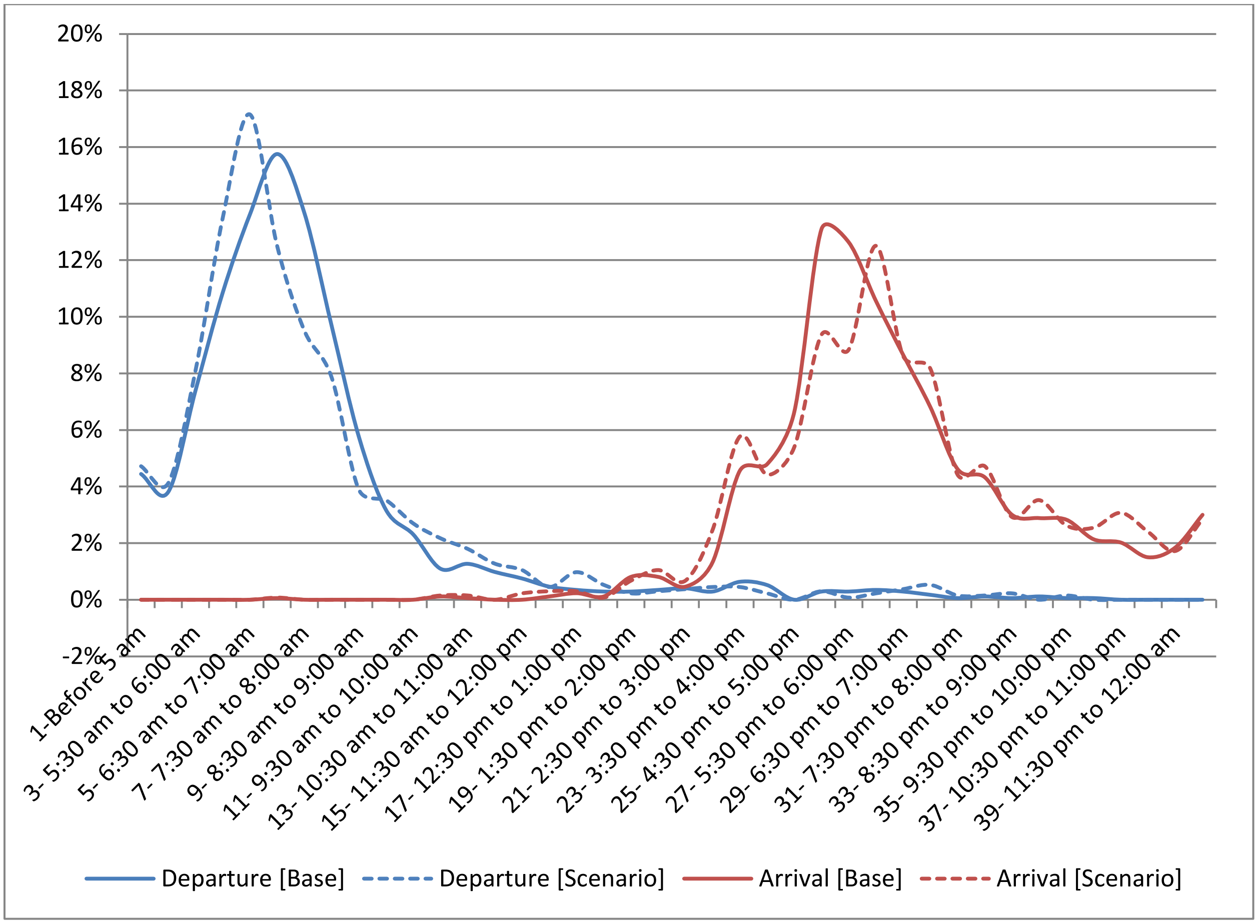
The second graph below (**Figure 16**) illustrates the congestion pricing impacts when the tolls were raised by a factor of 5 in the peak periods only (7:00am-9:00am and 4:00pm-6:00pm). The CT-RAMP model responded to this policy logically. There is a substantial reduction in toll users in these periods while there is less significant or no reduction in other periods. Since the CT-RAMP models process work tours as units of travel rather than single trips, the applied congestion pricing in the peak periods affects some other periods through tour-level scheduling constraints. Consider, for example, a worker who commuted at 7:00 am (outbound trip from home to work) and 3:30 PM (inbound trip from work to home) in the base scenario. In the congestion pricing scenario, only the first trip is affected by pricing. However, as a result, the person might switch to transit or reschedule the entire tour to earlier hours (such as 6:30am and 3:00pm) in order to keep the work duration fixed (which is a constraint for some workers). In this way, the time periods adjacent to the peak can also see reductions in toll users.

