SCAG Regional Travel Demand Model
and
2019 Model Validation

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Southern California Association of Governments

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Preface

The Southern California Association of Governments (SCAG) is a voluntary association of six counties—Los Angeles, Orange, Ventura, Riverside, San Bernardino, and Imperial—and of 191 cities within those counties. SCAG's organizational purpose is cooperative planning and governmental coordination at the regional level. SCAG is mandated by State and federal law to plan and implement a Regional Transportation Plan/ Sustainable Communities Strategy (RTP/SCS) (updated every four years), a bi-annual Federal Transportation Improvement Program (FTIP), and to identify and analyze Transportation Control Measures (TCMs) and Transportation Strategies for incorporation into the South Coast Air Quality Management Plan (AQMP).

The Regional Transportation Model provides a common foundation for transportation planning and decision-making by SCAG and other agencies within the Region. The Year 2019 base year travel data contained in this report will be referenced by, and of interest to, the general public, as well as local, State, and federal agencies involved in transportation planning and traffic engineering. Various state, sub-regional, and local agencies in the SCAG Region also perform travel demand model forecasting for their own transportation planning and engineering purposes. These modeling programs require a high degree of coordination and cooperation with SCAG's Regional modeling program.

Agencies involved in SCAG's model enhancement include the California Department of Transportation (Caltrans) Districts 07, 08, 11, and 12. Sub-regional agencies include the Los Angeles County Metropolitan Transportation Authority (LA Metro), the Orange County Transportation Authority (OCTA), the Riverside County Transportation Commission (RCTC), San Bernardino County Transportation Authority (SBCTA), the Ventura County Transportation Commission (VCTC), the Imperial County Transportation Commission (ICTC), the County of Orange Environmental Management Agency, and other regional and local transportation agencies. Local agencies include cities and counties within the Region also maintain transportation modeling programs. Several of these agencies have contributed directly to the preparation of SCAG's Year 2019 Model Validation.

This report summarizes the specification, calibration, and validation of the SCAG Regional Transportation Model to the new 2019 base year. Based on the four-year time frame, the base year for SCAG's 2024 RTP/SCS update should be 2020. However, due to unusual travel and traffic conditions during 2024 due to the Covid-19 pandemic, we moved the base year one year back to capture normal traffic and travel condition as the base year for the model calibration and validation. This model update was performed in preparation for the development and evaluation of the SCAG 2024 RTP/SCS. The new modeling capabilities introduced as part of this update address the need for evaluating a wide variety of projects and transportation policies, including the addition of pricing strategies, expansion of existing transit services, introduction of managed lane projects, and land use policies. This updated model has enhanced sensitivities to evaluate the land use and transportation policy scenarios that are envisioned by California's greenhouse gas (GHG) emission reduction legislation, Senate Bill (SB) 375, and meets the requirements and recommendations in the California Transportation Commission's 2017 RTP Guidelines.

The 2024 RTP Model is an Activity-Based Travel Demand Model (ABM). In an ABM, travel emerges from the desire to participate in activities. As such, activities are predicted first, and then travel is generated to link these activities in time and space.

The SCAG ABM is implemented in a micro- simulation framework, which calculates travel metrics (such as traffic flows and transit boardings) by predicting and aggregating the travel behavior of individual persons and households.

The model system addresses the requirements of the metropolitan planning process and relevant State and federal requirements. It is equally suitable for conventional highway and transit projects, and for a wide variety of policy studies such as highway pricing, managed lanes, and travel demand management. The SCAG ABM is a comprehensive, robust, and forward-looking tool that addresses the following requirements:

Produce 24 hours travel demand patterns with the necessary level of temporal resolution. The ABM structure essentially operates in continuous time and simulates a complete day for all individuals in the region. When the ABM is integrated with standard network procedures (highway and transit assignments) the corresponding trips are grouped by time-of-day periods (the implementation schema for all ABMs in practice so far). However, this ABM will also be ready for integration with more advanced Dynamic Traffic Assignment (DTA) operating in continuous time.

Sensitive to future land use, demographics and employment. The ABM structure takes advantage of the details of the synthetic population and addresses demographic changes including population age distribution and household composition, amongst others. The future labor force scenarios and job allocation scenarios are logically integrated starting from the population synthesis. In this regard, future structural shifts in the land-use and employment types will affect all sub-models including the synthetic population itself. All demographic, land-use, and employment inputs also affect tour and trip choices of destination, mode, and time of day.

Sensitive to the implementation of various planning and transportation policies or visions. The ABM and supporting network procedures are designed to address a wide range of policies including different infrastructure capacity improvements and pricing schemes. Beyond the standard sensitivity of mode choice to travel time and cost, the ABM has a rich set of behavioral accessibility measures. Through these measures, the impacts of various policies on car ownership, commuting frequency, daily activity patterns, trip chaining, and joint travel arrangements can be captured.

Sensitive to changes in transportation facilities and services. The ABM is supported by highway assignment and skimming procedures sensitive to the details of transportation facilities and services for highway, transit, and non-motorized modes.

Produce quality information for project evaluation, including the assessment of economic benefits (e.g. variation in travel time and vehicle operation cost) and environmental impacts (e.g. energy consumption, pollutant emissions and greenhouse gases).

The Year 2019 model results have been compared to independent sources of travel data within the Region, such as auto and truck traffic counts, transit boarding counts, Vehicle Miles of Travel (VMT) from Highway Performance Monitoring System (HPMS), speed data from Freeway Performance Measurement System (PeMS), and other travel data. The Regional Transportation Model sufficiently replicates the observed validation data as described herein. As such, the model is validated for use in preparing travel forecasts for the SCAG 2024 RTP/SCS.

Overview of Report

The input data, model enhancements, calibration, validation, and results of each of the modeling components of the SCAG 2019 Regional Model are summarized in the respective chapters:

Chapter 1 – Overview
Chapter 2 – General Design of SCAG ABM
Chapter 3 – Model Inputs
Chapter 4 – Transportation Networks
Chapter 5 – Long Term Choice
Chapter 6 – Mobility Choice
Chapter 7 – Daily Activity Pattern (CDAP)
Chapter 8 – Mandatory Activity Generation and Tour Formation
Chapter 9 – School Escorting and Scheduling Consolidation
Chapter 10 – Fully Joint Tour
Chapter 11 – Individual Non-mandatory Activity Generation
Chapter 12 – Tour Formation
Chapter 13 – Mode Choice
Chapter 14 – Time of Day
Chapter 15 – Heavy Duty Truck Model
Chapter 16 – Trip Assignment

Supplemental information is contained in the following appendices:

Appendix A1 - Highway Network Coding Conventions
Appendix A2 – Auto Operating Costs
Appendix A3 – SCAG Model Peer Review
Acronyms

Chapter 1 Overview

Introduction

SCAG has evolved over the past four decades into the largest of nearly 700 councils of government in the United States. SCAG functions as the Metropolitan Planning Organization for six counties: Los Angeles, Orange, San Bernardino, Riverside, Ventura, and Imperial. The region encompasses a population exceeding 19 million persons in an area of more than 38,000 square miles.

SCAG is the primary agency responsible for the development and maintenance of travel demand forecasting models for the SCAG region. SCAG has been developing and improving these travel demand forecasting models since 1967. SCAG applies the models to provide state of the practice quantitative analysis for the RTP/SCS, the FTIP, and AQMPs. The Regional Model is also used to evaluate other transportation proposals within the region. The model is based on Caliper Corporation's TransCAD modeling software and the latest generation of the Coordinated Travel – Regional Activity Modeling Platform (CT-RAMP3).

This report combines information from several documents and other sources related to the enhancement and validation of the 2019 Regional Travel Demand Model (Regional Model) for Southern California. The Regional Model is managed and operated by the SCAG with development assistance from private consulting firms. The model is one of several tools used by SCAG to forecast land use and travel demand. Expert panels have reviewed the development/enhancement of the SCAG land use and travel demand modeling tools.

Transportation Model Overview

SCAG develops and maintains state-of-the-art transportation models to support SCAG's planning program. These models include:

Activity-Based Model

The Activity-Based Model (ABM) is a new generation of travel demand model. The ABM simulates daily activities and travel patterns of all individuals in the region, as affected by transportation system level of service. This new modeling system is designed to meet or exceed federal regulations and state laws/requirements. The ABM Model is in the late stages of development/testing and is expected to be the primary transportation model used in the development of the 2024 RTP/SCS.

Trip-Based Model

The Trip-Based Model (TBM) has historically been the main demand forecasting tool used by SCAG. Its base year is updated every four years, but otherwise retains the model structure as the 2019 RTP/SCS travel demand model. The TBM was peer-reviewed in May 2011 and found consistent with the state-of-the-practice. SCAG updated TBM for 20RTP/SCS.

Heavy-Duty Truck Model

Southern California Association of Governments developed the Heavy Duty Truck (HDT) model to evaluate policy choices and investment decisions. The HDT model is a primary analysis tool to support the goods movement policy decisions made by SCAG and regional stakeholders.

Air Quality Model

EMFAC is an emission factors model developed by the California Air Resources Board (CARB) for calculating emission inventories for vehicles in California. This is the emission model approved by the Environmental Protection Agency (EPA) for calculating vehicle emissions for conformity purposes in California.

SCAG Travel Demand Modeling Process

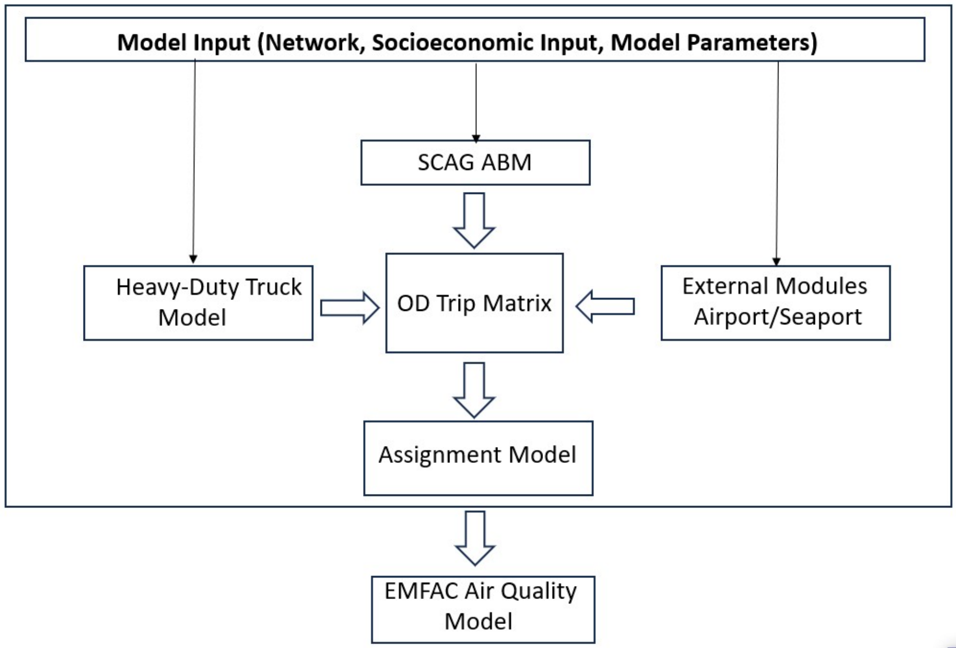
SCAG travel demand process is composed of two main components:

1. SCAG ABM (Coordinated Travel-Regional Activity Modeling Platform – 2nd version) which simulates daily activity participation and scheduling for each individual, with travel being viewed as a derivative of out of home activity participation and scheduling decisions.

2. A network assignment loads vehicles onto appropriate facilities to produce traffic volumes, congested speeds, vehicle-miles traveled (VMT), and vehicle-hours traveled (VHT) estimates for each of the five time periods. The SCAG Travel Demand Modeling process is shown in Figure 1-1. A series of multi-class highway assignment simultaneously loads the vehicle forecasted by

SCAG ABM, pre-calculated OD input matrices (airport, seaport, inter-regional; by passenger vehicles and three classes of heavy-duty trucks from Heavy Duty Truck model.

Figure 1-1 SCAG Travel Demand Process



California SB 375

One of the key factors behind the current model update is California's SB 375 that requires metropolitan areas, such as the SCAG region, to meet regional GHG emission reduction targets for 2024 and 2035.

California Senate Bill 375 and Sustainable Communities Strategies

SB 375 became law in California effective January 1, 2009. This law requires California's Air Resources Board (ARB) to develop regional greenhouse gas emission reduction targets for passenger vehicles for 2024 and 2035 for each region covered by one of the State's 18 MPOs, including SCAG. SB 375 was adopted as an "implementation mechanism" for California's Assembly Bill (AB) 32, the Global Warming Solutions Act, which requires 2024 greenhouse gas emissions statewide to be no higher than 1990 levels.

Each Metropolitan Planning Organization (MPO) is required to develop a Sustainable Communities Strategy that demonstrates how the region will meet the greenhouse emission reductions specified by the ARB targets through an integrated process that combines land use, housing, and transportation planning. The SCS becomes part of the Regional Transportation Plan.

SCAG's SCS scenarios comprise following strategies:

- Land Use and Growth
- Highways and Arterials
- Transit
- Travel Demand Management (TDM)
- Non-Motorized Transportation System
- Transportation System Management (TSM)
- Pricing

ARB's website for SB 375 is located at:
www.arb.ca.gov/cc/SB 375/SB 375.htm

Overview of SCAG ABM

SCAG Regional Travel Demand Model, or SCAG Activity-Based Model (SCAG ABM), was developed and used for the analysis to SCAG's 2024 RTP/SCS. This model exhibits the following characteristics:

Based on *advanced principles of modeling* individual travel choices with high behavioral realism. The model addresses both household-level and person-level travel choices including intra-household interactions between household members across a wide range of activity and travel dimensions. It predicts travel as emerging from activity participation, using various innovative sub-models, such as a combinatorial mode choice model that predicts tour mode and trip mode simultaneously.

Proven design concept, based on the third generation of the Coordinated Travel – Regional Activity Modeling Platform (CT-RAMP3) framework. The CT-RAMP framework has been evolving since 2005, and it has been *tested in practice* in several regions, including New York, Chicago, the San Francisco Bay Area, Atlanta, Miami, Columbus and Phoenix.

Operates at a *fine level of temporal resolution*, with respect to modeling trip and activity timing and duration. Tour start and end times are modeled in discrete space with 15 min intervals. Subsequently, trip departure times and activity durations are modeled in continuous time. This ensures consistency of the generated activity and travel patterns and schedules at the individual level that are important for modeling congestion, road pricing and peak spreading. This level of temporal resolution also opens the door for integrating the ABM with an advanced network simulation model, such as Dynamic Traffic Assignment (DTA).

Reflects and responds to *detailed demographic and socio-economic information*, including household structure, aging, changes in wealth, and other key attributes observed or expected in the dynamic Southern California region. The SCAG ABM incorporates different household, family, and housing types including a detailed analysis of different household compositions in their relation to activity-travel patterns.

Extensive use of *various accessibility measures*. Accessibility measures are important behavioral components of an ABM that express closeness of the modeled individual to potential locations where the activity "supply" (employment of the corresponding type) is present. Accessibility has a strong impact on individual activity patterns and travel behavior. The SCAG ABM extends commonly used accessibility measures by properly differentiating them by hour of day so that they can be linked to the corresponding time-of-day specific choices.

Accounts for the *full set of existing and planned travel modes*. The SCAG ABM allows for addressing details of different auto modes (distinguished by occupancy), transit modes, taxi, Transportation Network Company (TNC) modes, and non-motorized modes.

The core demand model can be *easily integrated with other components* such as the existing truck model, the model of external travel to and from the region, and eventually, models of non-resident visitor travel, airport travel, and/or special event travel.

Flexibility with respect to the network simulation platform available. This version of the SCAG ABM is implemented in combination with a conventional static assignment, since this is the only network simulation procedure feasible for Southern California region. However, the SCAG ABM structure can provide the *detailed inputs needed by traffic micro-simulation software* for engineering-level analysis of corridor and intersection design. Moreover, when coupled with DTA software, it will be possible to fully integrate transport demand and supply models in one coherent framework based on individual microsimulation. The proposed design of SCAG ABM fully accounts for this future possibility.

Model Enhancements

SCAG ABM has undergone major enhancements to improve its operation and analysis for Connect SoCal 2024. Model enhancements performed specifically for the 2019 Model include refined and re-estimated coefficients for several sub-models using the latest available data, as well as the addition of two new sub-models for future planning and policy analysis.

Sub-model refinements – SCAG revised and re-estimated coefficients of several key sub-models, using currently available data.

New sub-models – for future planning and policy analysis, SCAG added two new sub-models into SCAG ABM model system. Trip departure time – to improve the model sensitivity to policy analysis such as peak hour congestion, enhancement have been made to consistency between activity and travel schedule. New trip departure time choice model was added to SCAG ABM system. SCAG ABM has also incorporated an in-home/out of home choice model for non-mandatory activities- telemedicine and online shopping.

Software has been updated with significant improvements in run time, code optimization, upgraded version of Java (Java18), Java code update, writing outputs to binary format directly.

Tested and documented the ability of activity-based models to restart from intermediate sub-model locations. Useful feature for calibration work and for model application studies.

SCAG implemented version control – with Azure DevOps to efficient tracking of changes made to software code and input data, ensuring versioning and history tracking for better collaboration.

Model has been calibrated and validated using several data sources including CHTS (reweighed for the new base year), 2017 NHTS, 2019 ACS, LEHD 2018, DMV 2019, CTPP 2012-2016, PeMS, Streetlight, Caltrans HPMS and Pems data, SCAG 2017 Screenline Vehicle classification.

Other updates to the model include implementing emerging technologies such as transportation network companies (TNC, micro-mobility), updating heavy duty truck model, updates to TAZ and networks.

The methodologies used to develop key model inputs, such as Auto Operating Cost (AOC), work from home, and telemedicine, have undergone improvement as part of the model enhancement process. These enhancements aim to ensure that the model accurately captures the dynamic nature of travel behavior influenced by these inputs. Comprehensive research and analysis have been conducted. Please refer to Appendix B for further details.

Re-calibration of the models to targets developed based on a wide range spectrum of timely and local target data.

Additionally, two data collection were conducted in the SCAG region to better understand the impacts of the pandemic on transportation (COVID 19 survey).

Enhancement of sensitivity to potential SCS strategies such as AOC and pricing

Extensive collaborations have been established with various agencies (LA Metro, LADOT) and universities (UC Davis, UCLA, UC Santa Barbara, USC, UC Berkely). SCAG ABM has been successfully integrated with LA County MATSIM model, LA EPISIM – to understand the nonpharmaceutical interventions (NPIs) for COVID 19, and as well as planning tool of CAV model.

SCAG is collaborating with WSP to build an Access Equity Calculator (AEC) add on for the SCAG ABM. The AEC will estimate and visualize transport equity metrics based on "accessibility" of various population groups to life opportunities including employment locations, schools, shopping places, healthcare facilities, local and state parks, and high-quality transit stops.

SCAG successfully incorporated several short-term recommended items into for the final 2024 RTP/SCS.

Auto-Operating Cost (AOC): SCAG conducted comprehensive research to incorporate new data and assumptions into auto operating cost methodology based on comments from CARB. This process was conducted in coordination with modeling departments of other MPOs in California. Please refer to Appendix B1 for details.

Mode choice model has been enhanced to accommodate the changes of future transit route patterns outlined in LA Metro's NextGen bus plan (the full plan deployment is expected to start from 2025). Additionally, an integration of a commuter rail access variable has been introduced to the model to more accurately capture the improvements in service resulting from Metrolink's Southern California Optimized Rail Expansion (SCORE) capital improvement endeavor.

- Transit Access: The effect of transit access, measured as the distance to a bus stop or rail station, is significant on transit ridership and share of trips by transit.
- Transit access areas: based on literature (Ewing and Cervero, 2010; Baily, Mokhtarian, and Little, 2008), SCAG revised the transit access area for high-frequency transit corridors to a radius of 1 mile. Residents residing within the transit access area are more likely to use transit services compared to those residing outside of it. Subsequently, all sub-models using this variable were calibrated after the revision.
- Commuter rail access: Similar to the concept of transit access area, a new *Commuter Rail Access* variable has been formulated to reflect increased usage of commuter rail services among residents residing closer to the stations. To accommodate larger catchment areas associated with commuter rail services, this variable has been created as a weighted average of three distinct distance bands from a commuter rail station: 2 miles, 5 miles and 10 miles.

Bike land density: SCAG added bike-lane density variable to school escorting model and conducted model calibration. This enhancement improves the sensitivity of bike share for school purpose with respect to bike lane infrastructure.

Technical Approach of the Validation Process

Model validation is defined as the process by which base year model results are compared to actual, observed travel pattern data such as traffic counts and transit ridership data. SCAG performs a validation of its transportation model for each planning cycle for the Southern California region. A planning cycle is typically four years, corresponding to the update of the RTP/SCS. The "base year" for the current planning period and model is 2019; the long-term forecast year is 2050.

Model validation is a regular and essential modeling process that supports the development of the RTP/SCS, FTIP, and AQMPs. In the past, SCAG has prepared a model validation report for each of the previous planning cycle model base years: 1980, 1984, 1987, 1990, 1994, 1997, 2000, 2003, 2008, 2012 a 2016 and 2019. The base year of 2019 in the current model replaces the previous base year of 2016.

The SCAG modeling team assembled a wide spectrum of timely and local target metrics for the purpose of model calibration and validation for 2024 RTP/SCS. The main data sources that have been used for ABM sub-model calibration are listed below. It should be noted that from each data source the closest available dataset to the model base-year (2019) has been used.

- California Household Travel Survey (CHTS) of 2011 weighted for 2019 population
- National Household Travel Survey (NHTS) of 2017
- Longitudinal Employer-Household Dynamics (LEHD)
- American Community Survey (ACS)
- California Department of Motor Vehicles (CADMV)
- Census Transportation Planning Products (CTPP).

For highway and transit assignment validation, the main data sources that have been used are listed below.

- Caltrans Performance Measurement System (PeMS)
- StreetLight
- Replica
- Caltrans Traffic Counts (All Vehicles and Trucks)
- SCAG's 2017 Screenline Vehicle Classification (One Day Field Counts)

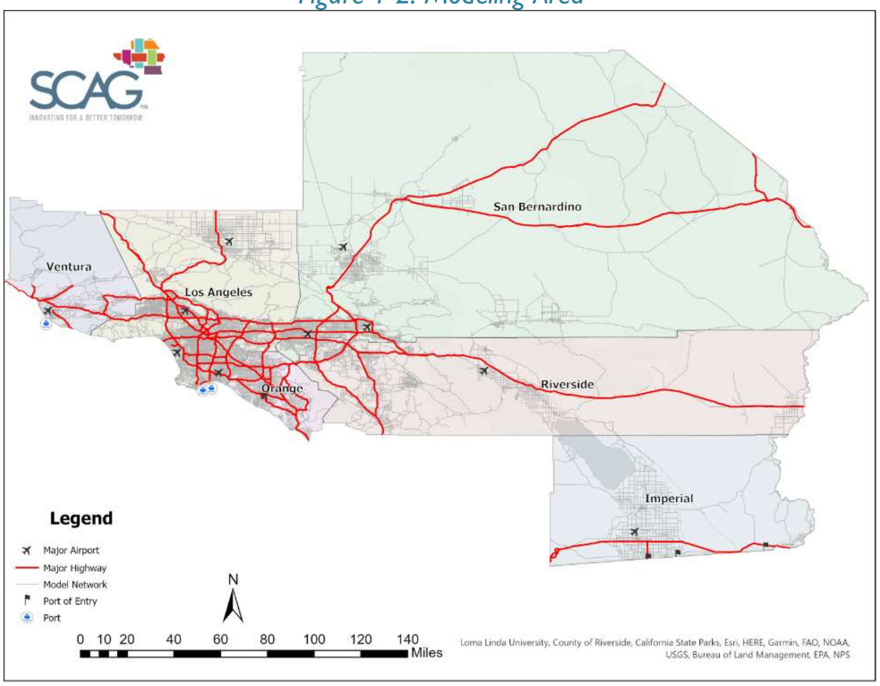
MODELING AREA

The modeling area of the SCAG 2019 Regional Travel Demand Model is same as the modeling area of 2019 Model and covers the following six counties in their entirety:

- Imperial County,
- Los Angeles County,
- Orange County
- Riverside County,
- San Bernardino County, and
- Ventura County

Figure 1-2 shows the Modeling Area. The figure also indicates how the modeling area has expanded over time.

Figure 1-2: Modeling Area



Zone System

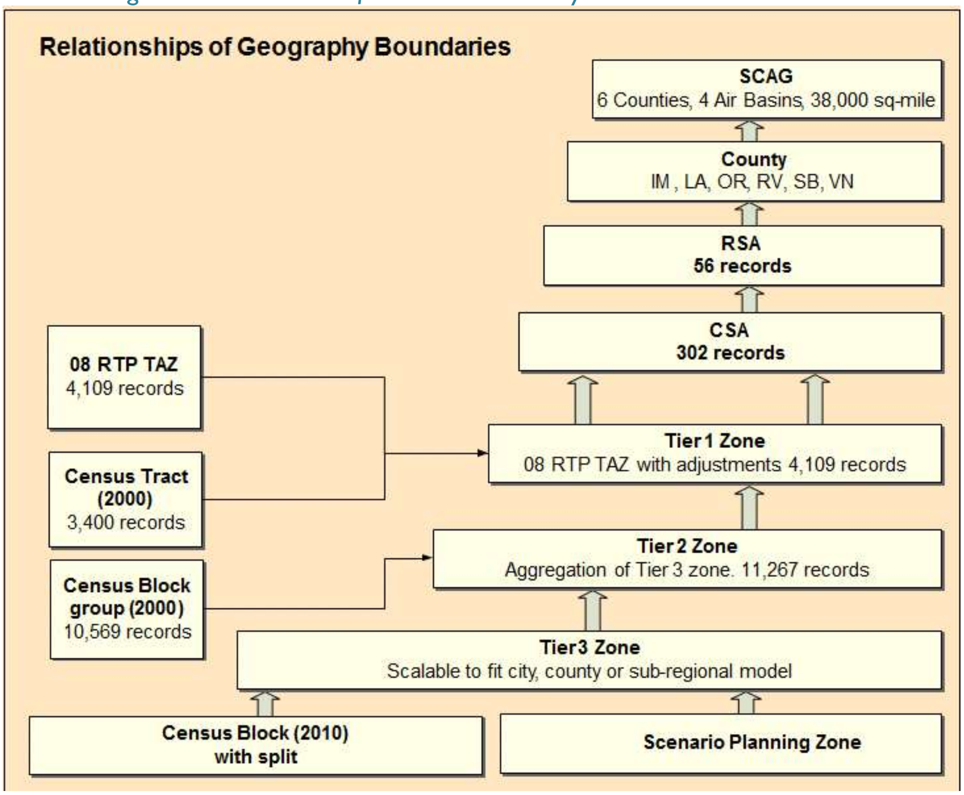
Socioeconomic data and other information for the model are contained in geographically defined areas known as Transportation Analysis Zones (TAZ). The TAZs are attached to the networks using centroid connectors that allow travelers (trips) to access to the transportation system by simulating local and neighborhood streets. They provide the spatial unit (or geographical area) within which travel behavior and traffic generation are estimated. TAZs are ideally, but not always, sized and shaped to provide a relatively homogeneous amount and type of activity.

The SCAG model uses a tiered zone system structure as shown in Figure 1-3 that allows for micro (i.e., neighborhood) and macro-scale (i.e., regional) analysis and reporting. The TAZ structure was last modified in 2021 to enhance the precision of micro-level land use and smart growth analysis for the RTP/SCS. The TAZ modification process involved extensive coordination with sub regional modeling agencies throughout the region. The Regional Model includes two tiers of TAZ. The first tier contains 4,109 internal zones, while the second tier contains 11,267 internal zones. All Tier 2 zones nest within Tier 1 zones. Table 1-1 and 3 provide statistical information and a graphical display of the zone structure. In addition, the Regional Model contains 40 external stations to facilitate modeling of trips to, from, and through the region.

Table 1-1: Geographic Zone Summary

Modeling Area	Regional Statistical Area (RSA)	Community Statistical Area (CSA)	Tier 1 TAZ (Internal)	Tier 2 TAZ (Internal)
Imperial County	1	24	110	239
Los Angeles County	21	175	2,243	5,697
Orange County	10	52	666	1,741
Riverside County	11	49	478	1,532
San Bernardino County	7	44	402	1,395
Ventura County	6	25	210	663
Total	56	369	4,109	11,267

Figure 1-3: Structure of the Tiered Zone System in the SCAG Model



Methodology

A tiered TAZ system was jointly developed by SCAG and its member agencies, based on sub-regional TAZs and SCAG MPUs (Minimum Planning Units) and some splits added according to major road, natural and artificial barriers, satellite photo, land use, and local inputs. TAZ Tier 2 is an aggregation of SPZ (Scenario Planning Zone) and TAZ Tier 1 is an aggregation of TAZ Tier 2 Zones, which matches the total number and general geography of the previous Regional TAZs.

The following provides a description of the principles that guided the development of the new Regional TAZ System. These principles follow standard modeling practice.

> ***Consistency with 2020 TIGER/Line Tract Boundaries*** – Both tiers of the Regional TAZs are consistent with Census 2009 Topographically Integrated Geographic Encoding and Referencing (TIGER)/Line Tract boundaries. Regional TAZs are either entire census tracts or are wholly contained within a census tract. When the tract boundary splits parcels with developable land use, parcel boundaries are accepted.
>
> Consistency with 2020 TIGER/Line Block Group or Sub-regional TAZ Boundaries
>
> To ensure the consistency, our TAZ boundary is maintained the same as the SCAG 2008 Model development excluding Orange County Tier 2 TAZ. By suggestion from the OCTA, by the counts of Tier 2 TAZ ID, 10 zones were dissolved into their neighborhoods, and another 10 zones were

created. Therefore, total number of Tier 2 in Orange County stays same to the original version, but 10 TAZ IDs were removed, and 10 TAZ IDs were added.

Consistency between the Two Tiers of the Regional TAZ System – The Tier 2 zones of the Regional Model's TAZ system are consistent with the Tier 1 zones. Tier 2 zones consist either of an entire Tier 1 zone or are wholly contained within a Tier 1 zone.

Consistency with 2020 TIGER/Line Block Boundaries –To ease data collection and creation, zonal boundaries generally do not cross Census 2020 Blocks (updated boundary in 2009). Some exceptions occur where Census Blocks consist of multi-part polygons or splits properties (developed parcels).

Complement the Transportation System – A critical step in developing the TAZ system is defining the level of roadway facilities for which accurate forecasts are desired. To ensure an accurate distribution and traffic assignments, existing and future freeways and principal arterials are generally represented as regional TAZ boundaries, consistent with other zonal creation criteria.

Homogeneous Land Use – Land use maps and general plan maps were used to identify existing and future land use. Ideally, it is best to limit the number of different land uses contained within a zone. However, given the geographic size of the regional TAZs and the mixed-use development patterns within the urban area, creating zones with uniform land uses was often difficult.