Figure 16: Impact of Pricing Increase in Peak Periods



In the third graph below (**Figure 17**), the same data is presented as in the second graph but in terms of diurnal percentage distributions rather than absolute numbers. This way, we can analyze the shifts in the peak factors between the base and congestion pricing scenarios. Again, a very logical peak-shifting effect is observed showing that both peaks shift but in different directions. The AM peak is slightly shifted towards the earlier hours while the PM peak is shifted towards the later hours. The congestion pricing policy strongly affects those who commuted in both AM and PM periods. The commuters who would avoid the raised tolls completely are those who commute after 9:00am and before 4:00pm (a smaller group of commuters since the associated work activity duration is relatively short – 7 hours or less) or those who commute either before 7:00am or after 6:00 PM (a large group of commuters). Due to the work duration constraint, we observe a logical shift of the peaks in opposite directions rather than towards each other or in the same direction. However, this effect is bound to the congestions pricing scheme in the relatively short 2-hour peaks. If the congestion pricing intervals are extended to 3-4 hours the results might be different and peak spreading might take a different form. For this reason, it is important to use a flexible ABM rather than a simplified trip-level departure time choice model to evaluate congestion pricing scenarios.

Figure 17: Peak Spreading as a Result of Pricing Increase in Peak Periods



CT-RAMP Application Distributed Configuration

A typical computer hardware cluster structure and distributed configuration required for a CT-RAMP application for a large metropolitan area of Chicago's size (10 million people) is shown in **Figure 18** (which shows the SANDAG setup). CMAP purchased a cluster of 4 identical servers that were used to install and run the CMAP CT-RAMP ABM during the last month of the project (June 2011). The CMAP server specifications and costs are summarized in

Table 31.

Figure 18: Typical CT-RAMP Distributed Configuration

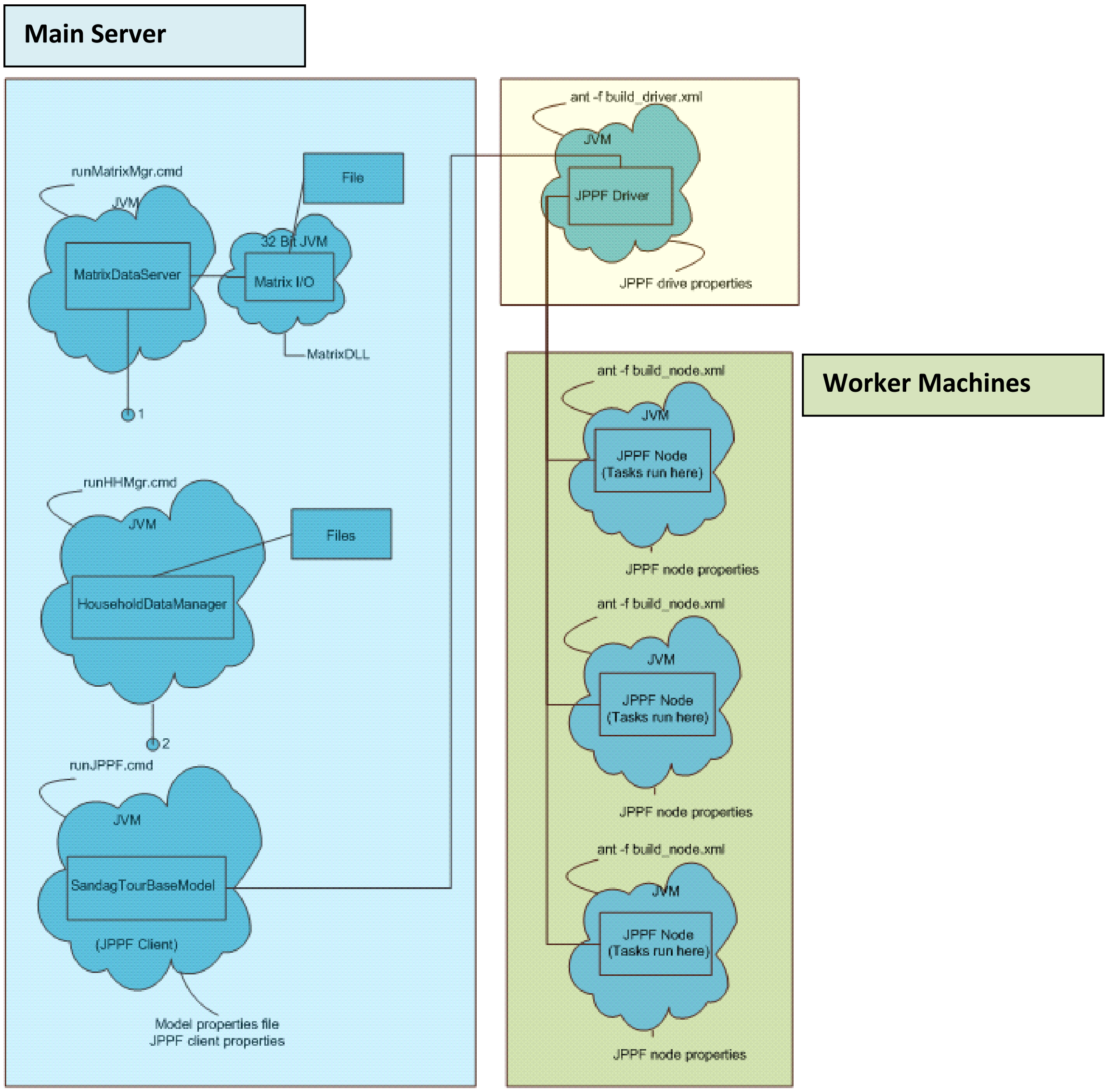


Table 31: Cluster Server Specifications

Base System	Quantity
Rack, kvm switch, ups	1
Chassis	1
DVD-RW optical drive	1
750W Power Supply	1
3 Year HP Care Pack	1
Processor	**Quantity**
Six-Core 2.66GHz 12M Cache	2
Memory	**Quantity**
72 GB PC3 Memory	2
Disk Storage	**Quantity**
1 TB SAS 6G 7.2K - RAID	5

The specifications in this table reflect the setup for each of the four servers in the cluster. In initial run time testing, CMAP estimates that 3 full global iterations of CT-RAMP with EMME skimming would require approximately 48 hours to run (with the current cluster of servers). Adding to the cluster obviously would reduce run times. If CT-RAMP were to be used for Air Quality Conformity studies, then the 48 hour run time is not acceptable. However, in the immediate future, CT-RAMP's applications are likely to be limited to planning studies in which case CT-RAMP only needs to be run for 20% of the regional population, resulting in run times of less than 24 hours with 3 global iterations. If the cluster is expanded in the mid-term future, CMAP envisions adding no more than four high-end servers similar to the ones already purchased. Interestingly, as a result of its run time tests to date, CMAP believes that high-end desktop machines could serve as suitable and more economical substitutes for additional high-end servers.

Storage needs:

The uncompressed size of a single CMAP CT-RAMP model directory is 70 GB. Approximately 50 GB of this space is devoted to EMME databanks for the 8 time-of-day periods. It should be noted that the MTC (Bay Area) CT-RAMP implementation only requires 6 GB of storage for one run. While the Bay Area has a similar population size, it has fewer time-of-day periods for assignment, and uses different assignment software that apparently stores data more efficiently than EMME. However, CMAP does have sufficient backup storage capacity to handle any runs that cannot be stored on the cluster of 4 machines (which together contain 7 TB of storage).