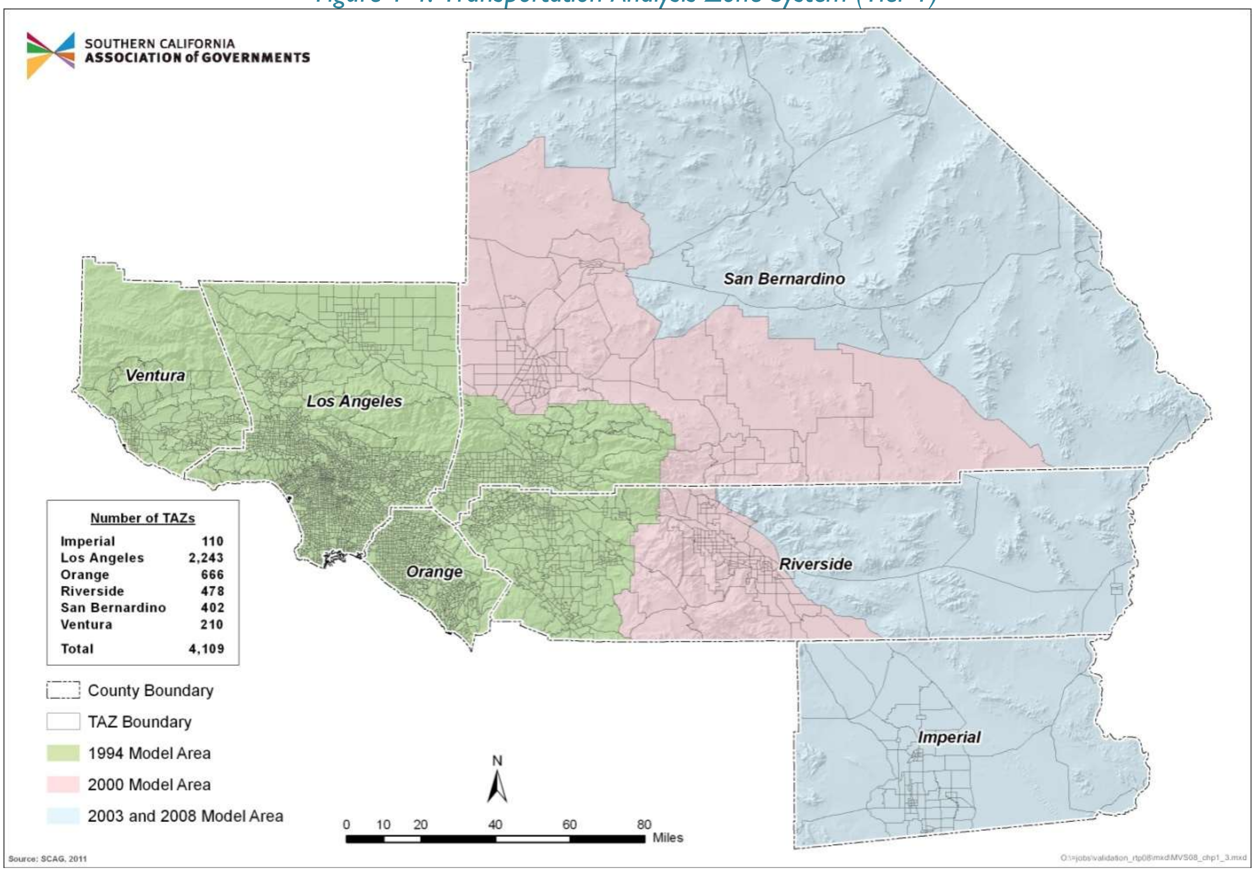
Similar Population/Employment Size – Zones were developed to represent similar levels of future development (population and employment). This parameter was not strictly enforced given the sparse development of some areas, the intensity of nonresidential land uses within urban areas, and consideration for special generators (example - universities and airports).

Other Considerations – Natural and man-made boundaries are also considered in the definition of the zone system. Political jurisdictions, railroad lines, rivers, mountain ranges and other topographical barriers were considered in developing the two tiers of regional TAZs.

Procedures

Tier 2 zones originated from the 2009 TIGER/Line block group and sub-regional TAZ boundary files. 2019 regional parcel boundary was aggregated into 107,562 SPZs, considering the detailed transportation network, land use and natural terrains. Then SPZs were aggregated into TAZs according to the principles above.

Figure 1-4: Transportation Analysis Zone System (Tier 1)



Chapter 2 GENERAL MODEL DESIGN

OVERVIEW

The general design of the SCAG ABM is shown in Figure 2-1 below. It consists of the following basic sequence of sub-models and associated travel choices:

1. ABM input -Population synthesis, Zonal SED, Land Use, Accessibility measures and Network

2. Long term choice – predicts choices of usual location for each mandatory activity for each household worker and student (workplace, university, school) including work or school from home (home-schooled) as one of the alternatives

3. Mobility choice – predicts decisions of holding driver license and number of cars owned by each household

4. Day-level models for activity generation

   4.1. Coordinated daily activity travel pattern - Daily activity-travel pattern type for each household member, with a linkage of choices across household members; this model includes a binary indicator of fully joint maintenance or discretionary tours Individual mandatory activities/tours for each household member

   4.2. Mandatory activity generation and tour formation

   - Frequency of mandatory activity generation and tour skeleton
   - Mandatory activity preliminary time of day (start-end time combination)
   - Escorting children to school by school half-tours

   4.3. Non-Mandatory activity generation

   - Maintenance activities that are generated by the household and allocated as tasks to an individual for implementation

- Household frequency of maintenance tasks by purpose
- Maintenance task allocation to one person in household
- Individual discretionary activities (conditional upon the available time window left for each person after the scheduling of mandatory and household-level non-mandatory activities)
- At home non-mandatory activity choice

5. Fully joint activity scheduling - Joint travel tours for shared non-mandatory activities (conditional upon the available time window left for each person after the scheduling of mandatory activities)
   - Household joint tour frequency and person participation
   - Tour formation that includes primary destination, stop frequency, and location for each joint tour
   - Time-of-day choice for joint tour

6. Tour/Trip Scheduling

   6.1. Individual tour formation

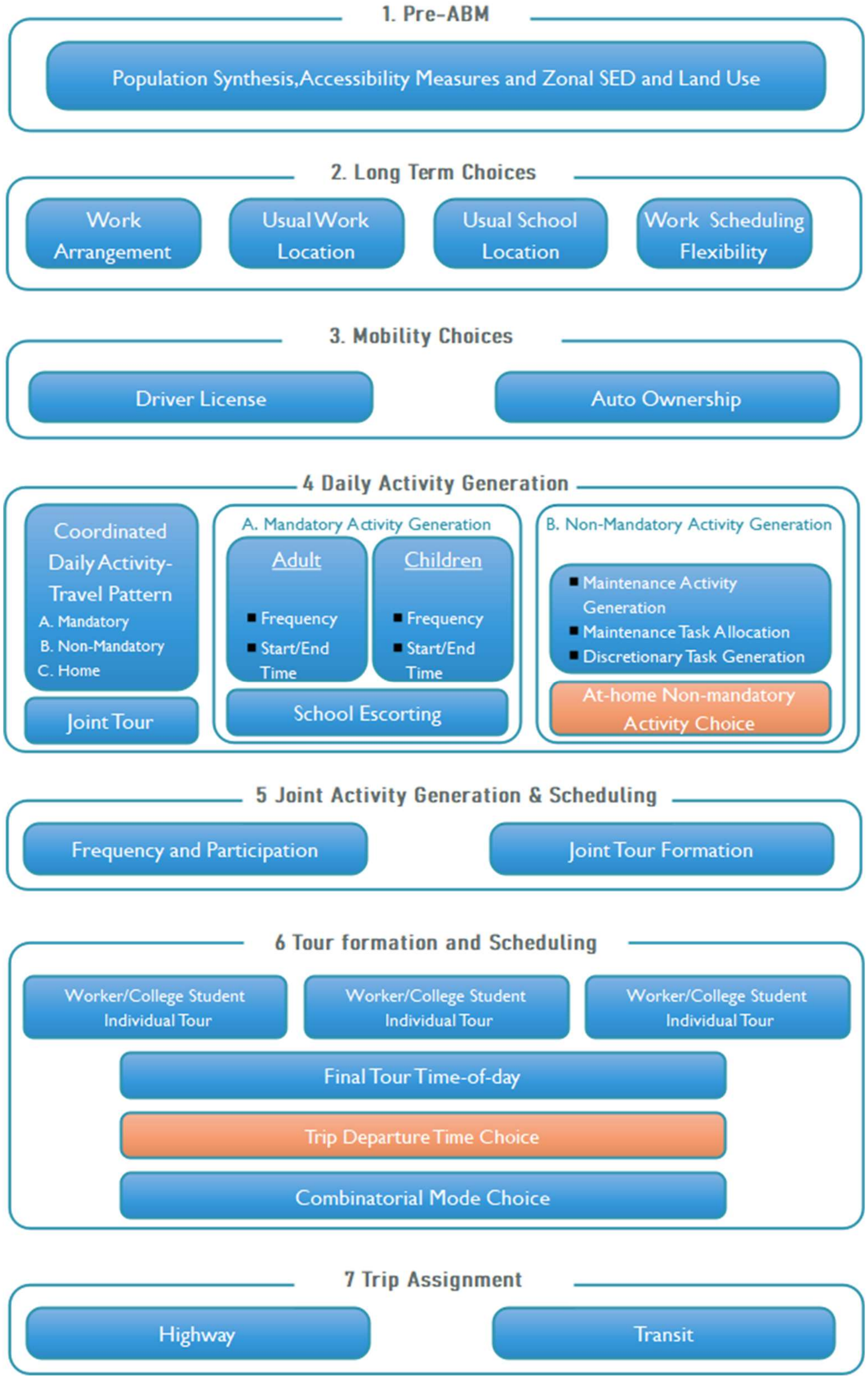
   - Allocation of individual non-mandatory activities to day segments for each person
   - Tour frequency and "breaks" (i.e. stops at home) for each person and person day segment
   - Activity sequence for each tour and sub-tour

   6.2. Tour and sub-tour time-of-day choice (from departure from home or work to arrival back home or to work)

   6.3. Trip Departure Time

   6.4. Mode choice : In SCAG ABM, the tour-level and trip-level mode choices are integrated in a network combinatorial representation. The model considers all feasible trip mode combinations on the tour

Figure 2-1: SCAG ABM System Design



Market Segmentation

Decision-Making Units

Decision-makers in the model system include both individual persons and households. These decision-makers are created (synthesized) for each simulation year based on tables of households and persons from the Census data persons by key socio-economic categories. These decision-makers select a single alternative from a list of available alternatives, following a probability distribution at each step of the entire-day decision-making process. These probability distributions are generated by discrete-choice models which account for the attributes of the decision-maker and the attributes of the various alternatives.

The decision-making unit is an important element of model estimation and implementation and is explicitly identified for each model specified in the following sections. In the SCAG ABM, there are five basic decision-making units that are used in most of the choice models:

Household. Examples of choice dimensions pertinent to this unit include car ownership and frequency of joint travel tours.

Person. Examples of choice dimensions pertinent to this unit include usual workplace and/or school location, frequency of individual discretionary activities and their allocation to person day segments. While these decisions are related to person attributes, the household which the person belongs in also plays an important role and provides additional variables and constraints explaining the person choices.

Person day segment. Examples of choice dimensions pertinent to this unit include tour formation frequency and destination (activity location) choice. The key attribute of a person day segment is a time window defined by the prioritized activities that constrain the segment start and end.

Tour. Examples of choice dimensions pertinent to this unit include time-of-day and tour mode choice that defines the sequence of trip modes on the tour. The person (or group of persons for joint tours) that implements the tour and their household provide additional important variables and constraints explaining the choice.

Trip. Examples of choice dimensions pertinent to this unit include trip departure time and parking location (currently applied to park-and-ride trips only). The tour that includes the given trip, person implementing it, and household provide additional important variables and constraints explaining the choice.

Activity. Examples of choice dimensions pertinent to this unit include the person to whom this activity is allocated (for household maintenance activities) and time allocation to the activity within the tour where this activity is included either as a primary destination or intermediate stop. Depending on the choice context all relevant tour, person, and household attributes are used as explanatory variables and/or constraints.

Person-Type Segmentation

Person types are assigned to the synthetic persons based on key socio-economic attributes: age, student status and employment status. A total of eight (8) person type segments are used in the SCAG ABM, as shown in Table 2-1. Person types are exhaustive and mutually exclusive, that is, every person in the synthetic population is assigned one, and only one, person type. Person types are used as explanatory variables and as model segmentation variables.

Table 2-1: SCAG ABM Person Type Definitions

Person Type	Name	Definition
1	Full-time worker	Age >=16, employed, work duration >= 35 hours, non- student Age >=16, employed, work duration >= 35 hours, attending 2-year college, 4-year college or graduate school
2	Part-time worker	Age >=16, employed, work duration < 35 hours, non- student Age >=16, employed, work duration >= 20 hours & work duration < 35 hours, attending 2-year college, 4-year college or graduate school
3	College student	Age >=16, employed, work duration < 20 hours, attending 2-year college, 4-year college or graduate school Age >=16, unemployed, attending 2-year college, 4-year college or graduate school
4	Non-worker	Age >= 16 & age < 65, unemployed, non-student
5	Retired	Age >= 65, unemployed, non-student
6	Driving age child	Age > 15 & age =< 18, attending high school
7	Pre-driving age child	Age > 5 & age =< 15, attending school
8	Pre-school children	Age <= 5

Activity-Type Segmentation

The California Household Travel Survey (CHTS) provided respondents with approximately 40 options to record the purpose of each trip. The model however understands a more concise set of activity purposes, which nonetheless capture the variety of activities reported. The extended set of options is useful to aid respondents in remembering everything they did during the survey day, and to maintain consistency across different respondents. For modeling, a more parsimonious classification is desirable to keep the number of sub-models manageable and avoid a proliferation of infrequent activity types. Table 2-2 shows the classification of survey trip purposes into the model activity purposes. All in-home activities, which comprise survey purposes 1-8, are modeled as the same type of activity in the SCAG ABM. Out of home activities are further grouped into two main categories, mandatory activities and non-mandatory activities, as follows:

Mandatory Activities	Non-Mandatory Activities	
• Work • University/School	• Escort • Shopping • Maintenance	• Eating out • Visiting • Discretionary

Table 2-2: Activity Purpose Classification

#	Survey Activity/Trip Purpose Description	SCAG ABM Activity Purpose #	SCAG ABM Activity Purpose Description
1	Personal Activities (Sleeping, Personal Care, Leisure, Chores)	0	
2	Preparing Meals/Eating	0	
3	Hosting Visitors/Entertaining Guests	0	
4	Exercise (With or Without Equipment)/Playing Sports	0	
5	Study / Schoolwork	0	
6	Work for Pay at Home Using Telecommunications Equipment	0	
7	Using Computer/Telephone/Cell or Smart Phone or Other Communications Device for Personal Activities	0	
8	All Other Activities at my Home	0	
9	Work/Job Duties	1	Work
10	Training	12	Work/Business
11	Meals at Work	1	Work
12	Work-Sponsored Social Activities (Holiday or Birthday Celebrations, etc.)	12	Work/Business
13	Non-Work-Related Activities (Social Clubs, etc.)	7	Discretionary
14	Exercise/Sports	10	Discretionary
15	Volunteer Work/Activities	7	Discretionary
16	All Other Work-Related Activities at My Work	1	Work
17	In School/Classroom/Laboratory	2	School / University
18	Meals at School/College	2	School / University
19	After School or Non-Class-Related Sports/Physical Activity	10	Discretionary
20	All Other After School or Non-Class Related Activities (Library, Band Rehearsal, Clubs, etc.)	7	Discretionary
21	Change Type of Transportation/Transfer (Walk to Bus, Walk To/From Parked Car)	0	

#	Survey Activity/Trip Purpose Description	SCAG ABM Activity Purpose #	SCAG ABM Activity Purpose Description
22	Pickup/Drop Off Passenger(S)	4	Escorting
23	Drive Through Meals (Snacks, Coffee, etc.)	6	Maintenance
24	Drive Through Other (ATM, Bank)	6	Maintenance
25	Work-Related (Meeting, Sales Call, Delivery)	12	Work-related
26	Service Private Vehicle (Gas, Oil, Lube, Repairs)	6	Maintenance
27	Routine Shopping (Groceries, Clothing, Convenience Store, Household Maintenance)	5	Shopping
28	Shopping for Major Purchases or Specialty Items (Appliance, Electronics, New Vehicle, Major Household Repairs)	5	Shopping
29	Household Errands (Bank, Dry Cleaning, etc.)	6	Maintenance
30	Personal Business (Visit Government Office, Attorney, Accountant)	6	Maintenance
31	Eat Meal at Restaurant/Diner	11	Eat-out
32	Health Care (Doctor, Dentist, Eye Care, Chiropractor, Veterinarian)	6	Maintenance
33	Civic/Religious Activities	7	Discretionary
34	Outdoor Exercise (Playing Sports/Jogging, Bicycling, Walking, Walking the Dog, etc.)	10	Discretionary
35	Indoor Exercise (Gym, Yoga, etc.)	10	Discretionary
36	Entertainment (Movies, Watch Sports, etc.)	8	Discretionary
37	Social/Visit Friends/Relatives	9	Visiting Friends/Family
38	Other (Specify)	13	Discretionary
39	Loop Trip (For Interviewer Only-Not Listed on Diary)	0	
97	No Additional Activities	0	
99	Don't Know/Refused	0	

Employment Classification

The SCAG ABM uses employment to represent the economic activity at each TAZ. The nine employment categories recognized by the model are shown in Table 2-3. Employment is used to specify trip attraction measures in the location choice models and in the accessibility measures.