Number of secondary worker machines:

The CT-RAMP model works with any number of worker machines, and run times decrease with more machines. Currently, CMAP uses its four cluster machines (the main server and three worker machines) to run network assignment and skimming for each time period in parallel (8 time periods total; 2 time periods on each machine). If we use MTC as a point of comparison, their configuration of a server with three workers produces a model result in 30-40 hours. Our team is currently working on profiling and optimizing that code. CMAP's new computers are faster and, with more cores, should put us in this ballpark, if not closer to 30 hours. Thus, one server and three workers to start with, should ensure a 30-hour runtime for 4-5 time-of-day periods. Once it's implemented, we can better estimate the impact of adding machines. Besides number of machines, the amount of RAM is also critical, especially with trying to optimize for 12 cores. As much as can be afforded is preferred, but at least 48 GB RAM on the workers is recommended.

Number of worker machines for the future:

As suggested above, the final number depends on number of time periods, whether or not CMAP expands its number of zones in the future, and how onerous the model runs are in the initial configuration. We also continue to try to optimize the base model code and believe we'll find ways to continue to trim runtime. An optimal configuration would be to max out at about 10 machines, assuming 8 or 9 periods and the need to process level of service skims for smaller geographic areas. However, as stated above, it should be possible to demonstrate the effect of one machine by taking one out and extrapolating from there to get to the runtime desired with the initial configuration.

Database needs:

The CT-RAMP model code does not require any database. Besides skim matrices, all input and output data are in text, comma-separated value files. There is support programmed in to write output files (household, person, tour, trip records with their stored model result fields) to a SQLite database in addition to or instead of the csv files. It would be very easy to add similar support for any other database, but other database interactions are not currently part of CT-RAMP.

Typical CT-RAMP Data Requirements

Introduction

This section summarizes input data necessary to implement the CT-RAMP model system in the Chicago region based on the similar CT-RAMP implementation for the Atlanta Regional Planning Commission (ARC). There are primarily two types of data required for input to the model: zonal data and network level-of-service skims. The model starts with the creation of a synthetic population according to control totals that are specified at the zonal (or region-wide) level. These control totals are specified for different household types. The model also requires employment data, parking costs, and transit walk percentages at the zonal level. Network level-of-service skims are specified for free and pay auto modes by auto occupancy (drive alone, shared-2, and shared 3+) as well as transit mode (local or premium) and transit access mode (walk or drive) combinations. Each input is described in more detail below. Also, readers are referred to the ARC Model User's Guide for additional information.

1: Synthetic population generation

As discussed, the population synthesis is based on the controlled variables discussed above and currently in use by CMAP. Note that various 2000 PUMS data variables for both households and persons are required for the model system, and are not described in this document.

2: Zonal Data

Zonal data is used to describe the quantities of households and employment and other characteristics of zones for use in tour frequency, destination choice, mode choice, and other models. The zonal data fields used by the ARC implementation of CT-RAMP are listed in

Table 32. Many of these fields are used as size terms in the various destination choice models. CMAP was able to supply a nearly complete set of similar fields. Enrollment by grade level (K-8 and 9-12) was used to attract the relevant school tours. Parking costs are a required input. CMAP supplied a suitable dataset representing CBD parking that can serve as a place holder while more comprehensive parking data sources are developed. The CBD code, county code, and district code variables are used for output summaries and can also be used for destination choice calibration factors (constants).

Table 32: Land Use File Fields

Variable	Description
1	Zone
2	Construction Employment
3	Manufacturing Employment
4	TCU (Transportation, Communication, Utilities)
5	Wholesale Employment
6	Retail Employment
7	Finance, Insurance, and Real Estate Employment

8	Service Employment
9	Total Private Employment
10	Government Employment
12	Total Employment
13	Population
14	Households
15	University Enrollment
16	Area (acres)
17	Total parking spaces
18	Long term parking spaces
19	Proportion free parking
20	Parking rate ($/hr)
21	CBD Flag
22	County Code
23	District code

In addition to the input zonal data, there are a few zonal data fields that are calculated on-the-fly based on model inputs. These include an area type variable, percent walk values, and accessibility measures for each zone.