Table 2-3: Employment Classification

#	NAICS codes	Industry Type
1	11, 21	Agriculture, Mining
2	48, 22, 23	Construction, Utility
3	31, 42	Manufacturing, Wholesale
4	44, 81	Retail, Other Service
5	51, 54, 55, 56	Information, Business Service
6	61, 62	Education & Health/Social Service
7	52, 53	Finance, Investment, Real Estate Services
8	71, 72	Arts, Entertainment, and Hospitality, Food Service
9	92	Public Administration

Temporal Resolution

The SCAG ABM functions at a *temporal resolution of fifteen minutes* for all sub-models that generate activities and tours; that is, up to sub-model Trip Departure Time. The Trip Departure Time sub-model operates with *continuous time*. The fifteen-minute increments begin with 3:00 A.M and end with 2:59 A.M the next day. Temporal integrity is ensured so that no activities are scheduled with conflicting time windows (overlapping in time for the same individual), except short activities/tours that are completed within a fifteen-minute increment. For example, a person may have a very short tour that begins and ends within the 8:30 A.M-8:44 A.M period, as well as a second longer tour that begins within this time interval, but ends later in the day.

Trip Mode Classification

The trip mode classification is shown in Table 2-4. The auto modes are defined by driver vs passenger, and in the case of drivers by car occupancy (single, 2-person carpool, 3+ person carpool). The transit modes are defined by access mode at the home end of the tour (walk, park and ride, kiss and ride), and primary mode combination (conventional transit, which includes local bus, rapid bus, and streetcars; and premium transit, which includes premium bus, BRT, urban rail, commuter rail or high-speed rail as the main line-haul option). Non-motorized travel is captured by the walk and bike modes. In addition, school bus is a choice for trips to/from school.

Each trip mode is associated with its own travel time and cost, also known as level of service (LOS). For the auto driver modes, LOS depends on the facilities which are available to each mode, as shown in

Table . The LOS for the auto passenger mode is the same as for 2-person carpools. For the transit modes, LOS includes in-vehicle time, out-of-vehicle time, transfer penalty, and fare. The path-building modes available to each skim set, corresponding to the trip modes, are shown in Table 2-5 and Table 2-6.

Table 2-4: Trip Modes

1. Auto driver, 1-person occupancy	8. Walk to premium transit
2. Auto driver, 2-person occupancy	9. Park and ride to premium transit
3. Auto driver, 3+ person occupancy	10. Kiss and ride to premium transit
4. Auto passenger	11. Walk
5. Walk to conventional transit	12. Bike
6. Park and ride to conventional transit	13. Taxi
7. Kiss and ride to conventional transit	14. School bus

Table 2-5: Highway Availability Settings for LOS Skimming

LOS Skim Set	GP Lanes	HOV Lanes (2p+)	HOV Lanes (3p+)	Toll Roads	Express Lanes (2P+)1	Express Lanes (3P+)2
Auto driver 1P	✓			✓	✓(pay)	✓(pay)
Auto driver 2P	✓	✓		✓	✓(free)	✓(pay)
Auto driver 3P+	✓	✓	✓	✓	✓(free)	✓(free)
Auto passenger	✓	✓	✓	✓	✓(free)	✓(pay)

1 Express lanes 2p+ are toll facilities where carpools with 2 or more occupants travel for free
2 Express lanes 3p+ are toll facilities where carpools with 3 or more occupants travel for free

Table 2-6: Transit Availability Settings for LOS Skimming

LOSSkim Set	Mode →	CT[1] Walk	CT PNR	CT KNR	PT[2] Walk	PT PNR	PT KNR
Walk Access	1	✓			✓		
Drive Access	2		✓	✓		✓	✓
Walk Transfer & Egress	4	✓	✓	✓	✓	✓	✓
Local Bus	30,31, 32	✓	✓	✓	✓	✓	✓
Rapid Bus	33	✓	✓	✓			
Express Bus	20, 21, 22, 23	✓	✓	✓			
BRT	19				✓	✓	✓
Urban Rail	11				✓	✓	✓
Comm. Rail	10				✓	✓	✓
HSR	12				✓	✓	✓

1 CT: Conventional transit
2 PT: Premium transit

Chapter 3 MODEL INPUTS

SOCIO-ECONOMIC DATA

Socioeconomic data, which describes both demographic and economic characteristics of the region by TAZ, is used as major input to SCAG's travel demand model. Travel demand analysis is based on the concept that travel is a derived demand of activity participation. Zonal demographic data, such as population, households, and income, is directly related to demand for activity participation of the area; economic characteristics, such as jobs by industry, are linked with supply of an activity.

The socioeconomic input data for year 2019 consists of various zonal and individual household and population based socioeconomic data. Zonal level data includes include population, households, school enrollments, household income, workers, and employment, etc. for 4,109 tier1s and 11,267 Tier2. Individual household and population based data are specifically designed and developed for Activity Based Model (ABM) (Table 3-1). The base year socioeconomic variables were developed using diverse public and private sources of data and advanced estimation methods. The major data sources include 2020 Census, American Community Survey (ACS), California Department of Finance (DOF), California Employment Development Department (EDD), firm based InfoGroup data, 2019 Land Use data and County Assessor's Parcel Database.

Population, households, employment are the three major variables anchoring other variables' development. They were developed by incorporating various latest survey data and collaboration with local jurisdictions. The secondary variables, attributes of the three major variables, including workers, household size, household income, and employment sectors were further developed as input for the ABM. These secondary variables at the TAZ level were estimated using the Small Area Secondary Variables Allocation Model (SASVAM). SASVAM is generally based on a probabilistic choice model that segments the population, household or employment control totals into subgroups (e.g., household size groups). The model was estimated with historical data. In application, the disaggregation reflects the change over time of the control total, as well as the change in the individual attribute (for example, reflecting a trend in average household size). The following zonal level variables are maintained for the ABM. More detailed population and employment attributes, shown in Table 3-1, are also maintained for use in the population synthesis.

Major Variables	
• Population	• Employment (including self-employed)
• Residential population	• Agriculture and mining
• Group quarters population	• Construction
• Occupied housing units	• Manufacturing
• Median household income ($2011)	• Wholesale trade
• Student enrollment by place of school (public and private)	• Retail trade
• Kindergarden to 8th grade	• Transportation and warehousing
• 9th grade to 12th grade	• Information
• College/university	• Finance, insurance and real estate
	• Professional and business service
	• Education and health service
	• Leisure and hospitality service
	• Other service
	• Public administration

Table 3-1: Household and Person Variables

1. Household	2. Residential Population[1]
1.1 Household type	2.1 Age
1) Residential	2.3 Gender
2) Institutional group quarter	2.4 Ethnicity
3) Non-institutional group quarter	2.5 Employment status
1.2 Number of people in a household	2.6 Worker by industry[2]
1.3 Annual household income	2.7 Worker by occupation[3]
1.4 Housing type	2.8 Person by type[4]
1) Single detached	2.9 Person by education attainment
2) Single attached	2.10 Student by grade
3) Multiple	
4) Other	
1.5 Housing tenure	
1) Owned with mortgage or loan	
2) Owned free and clear	
3) Rented	
4) Occupied without payment of rent.	

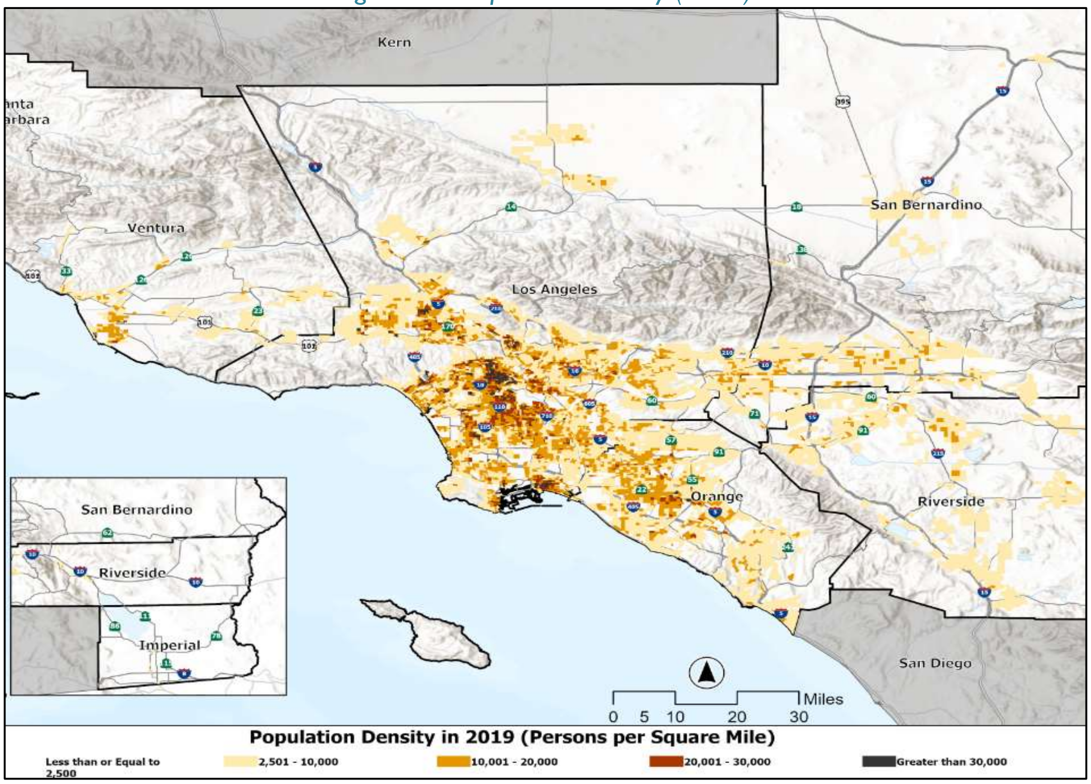
Socioeconomic Input Data Summary

Selected socioeconomic data input totals are presented in the following tables and figures. Table 3-2 presents a summary of 2019 socioeconomic data totals by county and for the SCAG Region. Figure 3-1 to Figure 3-3 show 2019 population density, household income distributions, and employment density for the Tier 2 level TAZs.

Table 3-2: Year 2019 SCAG Model Socioeconomic Input Data

County	Persons			Households	Employment	School enrollment	
	Total	Residential	Workers			K-12	College
Imperial	180,727	172,273	59,495	51,598	69,465	36,910	10,119
Los Angeles	10,047,272	9,862,893	4,653,447	3,392,543	5,031,408	1,578,570	745,279
Orange	3,192,514	3,140,352	1,521,817	1,069,175	1,805,476	510,923	291,363
Riverside	2,385,377	2,353,095	973,407	744,440	847,058	447,783	109,876
San Bernardino	2,174,577	2,135,084	882,795	657,188	859,874	417,831	91,493
Ventura	848,902	837,848	391,166	278,076	362,824	145,438	46,982
Total	18,829,369	18,501,545	8,482,127	6,193,020	8,976,105	3,137,455	1,295,112

Figure 3-1: Population Density (2019)



Note:TAZs with "Less than or Equal to 2500 population density (persons per square mile)" are not included

Figure 3-2: Household Income Distribution (2019)

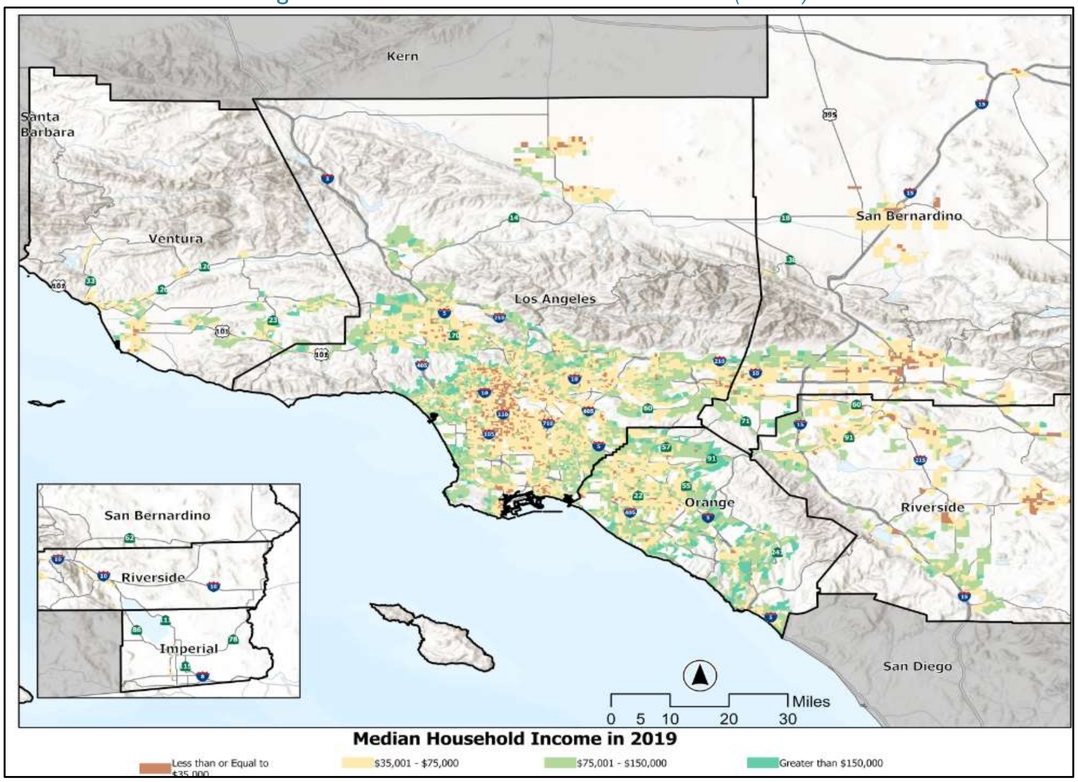
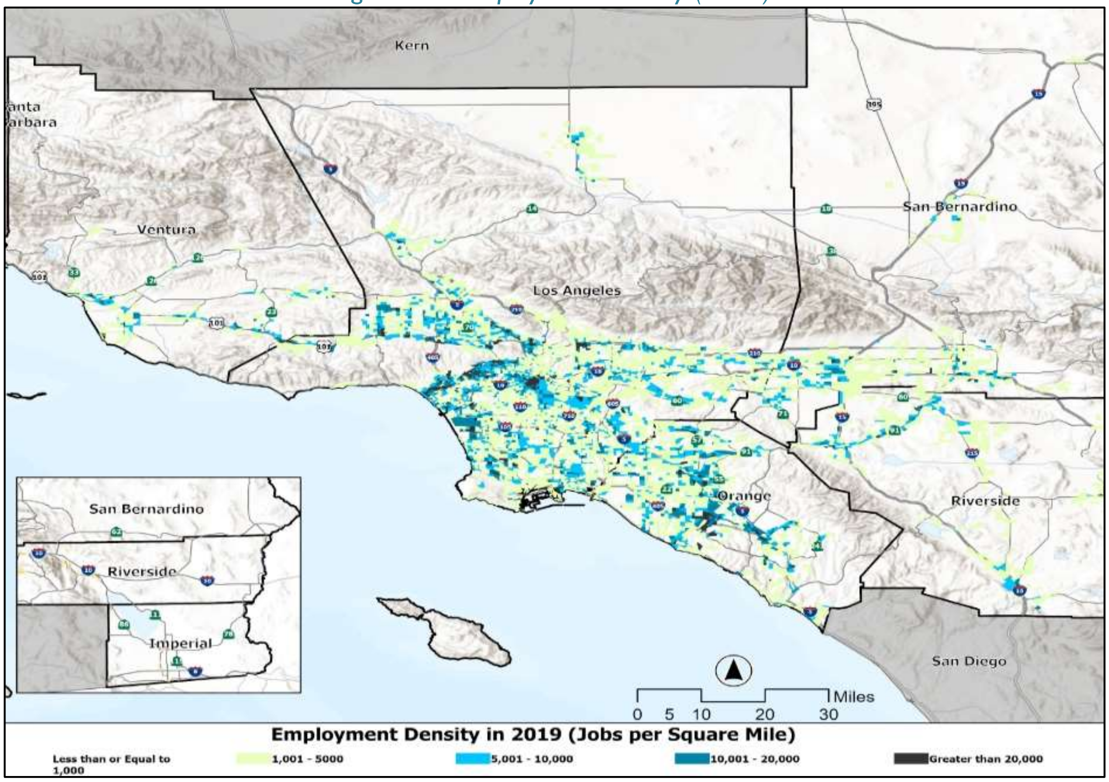


Figure 3-3: Employment Density (2019)



SYNTHETIC POPULATION

The SCAG ABM predicts travel for each person in the region. The population synthesis sub-module creates a list of households and persons for the entire model area that represents the region's population for each horizon year. Two types of persons are generated independently of each other – household residents and group quarter residents. In the ABM, group quarter residents are treated as one-person households.

Table 3-3: PyPopSyn Control Totals

Table	Columns
rescontrol	• **Geographic IDs**: region (always 1), county, puma, taz, tazid • **household:** total number of households in the Tier2 TAZ • **res:** residential population • **res by age category:** 0-4, 5-17, 18-24, 25-64, 65+ • **res by race:** Hispanic, Non-Hispanic While, Non-Hispanic Black, Non-Hispanic Indian, Non-Hispanic Asian, Non-Hispanic Other • res by employment status: employed, unemployed • household by size: 1, 2, 3, 4, 5+ • household by housing type: SFD, SFA, MF, Other • **household by income category**: 0 – 25K – 50K – 100K – 150K (2011 dollars)
county control	• county • **half of households:** half of total county households (to match the number of households of which income is lower than the median income) • **half of household by size:** 1, 2, 3, 4, 5+. To match the number of households of each size category whose income is lower than the median income of the size. • **number of workers:** of household by county, by 0, 1, 2, 3+
region control	• **total:** total worker • **workers:** by 20 Sectors (n11=Ag, n21=extract/Mine, n22=Utility, n23=Construct, n31=Manufacture, n42=wholesale, n44=Retail, n48=Transport, n51=Information, n52=Finance, n53=Real Estate, n54=Prof Service1, n55=Management, n56=Prof Service2, n61=Education, n62=Personal Care, n71=Entertainment, n72=Accommodation ,n81=Service, Admin, n99=Military Other • **workers in Imperial County:** by same 20 sectors of regional worker control
gqcontrol	• **Geographic IDs**: region (always 1), county, puma10, taz, tazid • **gq, gi, gn :** total, institutional and non-institutional population • **res by age category :** 0-4, 5-17, 18-24, 25-64, 65+ • **res_race:** (see the rescontrol categories)

Table 3-4: Comparison of 2019 Base Year PyPopSyn Input and Output

Variable	Output	Control	%Diff
Households	6,193,020	6,193,020	0.00%
Number of 1 person households	1,285,291	1,284,875	0.03%
Number of 2 person households	1,700,784	1,701,096	-0.02%
Number of 3 person households	1,063,935	1,063,804	0.01%
Number of 4 person households	1,039,966	1,040,274	-0.03%
Number of 5+ person households	1,103,044	1,102,971	0.01%
Single family detached	3,358,763	3,359,152	-0.01%
Single family attached	475,502	475,438	0.01%
Multifamily	2,139,118	2,139,115	0.00%
Other	219,637	219,315	0.15%
Persons	18,829,369	18,827,367	0.01%
Age 0-4	1,070,232	1,075,791	-0.52%
Age 5-17	3,136,791	3,138,012	-0.04%
Age 18-24	1,997,967	1,995,557	0.12%
Age 25-64	9,902,817	9,901,161	0.02%
Age 65 over	2,721,562	2,716,846	0.17%

Land Use and Built Environment (LUBE)

The SCAG ABM uses various measures to characterize land use and the built environment, listed in Table 3-5.

Table 3-5: Land Use and Built Environment Measures

Measure	Description and Formulas
Household Density	LN_HHDEN = Ln(1 + (hh/area))
Retail and Service Employment Density	LN_RSEDEN = Ln(1 + ((ret_emp + fire_emp + artent_emp + othser_emp)/area))
Total Employment Density	LN_EMPDEN = Ln(1 + (total_emp/area))
Population Density	LN_RESPOPDEN = Ln(1 + (res_pop/area))

Measure	Description and Formulas
Employment Mix	EMPMIX = 1 - (numerator / (4/3)) L = pop + emix_factor * (ci_emp + other_emp) numerator = Abs((pop/L) - 1/3) + Abs((ci_emp/L) - 1/3) + Abs((other_emp/L) - 1/3)
High-Frequency Bus Stop Density (all rail & local bus headway <= 15 mins peak periods) at home location	Ln(1 + (stops/area))
Total Bus Stop Density at home location	Ln(1 + (stops/area))
Commuter Rail Station Accessibility	Commuter rail service frequencies within 2, 5 and 10 miles from a commuter rail station. The three different distances and two time periods (peak & off-peak) are combined with different weights: min{Sqrt(crfreq2mi_pk*crfreq2mi_op*0.6+crfreq5mi_pk*crfreq5mi_op*0.3+crfreq10mi_pk*crfreq10mi_op*0.1), 56}
Percent of households in multi-family dwelling units (DU)	Occupied multi-family DU / total occupied DUs
High quality transit percentage	Percent of a TAZ that is a high quality transit area
Bike Lane Density Indicator	Bike lane density (weighted by class)

Accessibility Measures

Accessibility measures are important behavioral components of the ABM that express closeness of the modeled individual to potential locations where the activity "supply" (employment of the corresponding type) is present. Accessibility has a strong impact on individual activity patterns and travel behavior.

Multiple sets of accessibility measures are used across different parts of the SCAG ABM. Each set corresponds to a given activity purpose and are sometimes further segmented by travel arrangement type, user class, and/or mode. Special effort was made to make these accessibility measures properly differentiated by hour of day so that they can be linked to the corresponding time-of-day specific choices.

Origin-based accessibility measures are defined as the logsum for the destination choice that is calculated over all attractions in the region discounted by the travel impedance. The size and impedance terms both should correspond to the same period for which the accessibility measure is desired.

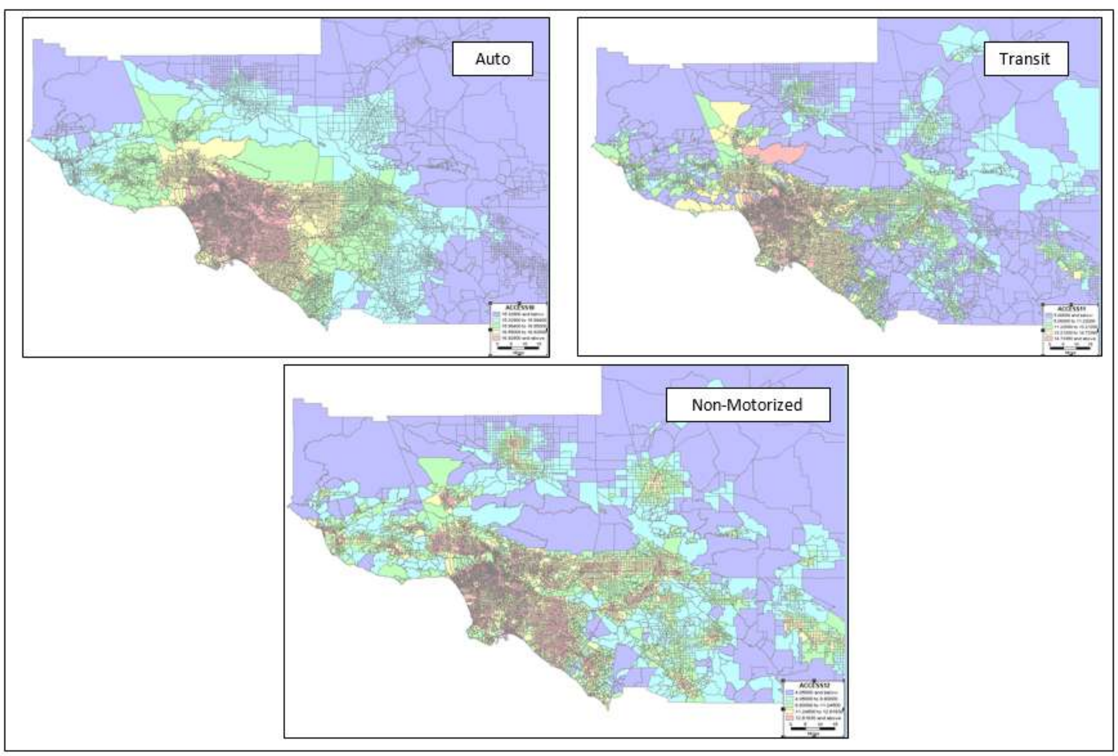
Table 3-6: Travel Impedance Measures

#	Description	Type of travel	User class	Applicable mode set
1	School accessibility	School		SOV-HOV-WT-NM
2	University accessibility	School		SOV-HOV-WT-NM
3	Non-mandatory accessibility			SOV-HOV
4				WT
5				NM
6	Non-mandatory accessibility	Individual	Zero cars	HOV-WT-NM
7			Car insufficient	SOV-WT-NM
8			Car sufficient	SOV-WT-NM
9	Non-mandatory accessibility	Joint	Zero cars	HOV-WT-NM
10			Car insufficient	SOV-WT-NM
11			Car sufficient	SOV-WT-NM
12	Work accessibility	Work		SOV-HOV-WT-DT-NM

Table 3-7: Non-Mandatory Accessibility Size Variable Coefficients

Figure 3-4: Representative Accessibilities by Mode

	Escort	Shop	Main	Visit	Eat	Disc	At work	Non mand.
Population	0.129							
Households		0.161	0.207	0.155	0.069	0.216		0.808
Agriculture, mining		0				0.144		0.144
Transportation, construction		0	0.06				0.021	0.081
Manufacturing, wholesale		0	0					
Retail, other services		1.327	0.552	0.068	0.38	0.187	0.09	2.604
Information, professional			0.085			0.061	0.07	0.216
Education, health	0.101	0.037	0.206	0.04	0.033	0.069	0.02	0.506
Finance, insurance, real estate					0.283		0.114	0.397
Food and hospitality	0.196	0.176	0.171	0.042	0.181	0.366	0.042	1.174
Public administration			0.087		0.097	0.027	0.018	0.229



Chapter 4 Transportation Networks

Introduction

The Year 2019 highway network went through an extensive review to examine network coding accuracy and ensure proper network connectivity. Once complete, the transit network was built directly off the highway network ensuring an integrated network approach. Attributes for the Year 2019 highway network were determined based on the Federal Highway Functional Classification system, SCAG highway network, and inputs from sub-regional and regional agencies. The new highway network was distributed to interested county transportation commissions and Caltrans' districts for further review. Several meetings with these agencies were conducted to discuss coding conventions and accept comments. The transit network is a key input to the mode choice model and is used in the transit trip assignment process. All elements used to determine level of service for transit mode choice calculations are identified and defined in this section.

Highway Networks

The Highway Inventory was built on a very detailed geographic information system (GIS) network that included over 23,000 centerline miles for all freeways, arterials, and urban major collectors. This GIS data was later transferred to the TransCAD-based 2008 highway network. Subsequently, periodic detailed reviews and updates of the highway network have been completed using aerial photography to ensure that the base year network accurately represents 2019 conditions.

As part of the network inventory, primary and secondary attributes were geo-coded. Primary attributes are those identified as critical to the performance of the travel demand model.

• Primary attributes: • Speed limits • Number of lanes (by time period) • Intersection control (at model nodes) • Median type • Directionality (one-way versus two-way streets)	**Secondary attributes:** • Linear reference system • Shoulder type • Other controlled Intersections • Parking • School zones • Advisory speeds • HOV access • Ramp gore points • Bike lanes

The highway network was prepared using the TransCAD Transportation Planning Software. TransCAD uses a GIS-based network approach to ensure geographic accuracy and provide enhanced editing capabilities. The GIS-based database structure allows for an almost unlimited number of attributes. The Year 2019 highway network includes detailed coding of the region's freeway system (e.g., mixed-flow lanes, auxiliary lanes, HOV lanes, express lanes, toll roads and truck lanes), arterials, major collectors, and some minor collectors. To simulate roadside parking restrictions and other lane changes during the day, separate networks were developed for each of the following five modeling time periods:

- AM peak period (6:00 AM to 8:59 AM)
- Midday period (9:00 AM to 2:59 PM)
- PM peak period (3:00 PM to 6:59 PM)
- Evening period (7:00 PM to 8:59 PM)
- Night period (9:00 PM to 5:59 AM)

Facility Types

The facility type (FT) definitions used in SCAG's Year 2019 highway network are generally consistent with the Federal Functional Highway Classification system. The major categories used for defining facility type are as follows:

- FT 10 - Freeways
- FT 20 - HOV
- FT 30 - Expressway/Parkway
- FT 40 - Principal Arterial
- FT 50 - Minor Arterial
- FT 60 - Major Collector
- FT 70 - Minor Collector
- FT 80 - Ramps
- FT 90 - Truck lanes
- FT 100 - Centroid connector (Tier 1)
- FT 200 - Centroid connector (Tier 2)

Area Types

The area types (AT) used in the highway network were prepared based on development density (population and employment density) and other land use characteristics. The area types used in the highway network are:

- AT 1 - Core
- AT 2 - Central Business District
- AT 3 - Urban Business District
- AT 4 – Urban
- AT 5 - Suburban
- AT 6 - Rural
- AT 7 - Mountain

Free-Flow Speeds and Capacities

Free-flow speeds and capacities assigned to each link in the highway network were determined based on posted speed (PS), facility type (FT) and area type (AT) of each link. Free flow speeds and capacities are presented in Table 4-1 through Table 4-6.

Table 4-1: Year 2019 Freeway/Expressway Free-Flow Speed

Facility Type	AT1	AT2	AT3	AT4	AT5	AT6	AT7
Freeway	PS+5	PS+5	PS+5	PS+5	PS+5	PS+5	PS+5
HOV	PS+5	PS+5	PS+5	PS+5	PS+5	PS+5	PS+5
Expressway (Limited Access)	PS+5	PS+5	PS+5	PS+5	PS+5	PS+5	PS+5
Fwy-Fwy Connector	45	45	50	50	55	55	55
On-Ramp (peak)	15	15	20	20	30	35	35
On-Ramp (off-peak)	25	25	30	30	35	35	35
Off-Ramp	25	25	30	30	35	35	35

Notes:
AT1: Core *AT3: Urban Business District* *AT5: Suburban* *AT7: Mountain*
AT2: Central Business District *AT4: Urban* *AT6: Rural* *PS: Posted Speed*

Table 4-2: Year 2019 Arterial Free-Flow Speed

Posted Speed	AT1	AT2	AT3	AT4	AT5	AT6	AT7
	-- Principal Arterial --						
20	21	22	22	24	25	27	27
25	23	24	25	27	28	31	31
30	25	26	27	29	31	34	34
35	27	28	29	32	35	38	38
40	28	30	32	34	37	41	41
45	30	32	34	37	40	45	45
50	33	35	37	41	45	51	51
55	34	38	39	44	49	56	56
	-- Minor Arterial --						
20	19	20	21	23	24	27	27
25	21	22	23	25	27	30	30
30	22	24	25	28	30	34	34
35	24	26	27	30	33	37	37
40	25	28	29	32	36	41	41
45	27	29	31	34	38	44	44
50	29	32	33	38	43	50	50
55	30	33	35	40	46	55	55
	-- Major Collector --						
20	17	18	19	21	23	26	26
25	18	20	21	23	26	30	30
30	19	21	22	25	28	33	33
35	20	22	24	27	31	36	36

Posted Speed	AT1	AT2	AT3	AT4	AT5	AT6	AT7
40	21	24	25	28	33	39	39
45	22	25	26	30	35	43	43
50	23	27	28	33	39	48	48
55	24	28	30	35	42	52	52

Notes:

Add 4% for divided streets.

AT1: Core *AT3: Urban Business District* *AT5: Suburban* *AT7: Mountain*

AT2: Central Business District *AT4: Urban* *AT6: Rural*

Table 4-3: Year 2019 Arterial/Expressway Capacity (Signal Spacing <2 miles)

On\Crossing	2-Lane	4-Lane	6-Lane	8-Lane
-- AT1 (Core) --				
2-Lane	475	425	375	375
4-Lane	650	600	500	500
6-Lane	825	700	600	550
8-Lane	825	700	650	600
-- AT2 (Central Business District) --				
2-Lane	575	525	475	475
4-Lane	725	675	550	550
6-Lane	875	750	650	600
8-Lane	875	750	700	650
-- AT3 (Urban Business District) --				
2-Lane	600	525	475	475
4-Lane	750	675	575	575
6-Lane	900	775	675	625
8-Lane	900	775	725	675
-- AT4 (Urban) --				
2-Lane	625	550	500	500
4-Lane	800	725	600	600
6-Lane	950	825	700	650
8-Lane	950	825	775	700
-- AT5 (Suburban) --				
2-Lane	675	600	525	525
4-Lane	825	750	625	625
6-Lane	975	850	750	675
8-Lane	975	850	800	750
-- AT6 (Rural) --				
2-Lane	675	600	525	525
4-Lane	825	750	625	625
6-Lane	975	850	750	675
8-Lane	975	850	800	750

On\Crossing	2-Lane	4-Lane	6-Lane	8-Lane
-- AT7 (Mountain) --				
2-Lane	575	500	425	425
4-Lane	750	675	550	550
6-Lane	925	800	700	625
8-Lane	925	800	750	700

Notes:
Capacities are in passenger car per lane per hour (pcplph).
Lanes are mid-block 2-way lanes.
Add 20% for one-way streets.
Add 5% for divided streets.