3: Calculated Zonal Data: Area Type

Certain components of the ARC implementation of CT-RAMP rely on an ordinal area type variable. The ARC area type variable is based on seven discrete intervals of a density calculation ([population + 2* employment]/ area) which is calculated based on a floating calculation considering a ½ mile buffer around the centroid of each TAZ. The seven classifications of area type are:

1. CBD
2. Urban Commercial
3. Urban Residential
4. Suburban Commercial
5. Suburban Residential
6. Exurban
7. Rural

4: Calculated Zonal Data: Percent Walk Values

There are two sets of transit percent walk buffers:

- Short walk, which is the percent of the zone within 1/3 mile walking distance of transit
- Long walk, which is the percent of the zone within 2/3 mile walking distance of transit

Percent walk values are calculated by performing area buffering around transit routes and stops. In the case of premium transit services with known fixed stops (such as express bus routes and fixed-guideway transit), the actual stop in the network is used as the center for the buffer. However, typically the transit network for local routes has generalized stop locations, whose actual stop location can be anywhere along the route. In order to account for this generalization, a buffer is performed along the entire route for local buses. The buffers for local and premium services are added together (in GIS terms, the union of the two buffers is taken) for each radius (1/3 mile and 2/3 mile). The walk percentage for short walk is calculated by computing the area of each TAZ covered by the 1/3 mile radius buffer, and the walk percentage for long walk is calculated by computing the area of each TAZ covered by the 2/3 mile radius buffer. Note that the long walk percentage should always be greater than the short walk percentage, and the sum of short and long walk percentages should never be greater than 100%. Also note that the percentages should be re-computed each time the model is run, since the transit networks can change in each scenario.

In the ARC version of the CT-RAMP model, each zone is treated as three separate zones (sub-zones) for the purposes of destination and mode choice; a short-walk accessible zone, a long-walk accessible zone, and a walk-inaccessible zone. The quantity of land use data (households, employment) in each sub-zone is assumed to be proportional to the percent of the zone in each sub-zone. The walk times computed from the transit path-builder used in mode choice are refined according to origin sub-zone and destination sub-zone for each tour and trip, in order to overcome zonal aggregation bias with respect to walk-to-transit accessibility. Note that in later versions of the ARC model, the use of transit sub-zones has been replaced with accounting for travel at a very fine unit of geography (equivalent to a Census block) coupled with explicit transit stop-to-stop levels-of-service.

5: Calculated Zonal Data: Aggregate Accessibilities

The CT-RAMP model system takes into account the effects of auto, non-motorized, and transit accessibility on the generation of tours and trips. Accessibility is represented as the logsum of a simplified destination choice model which utilizes a certain mode level-of-service as the measure of separation and a size term that incorporates the quantity of attractions in the zone.

Accessibility measures have the following general form:

$$A_i = \ln\left[\sum_{j=1}^{I} S_j \times \exp\left(\gamma c_{ij}\right)\right], \qquad \textbf{Equation 3}$$

Where:

$i, j \in I$ = origin and destination zones,

A_i = accessibility measure calculated for each origin zone,

S_j = attraction size variable for each potential destination,

c_{ij} = cost of travel between origins and destinations,

γ = dispersion coefficient.

Accessibilities used in the ARC models are shown in **Table 33**.

Table 33: Accessibility Measures Output File Fields

Accessibility Variable (A_i)	γ	c_{ij}	S_j
Peak Auto Retail accessibility	-0.05	AM Single Occupant Vehicle (SOV) Time	Retail Employment
Peak Auto Total accessibility	-0.05	AM SOV Time	Total Employment
Off-Peak Auto Retail accessibility	-0.05	Off-Peak (OP) SOV Time	Retail Employment
Off-Peak Auto Total accessibility	-0.05	OP SOV Time	Total Employment
Peak Transit Retail accessibility	-0.05	From AM premium walk transit skims: Transit in-vehicle time + total wait time + walk time	Retail Employment
Peak Transit Total accessibility	-0.05	From AM premium walk transit skims: Transit in-vehicle time + total wait time + walk time	Total Employment
Off-Peak Transit Retail accessibility	-0.05	From OP premium walk transit skims: Transit in-vehicle time + total wait time + walk time	Retail Employment
Off-Peak Transit Total accessibility	-0.05	From OP premium walk transit skims: Transit in-vehicle time + total wait time + walk time	Total Employment
Non-motorized retail accessibility	-1.0	OP SOV distance (set to -999 if distance>3 miles)	Retail Employment
Non-motorized total accessibility	-1.0	OP SOV distance (set to -999 if distance>3 miles)	Total Employment

Note that in order to take into account toll costs in the accessibility calculations (e.g. to let pricing policy affect tour and trip generation), a generalized auto cost must to be substituted for the C_{ij} field, as follows:

Generalized auto cost = VOT * SOV Time $_{ij}$ + Cost $_{ij}$ **Equation 4**

Where:

VOT = the value of time in dollars per minute, set to ½ the average hourly wage rate for the region in the base-year, and

Cost $_{ij}$ = the toll cost plus auto operating cost (distance * cost per mile) for the i-j pair.

6: Network Level-of-Service Matrices

The ARC version of the CT-RAMP model utilizes skims for two time periods, reflecting peak (AM) and off-peak (midday) level-of-service. Skims are created for highway modes by combination of occupancy (drive-alone, shared-ride 2, and shared-ride 3+) and pay versus free. All auto skims are created based on a generalized cost calculation, consistent with assignment procedures (see equation 4 above).

Transit skims are created by service type (local versus premium) and access mode (walk versus drive). Premium skims require weighting local services to be more onerous than premium services, to ensure that premium transit paths are found when there is competition between local and premium service.

Highway skims and matrices in each skim set are listed in **Table 34**. Transit skim types are listed in **Table 35**, and the matrices in each transit skim set are listed in **Table 36**.

Table 34: Highway Skims

Skim	Mode	Period	Toll	Matrices
sovff_free.skm	SOV	Offpeak	No	TOLL,DISTANCE,TIME
hov2ff_free.skm	HOV2	Offpeak	No	TOLL,DISTANCE,TIME
hov3ff_free.skm	HOV3	Offpeak	No	TOLL,DISTANCE,TIME
sovff_toll.skm	SOV	Offpeak	Yes	TOLL,DISTANCE,TIME
hov2ff_toll.skm	HOV2	Offpeak	Yes	TOLL,DISTANCE,TIME
hov3ff_toll.skm	HOV3	Offpeak	Yes	TOLL,DISTANCE,TIME
sovpk_free.skm	SOV	Peak	No	TOLL,DISTANCE,TIME,TOLLDISTANCE
hov2pk_free.skm	HOV2	Peak	No	TOLL,DISTANCE,TIME,TOLLDISTANCE
hov3pk_free.skm	HOV3	Peak	No	TOLL,DISTANCE,TIME,TOLLDISTANCE
sovpk_toll.skm	SOV	Peak	Yes	TOLL,DISTANCE,TIME,TOLLDISTANCE
hov2pk_toll.skm	HOV2	Peak	Yes	TOLL,DISTANCE,TIME,TOLLDISTANCE
hov3pk_toll.skm	HOV3	Peak	Yes	TOLL,DISTANCE,TIME,TOLLDISTANCE

Table 35: Transit Skims

Skim	Access Mode	Mode	Time-of-day
pnrppk.skm	Drive (park and ride)	Premium	Peak
pnrlpk.skm	Drive (park and ride)	Local	Peak
wlkppk.skm	Walk	Premium	Peak
wlklpk.skm	Walk	Local	Peak
pnrpop.skm	Drive (park and ride)	Premium	Off peak
pnrlop.skm	Drive (park and ride)	Local	Off peak
wlkpop.skm	Walk	Premium	Off peak
wlklop.skm	Walk	Local	Off peak