Table 4-4: Year 2019 Arterial/Expressway Capacity (Signal Spacing >=2 Miles)

Type	Posted Speed	Capacity
Multi-Lane Highway	45	1,600
	50	1,700
	55	1,800
	60	1,900
2-Lane Highway	--	1,400

Notes:Capacities are in passenger car per lane per hour (pcplph).

Table 4-5: Year 2019 Freeway Capacity

Type	*Posted Speed*	*Capacity*
Freeway/HOV	55 and below	1,900
	60 and 65	2,000
	70 and above	2,100
Freeway-Freeway Connector	40 and below	1,400
	45	1,600
	50	1,700
	55	1,800
	60 and above	1,900
Auxiliary Lane	--	1,000

Notes:Capacities are in passenger car per lane per hour (pcplph).

Table 4-6: Year 2019 Ramp Capacity

Type	AT1	AT2	AT3	AT4	AT5	AT6	AT7
On-Ramp (first lane)	720	720	720	720	1,400	1,400	1,400
On-Ramp (additional lane)	480	480	480	480	600	1,400	1,400
On-Ramp (off-peak)	1,300	1,300	1,300	1,300	1,400	1,400	1,400

Notes:
Capacities are in passenger car per lane per hour (pcplph).
Use arterial/expressway capacity estimation procedure for off-ramps.
AT1: Core AT3: Urban Business District AT5: Suburban AT7: Mountain

AT2: Central Business District *AT4: Urban* *AT6: Rural*

Toll Facilities

The 2019 highway network incorporates all toll facilities, including the Metro Express Lanes on I-110 and I-10 in Los Angeles County, the SR-91 Express Lanes in Orange and Riverside Counties, and the SR-73, SR-133, SR-241 and SR-261 Toll Roads in Orange County.

Heavy Duty Truck Designation

The Year 2019 highway network incorporates special network coding that allows for heavy-duty trucks to be converted into Passenger Car Equivalents (PCE). This conversion enables the model to account for the effects of trucks on link capacity in the mixed flow vehicle traffic stream. The highway network also includes coding to identify truck-only lanes and truck climbing lanes.

Freeway Lane Types

For the purpose of the Regional Model, the Year 2019 highway network includes a detailed coding of the region's freeway system. Freeway lanes are identified by the following three lane types:

Freeway Main Lane (Through Lane) includes continuous freeway lanes that extend more than 2 miles and that pass through at least one interchange.

Freeway Auxiliary Lane (Auxiliary Lane of Capacity Significance) includes auxiliary freeway lanes that extend more than one mile or that extend from interchange to interchange.

Freeway Acceleration/Deceleration Lane (Other Freeway Lane) includes all types of acceleration and deceleration lanes or freeway widening that do not satisfy the conditions for main lane and auxiliary lane classifications.

Year 2019 Highway Network Summary

Table 4-7 summarizes the Year 2019 Highway Network by tallying the number of highway facility centerline and lane-miles represented in the network for each county and facility type. The centerline mile summary includes both directions of travel, even if the roadway is represented by two separate one-way links in the coded network. Figure 4-1 through Figure 4-3 depict the Year 2019 highway network by facility type and area type. Figure 4-4 shows the locations of the external cordon sites on the network at the modeling area's boundary.

Table 4-7: Year 2019 Highway Network Summary

County	Centerline Miles	Lane Miles				
		AM Peak	Midday	PM Peak	Evening	Night
Freeway (Mixed Flow, excluding HOV and Toll Facilities)						
IM	95	379	379	379	379	379
LA	630	4,599	4,599	4,599	4,599	4,599
OC	165	1,322	1,322	1,322	1,322	1,322
RV	310	1,799	1,799	1,799	1,799	1,799
SB	471	2,558	2,558	2,558	2,558	2,558
VT	94	538	538	538	538	538
Subtotal	**1,765**	**11,195**	**11,195**	**11,195**	**11,195**	**11,195**
HOV						
IM	0	0	0	0	0	0
LA	237	474	474	474	474	474
OC	121	252	252	252	252	252
RV	40	80	80	80	80	80
SB	57	113	113	113	113	113
VT	4	8	8	8	8	8
Subtotal	**458**	**927**	**927**	**927**	**927**	**927**
Toll Facilities (Toll Roads and Express/HOT Lanes)						
IM	0	0	0	0	0	0
LA	27	84	84	84	84	84
OC	62	337	337	337	337	337
RV	11	35	35	35	35	35
SB	0	0	0	0	0	0
VT	0	0	0	0	0	0
Subtotal	**100**	**455**	**455**	**455**	**455**	**455**

County	Centerline Miles	Lane Miles				
		AM Peak	Midday	PM Peak	Evening	Night
Principal Arterial						
IM	222	701	701	701	701	701
LA	1,959	8,427	8,436	8,428	8,434	8,434
OC	701	3,586	3,586	3,586	3,586	3,586
RV	270	1,157	1,158	1,158	1,158	1,158
SB	510	1,822	1,822	1,822	1,822	1,822
VT	217	811	811	811	811	811
Subtotal	**3,880**	**16,505**	**16,515**	**16,507**	**16,513**	**16,513**
Minor Arterial						
IM	250	517	517	517	517	517
LA	2,856	8,931	8,933	8,931	8,929	8,929
OC	785	2,777	2,777	2,777	2,777	2,777
RV	1,032	3,088	3,088	3,088	3,088	3,088
SB	1,445	3,892	3,892	3,892	3,892	3,893
VT	356	992	992	992	992	991
Subtotal	**6,725**	**20,197**	**20,198**	**20,196**	**20,195**	**20,194**
Collector						
IM	1,221	2,463	2,463	2,463	2,463	2,463
LA	3,306	7,064	7,064	7,064	7,062	7,064
OC	418	1,026	1,026	1,026	1,026	1,026
RV	2,152	5,062	5,062	5,062	5,062	5,062
SB	2,911	6,190	6,189	6,189	6,189	6,189
VT	498	1,058	1,058	1,058	1,058	1,058
Subtotal	**10,505**	**22,863**	**22,862**	**22,862**	**22,861**	**22,863**
All Facilities (excluding truck lanes, freeway ramps and centroid connectors)						
IM	1,788	4,060	4,060	4,060	4,060	4,060
LA	9,015	29,579	29,590	29,580	29,583	29,585
OC	2,252	9,298	9,298	9,300	9,298	9,298
RV	3,815	11,222	11,222	11,222	11,222	11,222
SB	5,394	14,576	14,576	14,574	14,576	14,576
VT	1,169	3,406	3,406	3,407	3,406	3,406
Total	**23,433**	**72,142**	**72,153**	**72,142**	**72,146**	**72,148**