Table 36: Transit Skim File Matrices

Matrix	Description
wlkt	walk time
autt	auto time
iwait	initial wait
xwait	transfer time
loc	local bus ivt
hrt	Heavy rail ivt
xbus	express bus ivt
crail	commuter rail ivt
xfers	boardings
fare	fare
tottime	total time
xferwt	transfer walk time
firstmode	first mode boarded
trnivt	transit ivt
dist	total trip distance
trndist	transit vehicle dist

Conclusions and Recommendations for Next Steps

CMAP has made an important first step towards development and application of an advanced ABM on the regional scale. The current project has demonstrated that an advanced ABM of the CT-RAMP family can be successfully integrated with the CMAP socio-economic data, land use & employment data, and transportation networks. The Chicago area is the third largest metropolitan area in the US with a high level of complexity in terms of highway and transit networks, diversity of urban conditions, and diversity in population groups. The model testing results produced reasonable responses to different pricing policies and demonstrated advantages of the ABM in portraying such pricing effects as mode shift, car occupancy shift, and peak spreading in a consistent way that is difficult to achieve with an aggregate four-step model.

The CMAP CT-RAMP model is an advanced ABM that is characterized by a high level of conceptual complexity and large number of software components in the model system. It includes the core microsimulation demand model, EMME-based network procedures and ancillary models, and the Java Parallel Processing Framework for multithreading and distribution of computations over CMAP's cluster of 4 dedicated computers. With the current setup of the model system (see the User Guide for details), the CMAP staff involved in the project were able to run the model for different scenarios after minimal training by the PB team. This proves that it is realistic for CMAP to adopt an advanced ABM as its main modeling tool in near future.

However, it should be noted that the current project was not intended to deliver a fully functional ABM. It was rather defined as a software transfer and demonstration project to evaluate suitability of this type of model for CMAP planning work. Although the delivered software is fully functional and corresponds to the advanced CT-RAMP structure applied for the Atlanta (ARC) and San Francisco Bay Area (MTC) regions with many sub-models redeveloped for Chicago, there are some gaps and potential improvements that we recommend for consideration before the ABM can be adopted for planning studies at CMAP instead of the existing four-step model. The following important directions for model improvement should be considered:

- **Improvement of the transit side of the model**. As was specified in the project scope, the ABM demonstration at this stage was limited to highway pricing studies. The mode choice structure on the transit side was simplified and included only two main modes (bus and premium transit) and two access modes (walk and drive). Also, all transit network procedures and level-of-service skims were adopted from the existing CMAP practice with no revision. The Chicago region requires a more detailed transit model that would include at least 3 main modes (bus, metro, and commuter rail) and 3 access modes (walk, park and ride, kiss and ride). In parallel with the mode choice extension, the corresponding transit network procedures should be revised and better calibrated to address station choice and parking capacity constraints, crowding in transit vehicles, multimodal combinations and associated transfer options/penalties, etc. Transit networks and procedures have to be applied for all time-of-day periods instead of the current practice of using two broad (peak and off-peak) periods only. For multi-modal combinations like park-and-ride and kiss-and-ride, level-of-service skims have to be generated in both directions –

outbound from home (when the auto leg precedes transit leg) and inbound back home (when the transit leg precedes auto leg). The transit side of the model would also benefit tremendously from using a finer level of spatial resolution (as discussed below). Additionally, to make the ABM output compatible with the FTA New Starts requirements, an option to retain the same set of tours and destinations ("fixed tour table") across multiple alternative scenarios has to be implemented. It must be complemented by a converter from the individual record format to origin-destination (OD) format in order to transform the ABM output to the input file for the FTA Summit program. Both components (model restart with a fixed tour table and output converter to an OD format) were developed and approved by FTA for the MORPC CT-RAMP model.

- **Improvement on the non-motorized side of the model**. Placeholders have been created in the mode choice structure for walk and bike as non-motorized modes. However, the corresponding utility functions and level-of-service variables are currently greatly simplified. In particular, there is no real accounting for bike friendliness, special bike lanes, and associated travel time by bike. All travel times for non-motorized modes are derived from the highway distance skim by assuming average uniform speed. Improving this side of the model would make it a useful tool for assessing transportation and urban policies associated with improvement of pedestrian and/or bicycling conditions. The non-motorized side of the model would also benefit tremendously from using a finer level of spatial resolution (as discussed below).
- **Inclusion of additional advanced sub-models**. The CMAP CT-RAMP is currently based on the ARC/MTC design. There are several sub-models that we recommend adding to the model structure based on recent experience with the later CT-RAMP versions developed for San Diego and Phoenix. One of them relates to an explicit modeling of work from home as a special work arrangement. Another relates to modeling additional individual mobility attributes such as free parking eligibility and transit pass holding. There are several other sub-models that can be enhanced based on the recent advanced versions of CT-RAMP including parking location choice, integrated daily activity pattern and joint travel generation, improved population synthesis procedures that can handle both household-level and person-level controls, as well as a wider set of accessibility measures in all sub-models.
- **Improvement of the corresponding database and input variables**. Many of the input variables, for example, parking cost and capacity, were synthesized in a simplified way in order to get the model system up and running for demonstration purposes. The entire set of input variables must be carefully prepared with some additional data collection efforts undertaken if necessary.
- **Transferring the model structure and restructuring network procedures to a smaller geographic unit**. CMAP has prepared most of its socio-economic, land use, and employment variables for 16,819 subzones (based on PLSS quarter-sections). We strongly recommended taking a full advantage of this finer level of spatial resolution, such as in the San Diego CT-RAMP model. The transit and non-motorized procedures have to be adapted to a finer level of spatial resolution. However, the entire model benefits tremendously from a better modeling of transit access, non-motorized accessibilities, and location choice.

- **Estimation of all behavioral sub-models with the CMAP household travel survey data**. Currently only the sub-models essential for highway pricing studies have been fully estimated with the Chicago data (car ownership, tour mode choice, tour time-of-day choice, and workplace location choice). The rest of the model system was transferred from the ARC model with the alternative specific constants recalibrated to match the Chicago survey aggregate statistics. It is necessary to fully re-estimate all behavioral sub-models to address specific features and urban conditions of the Chicago region.
- **Accounting for the unique and diverse urban conditions of the Chicago region through a wide set of accessibility measures**. The Atlanta region is much more uniform and less transit-rich compared to the Chicago region; thus the full spectrum of these impacts could not be reflected in the ARC model system. In this regard, application of a wider set of accessibility measures (as applied in the SANDAG and MAG CT-RAMP ABMs) is very important for the future improvements of all sub-models of the CMAP CT-RAMP ABM.
- **Enhancements of the hardware cluster to improve runtimes.** Parallel processing is the most powerful method to handle complicated travel models. The size of the Chicago metropolitan area (population of 10 million) resulted in a long runtime with the existing configuration of the cluster (17 hours for one full model iteration). With the parallel processing software created for CT-RAMP it is possible to take advantage of a bigger cluster with the run time reduced almost proportionally to the number of computers. Doubling of the existing cluster (from 4 to 8 computers) would make a 24-hour run realistic with 3 full global iterations. It should be noted that this full run has to be implemented only for the baseline scenarios for each year (when the population, employment, or network data change significantly). For alternatives analysis, much shorter runs are needed with only some model components rerun at each iteration.
- **More extensive effort for model validation and calibration.** At the current stage of CMAP CT-RAMP ABM development, a very limited set of model validation and calibration steps was undertaken using the aggregate targets developed from the expanded household travel survey across major dimensions and sub-models. It is important to compare the model output to additional independent sources of information like traffic counts (preferably by hours of the day and vehicle types), transit ridership data from the transit operators and/or on-board transit surveys, and car-ownership and journey-to-work data from the Census and ACS.