Figure 4-1: Year 2019 Network by Facility Type

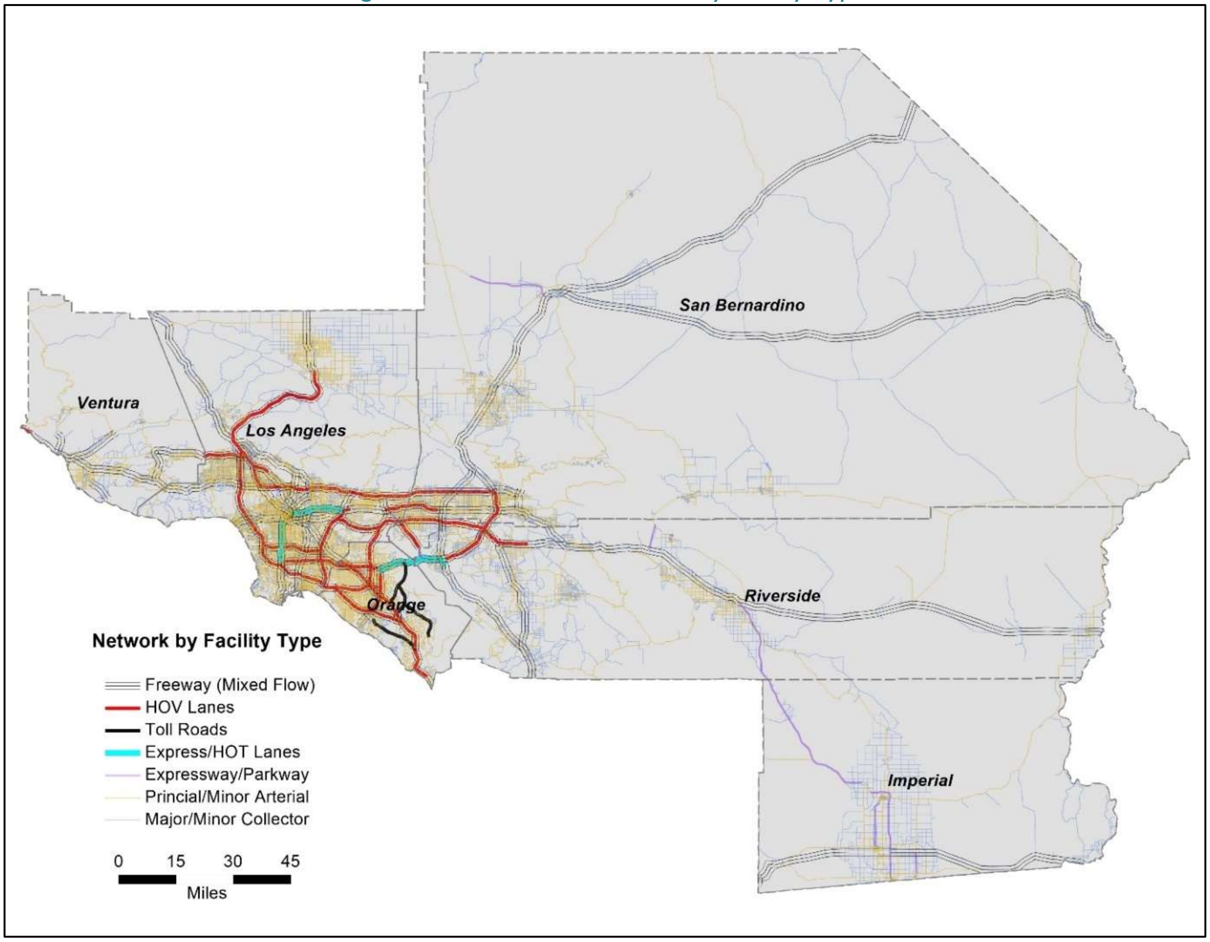


Figure 4-2: Year 2019 Modeling Area by Area Type

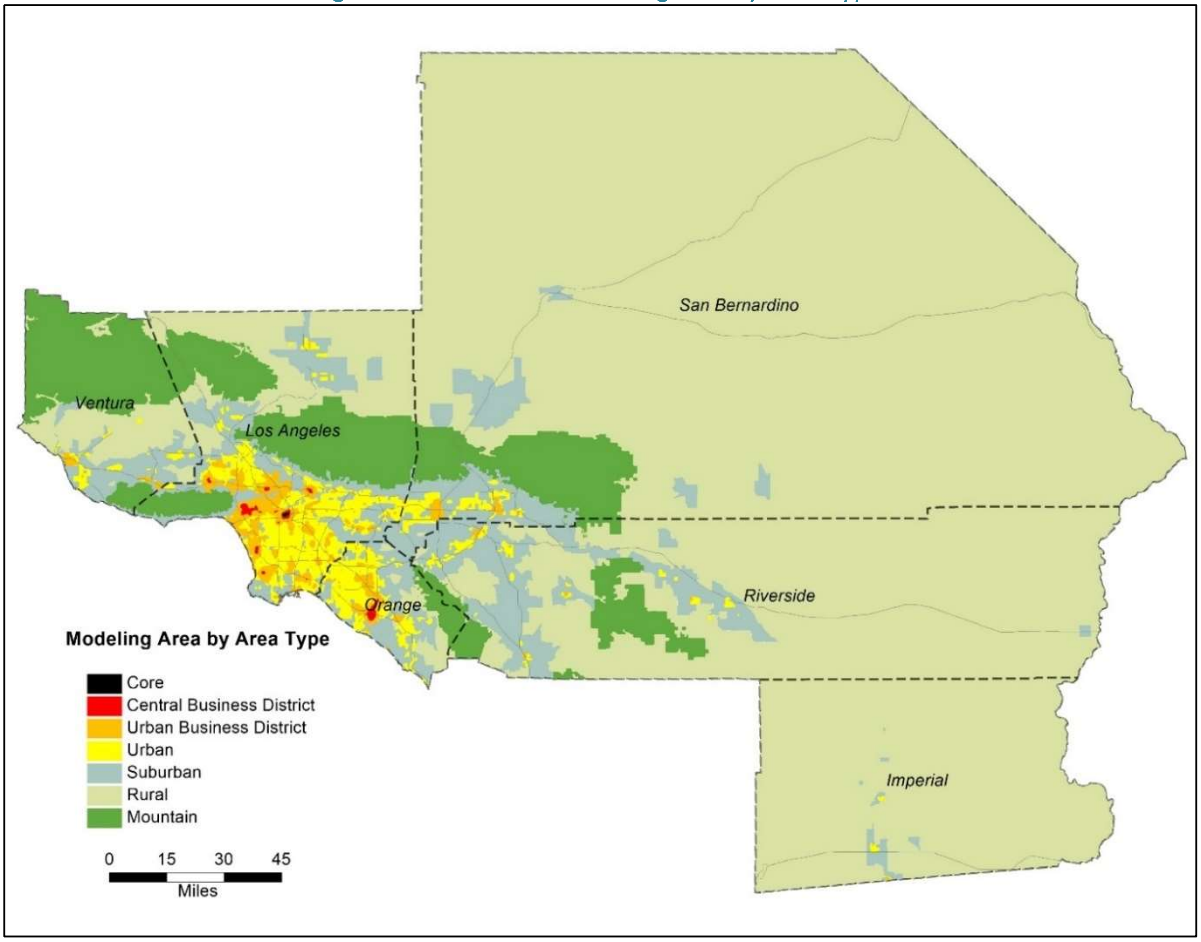


Figure 4-3: Year 2019 Network by Area Type

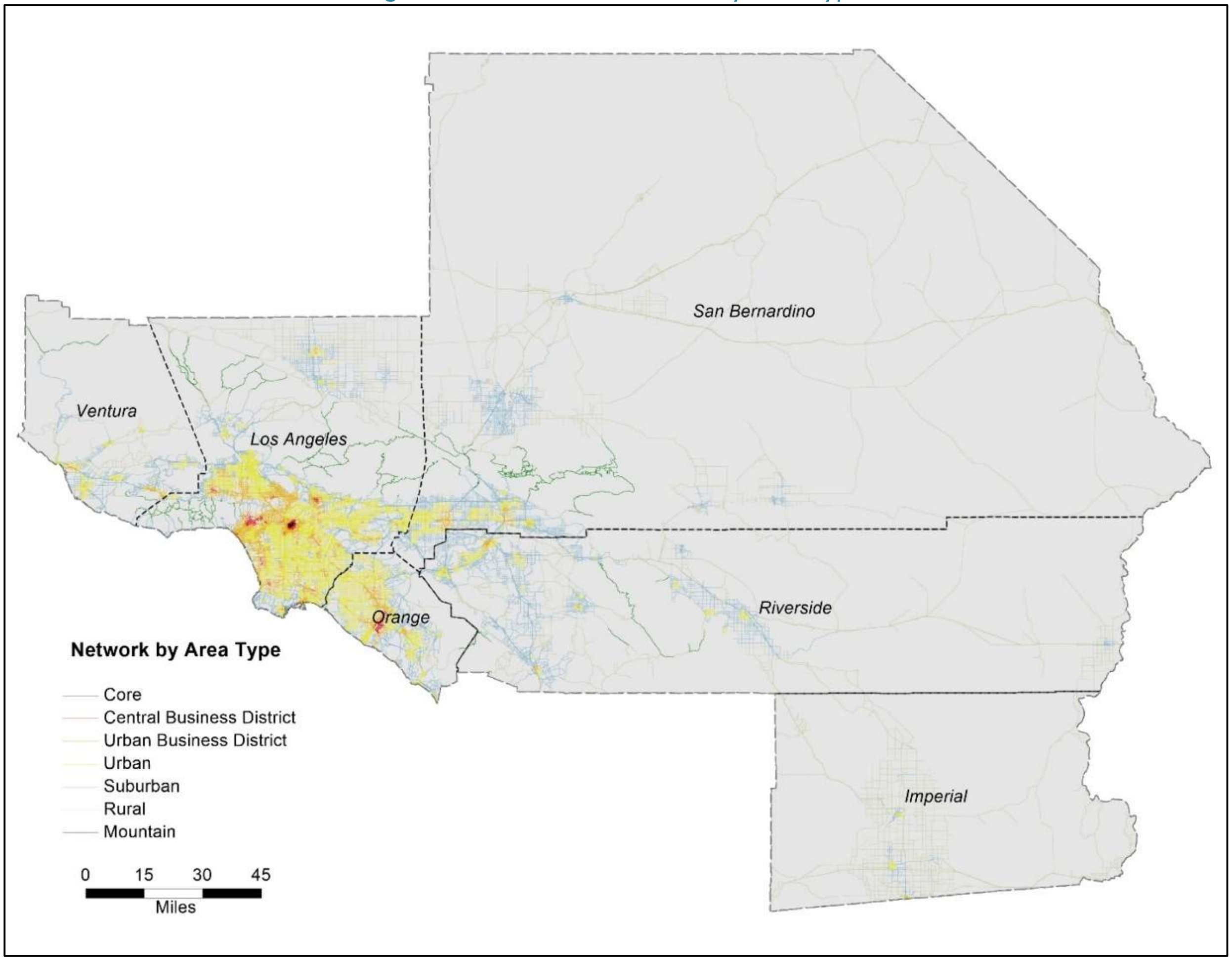
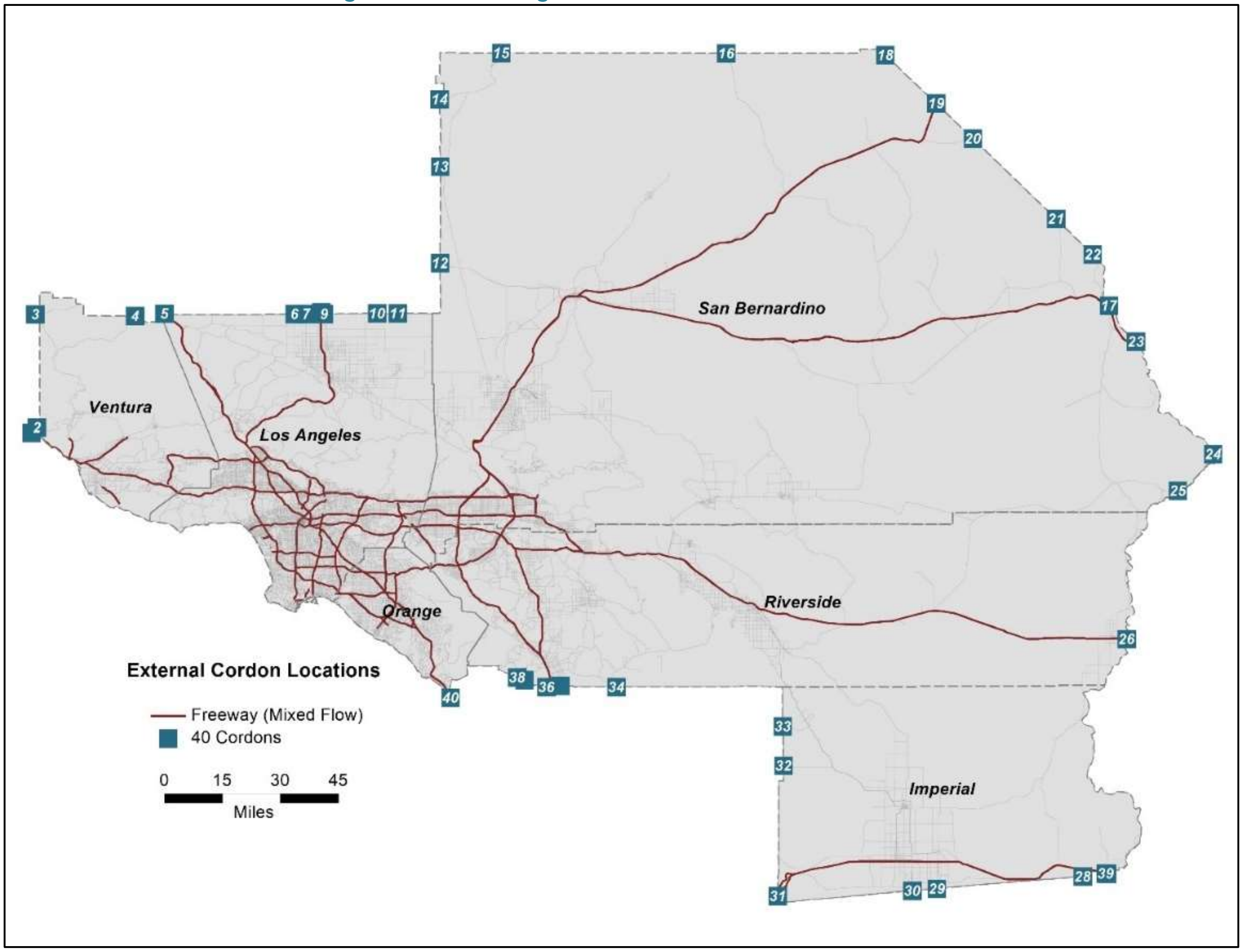


Figure 4-4: Modeling Area External Cordon Locations



TRANSIT NETWORKS

The Year 2019 transit network covers the entire SCAG region, with about 3,000 transit route patterns operated by about 70 transit carriers in the six-county model area. The year 2019 transit network includes the following key features:

- Collected GTFS (General Transit Feed Specification) for each transit carrier and converts into the TransCAD transit route systems using TransCAD 9.
- Separated out all route patterns that have different pairs of start and end stops to calculate headways more accurately.
- Coded fares at the route level and fare factors at the carrier level.
- Reflected transit operations by five times of day (AM, MD, PM, EVE, NT), rather than peak and off-peak.
- Used an "all-street" network to create transit walk access/egress links and compute average walk times of all paths from every street node in a TAZ to a nearby stop with the path cost weighted by Census Block Group data.

Transit services in the SCAG region are grouped into seven transit modes, based on their service characteristics and fare structures. An additional mode, High Speed Rail, has been added to future year networks. The Year 2019 transit network covers only fixed-route transit services. It does not include dial-a-ride, charter services, airport shuttles, limousines, or Uber/Lyft/taxicabs. Transit routes in each transit network are characterized by attributes such as route ID, route name, route head sign, transit operator, route distance, direction, transit modes, and fares. The transit network also includes detailed headway and frequency for each of the five time periods. Stops are placed along the route with information such as route ID, stop coordinates, milepost, and corresponding highway node ID. For rail transit (commuter rail and local rail), station-to-station rail time, rail station information, and Metrolink's fare zone are also coded in the network.

The following six transit modes are included in the Year 2019 transit network:

- Commuter Rail is defined as transit service that has a fixed-guideway, traverses long-distances, has distinctive branding and vehicles, and is mostly used by commuters. In the SCAG region, commuter rail includes Metrolink and Amtrak's Pacific Surfliner.
- Local Rail also has a fixed guideway, but mainly refers to subway and light rail. In the year 2019, Metro runs two subway lines (Red and Purple) and four light rail lines (Blue, Gold, Green and Expo).
- Express Bus is defined as transit service with limited stops and a limited span of service that operates partly in mixed-flow freeway traffic and may require an additional fare. Many transit operators in the SCAG region have express bus service. Some express buses operate on a semi-dedicated right of way (busway, HOV lanes) with limited stops at freeway stations. These services are also referred to as Transitway buses. An example is the Metro Silver line.

Rapid Bus has limited stops and distinctive branding, but usually does not operate on freeways.

Local Bus is the most common bus service that uses local streets and makes frequent stops. Almost every operator runs local bus service.

Bus Rapid Transit (BRT) has limited stops, a dedicated guideway, distinctive branding, and vehicles. In the year 2019, only the Metro Orange line is considered BRT.

Two types of transit access/egress links are coded in the Year 2019 transit network:

Walk access and egress links are coded as two-way walk links between a zone centroid and a transit stop location.

Park-and-ride lot to stop and transfers between stations links are coded as two-way walk links between a park-and-ride lot and a transit stop location, and connections between stations.

The Year 2019 transit network includes three types of transit fares:

Average initial boarding fares: published full cash fares at the route level are used as a base for initial boarding fares. To take complex fare structures into account, such as one-way walkup fares, daily/weekly/monthly passes, senior/student/disabled fares, and other special fares, fare factors at the carrier level were estimated from boarding and revenue data that SCAG collected through the Year 2008 Transit Level of Service Data Collection Program. By applying the fare factors to the published full cash fares, the resulting fares represent initial boarding fares paid by an average passenger.

Average transfer fares are defined at the transit mode level though a mode-to-mode transfer table. For example, the transfer fares from Metrolink to Urban Rail are specified as free in the transfer table.

Average zonal fares: the commuter rail service, Metrolink, has a distance-based zonal fare structure. To specify the station-to-station fares, a fare matrix was developed with fares paid by an average rider reflecting all discount types.

All fare types were converted to 2011 dollars using a Consumer Price Index (CPI) adjustment factor derived from the CPI factor published by the US Department of Labor for the Los Angeles-Riverside-Orange County metropolitan area.

Year 2019 Transit Network Summary

Table 4-8 summarizes the number of transit route patterns and route pattern miles represented in the peak and off-peak transit network, by transit mode as defined above. Figure 4-5 shows the geographic distribution of the existing rail transit network (Metrolink and Local Rail). Figure 4-6 shows the entire Year 2019 transit network.

Table 4-8: Year 2019 Transit Route Patterns and Route Pattern Miles

Mode Code	Description	Route Patterns		Route Pattern Miles	
		Peak	Off Peak	Peak	Off Peak
1CR	Commuter Rail	26	25	1,637	2,404
2LR	Local Rail	16	16	272	283
3EX	Express Bus	118	62	4,035	2,262
4RB	Rapid Bus	99	78	1,563	1,229
5LB	Local Bus	1,760	1,511	23,868	20,618
6TB	Transitway Bus	39	32	1,113	931
7BR	BRT	4	4	62	62
Total		**2,062**	**1,728**	**32,551**	27,790

Figure 4-5: Year 2019 Metrolink and Local Rail Network

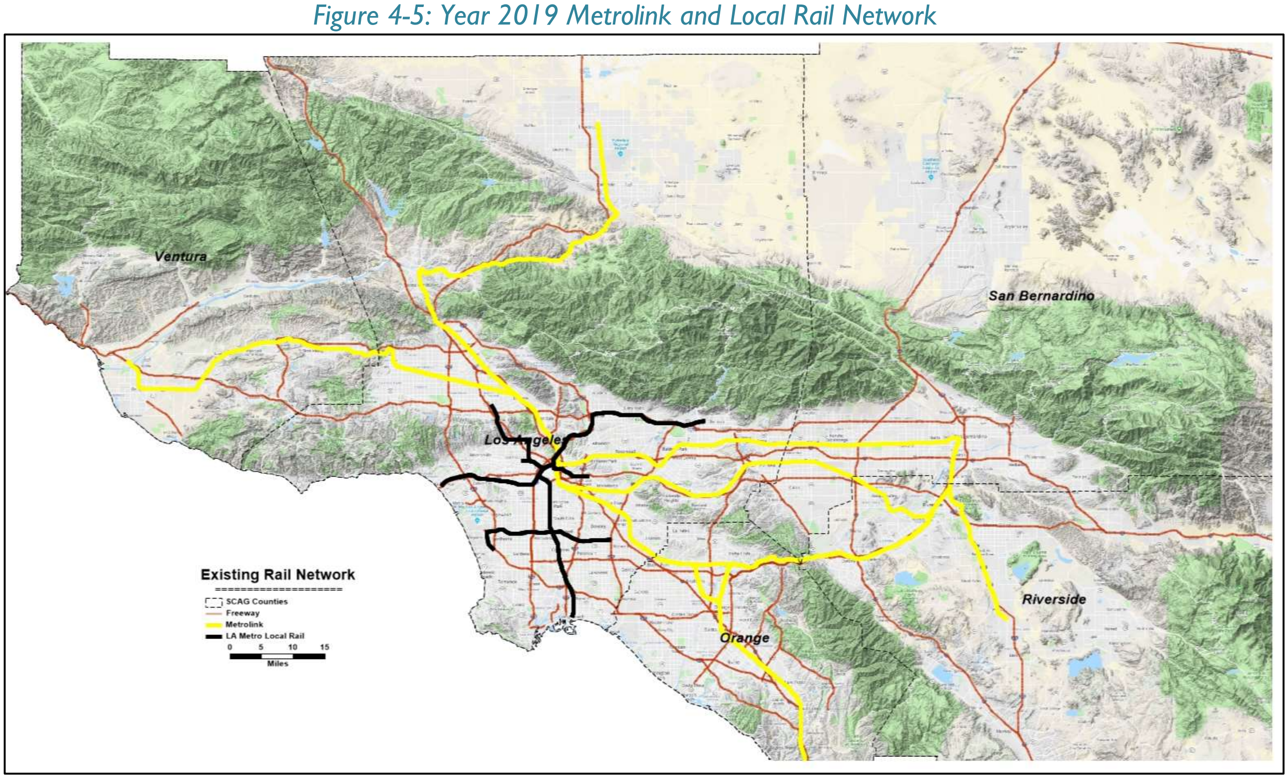
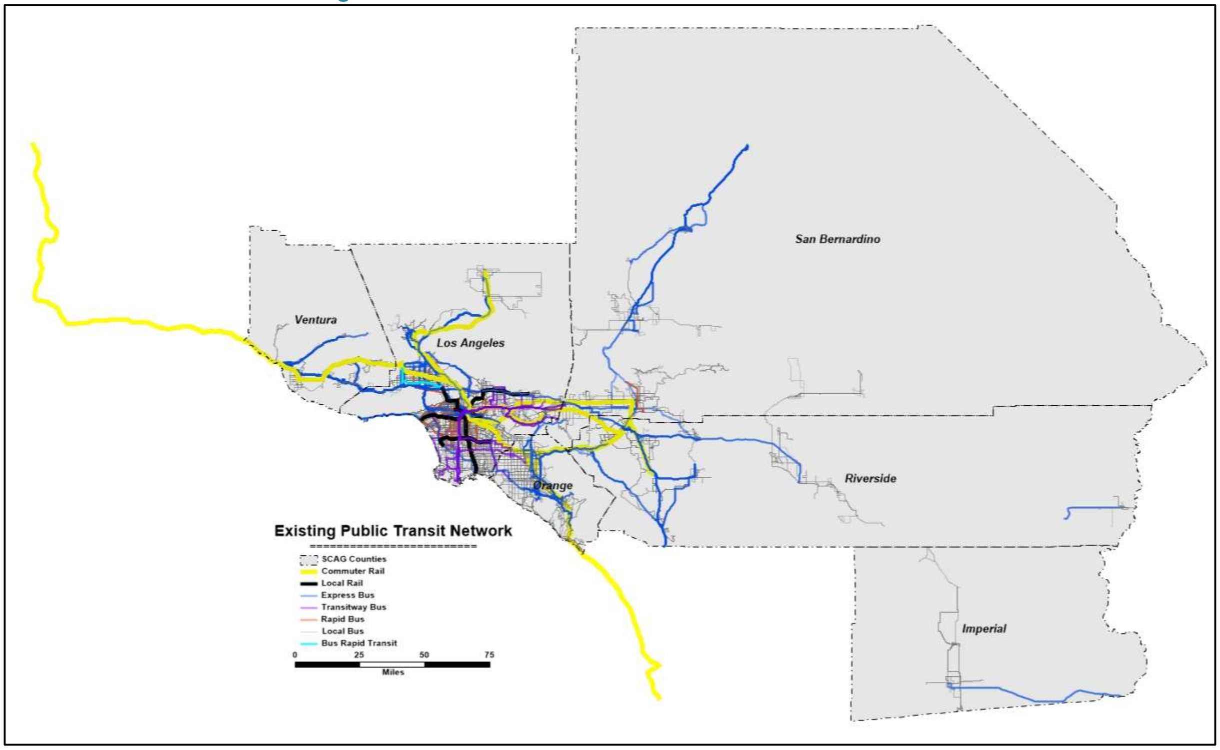


Figure 4-6: Year 2019 Rail and Bus Transit Network



Chapter 5 Long Term Choice

Introduction

Long term choice module of SCAG ABM includes Usual Work Arrangement model, Usual Workplace Location Choice model, Usual School Location model (fully segmented by type of student, as follows: pre-school students, grade school students and college/university students, and Usual Work Schedule Flexibility model.

Usual Work Arrangements

The usual work arrangement model simultaneously predicts three responses – (i) the weekly work hours for the primary job, (ii) the number of jobs, and (iii) the primary workplace location type. It applies to all workers in a household, including student workers. This model takes the form of a multinomial logit model, with choice alternatives defined by all possible combinations of the three main response variables. The categories defined for each response variable are defined below. The number of alternatives is the Cartesian product of these categories, for a total of 18 choices (3*2*3).

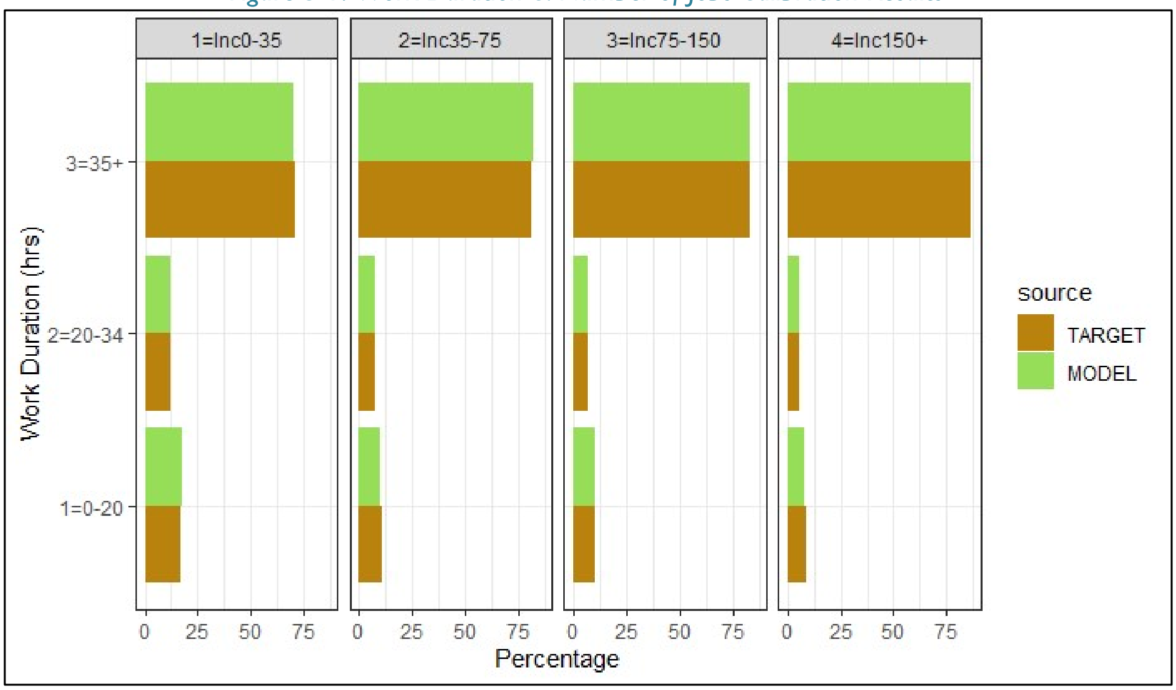
Weekly Work Duration On Primary Job	Primary Workplace Location Type	Number Of Jobs
• Less than 20 hours • 21-34 hours • 35 or more hours	• Fixed work place • Home • Variable work place	• One • Multiple

Table 5-1 shows the proportion of workers by workplace type for various household income levels, while Figure 5-1 shows the calibration results of the two other joint decisions. For all three model the target data is derived from the 2011 California Household Travel Survey (CHTS) which was weighted for the new base year of 2019.

Table 5-1: Workers by Work Location Type

		< $35k	$35k-$75k	$75k-$150k	>$150k	All
Target (CHTS)	Fixed	73.30%	83.40%	82.10%	82.50%	81.00%
	Home	8.20%	6.80%	7.40%	10.70%	8.00%
	Variable	18.40%	9.80%	10.50%	8.70%	11.30%
Model	Fixed	76.00%	83.13%	82.53%	79.74%	81.15%
	Home	6.85%	7.19%	8.48%	12.03%	8.75%
	Variable	17.15%	9.68%	8.99%	8.23%	10.10%
Difference	Fixed	-2.70%	0.27%	-0.43%	2.76%	-0.15%
	Home	1.35%	-0.39%	-1.08%	-1.33%	-0.75%
	Variable	1.25%	0.12%	1.51%	0.47%	1.20%

Figure 5-1: Work Duration & Number of Jobs Calibration Results



Usual Work Location Choice

The usual workplace location choice model assigns a workplace TAZ to every employed person in the synthetic population that does not work from home. That is, only workers with fixed or variable workplace type, as determined by the work arrangements model, are exposed to the usual work location model. The model takes the form of a multinomial logit destination choice model with size terms. Work location is segmented by the nine industry categories (Table 2-3). The size term or attraction variable is the number of jobs in each industry class in each TAZ. The total number of workers assigned to each TAZ is tracked by industry class, and constrained to not exceed the number of available jobs.

The California Household Travel Survey (CHTS) data collected in the year 2012 constitutes the principal data component used for estimating this model. The survey collected detailed information of 35,049 households including household composition, individual socio-demographics, residential, work, and school location information, and travel diary of all members in the household. In the entire sample, there are 42,506 workers. However, the sample size reduced to 22,946 workers after the following three data processing steps:

Exclude workers who work at home

Exclude records with missing work TAZ or work industry information

Exclude people who reported work TAZ in a zone where there is no zonal employment of that industry category

Given that the number of destination alternatives is large, it is not possible to include all alternatives in the estimation dataset. A sampling-by-importance approach was used to choose alternatives set for each worker. Each worker record was duplicated 4 times and different choice sets with 40 alternatives each were selected based on the size term and distance. This approach, statistically, is equivalent to selecting 160 alternatives for the choice set.

The core survey data, after importance sampling was merged with the accessibilities data, origin destination level mode choice logsum data, destination zonal attributes, and finally household and person characteristics. Some of the key observations are discussed next. The estimated variables have been grouped into the following categories: general impedance, accessibility, demographics and industry.

The industry variation in distance impedance is deduced using interaction between industry dummy variables and distance terms. The industries that have the least impedance to distance is the construction industry. This is followed by public administration, information technology, manufacturing and the FIRE (finance, insurance and real estate) industries (Figure 5-2)

Distance decay plots showing how the utility changes with distance for different segments are shown in Figure 5-2 and Figure 5-3 The observations discussed above can be seen in these plots also. One thing to note in the distance decay plot is that the distance decay for the construction industry has a shape that is bending upwards for longer distances. This is not desirable in the actual model application, so a calibration adjustment is made.

Figure 5-2 Plot Showing Distance Decay By Industry

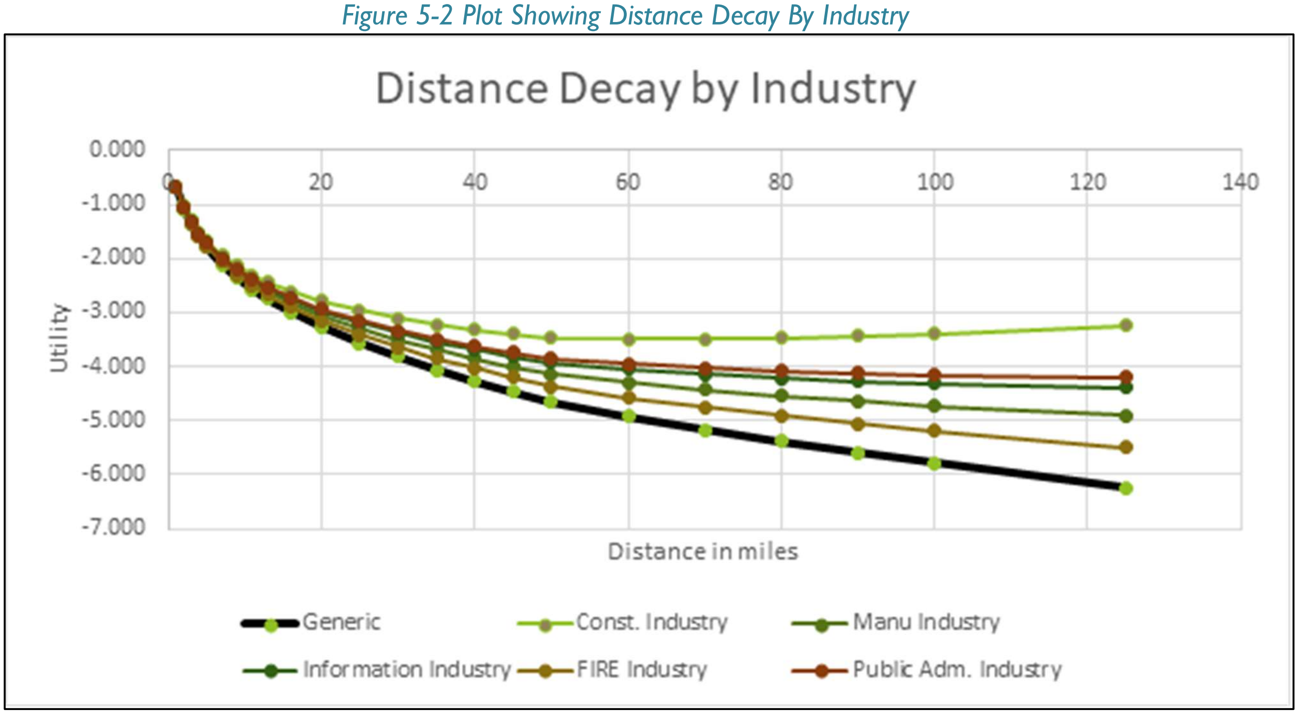
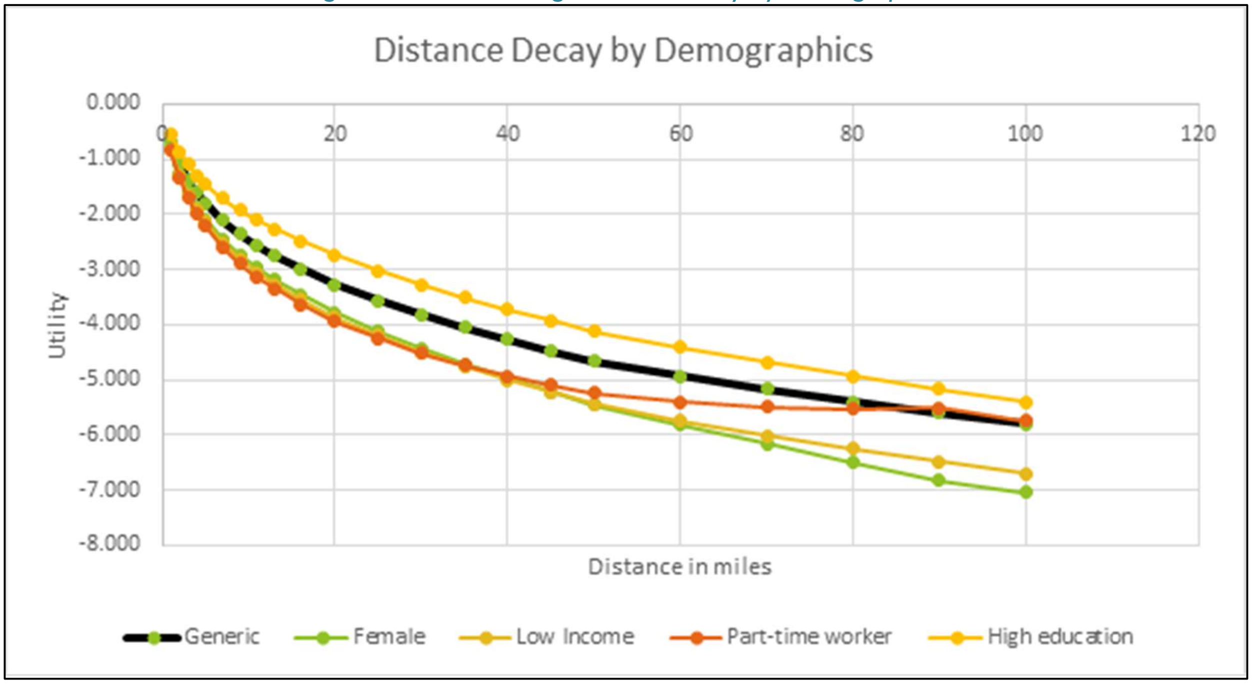


Figure 5-3 Plot Showing Distance Decay By Demographics

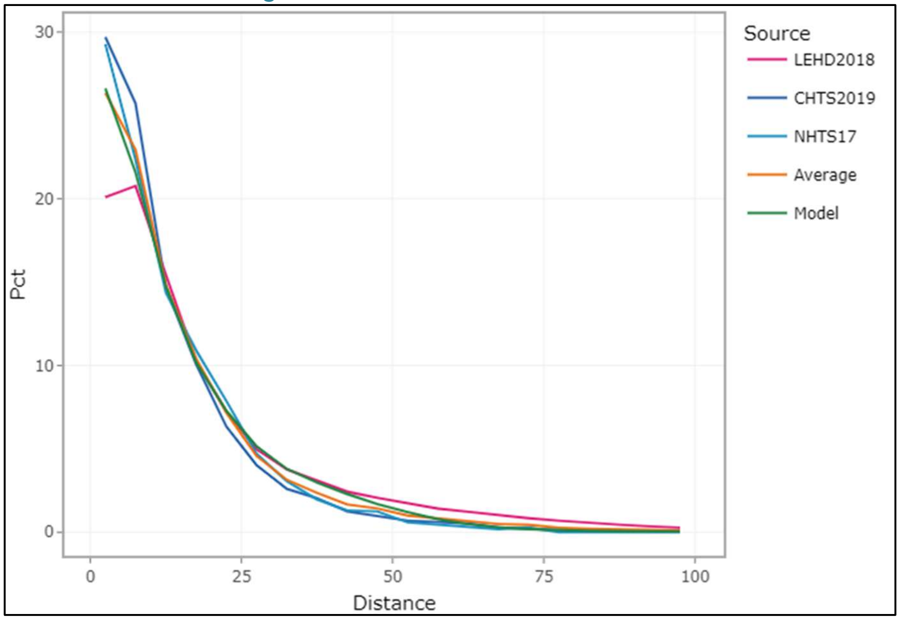


The workplace location model was compared to work trip length information obtained from the 2011 CHTS (weighted for the new base year 2019), the 2018 Longitudinal Employment Household Dynamics (LEHD) dataset, and 2017 National Household Travel Survey Data (NHTS). Table 5-2 and Figure 5-4 illustrates average and distribution of home to work trip distance based on the various target data sources compared to the model. The model calibration target is the average of all the three data sources (LEHD 2018, CHTS, and NHTS 2017).

Table 5-2: Average Home to Work Distance

Source	LEHD2018	CHTS2019	NHTS2017	Target	Model 2019
Weighted Length (mi)	20.1	13.0	13.2	15.4	14.52

Figure 5-4: Home to Work Distance



The county-to-county worker flow target data source is the average of worker flows obtained from the 2011 CHTS (weighted for the new base year 2019), the 2018 Longitudinal Employment Household Dynamics (LEHD) dataset, the 2019 Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES), the 2019 American Community Survey Integrated Public Use Microdata Series (ACS IPUMS), and Census Transportation Planning Products (CTPP 2012-16). The average target and model estimate of county-to-county work flows with the relative difference is illustrated in Table 5-3 The subcounty-to-subcounty worker flow target data source is the average of worker flows obtained from the 2011 CHTS (weighted for the new base year 2019), the 2019 Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES), and Census Transportation Planning Products (CTPP 2012-16). The average target and model estimate of county to county work flows with the relative difference is illustrated in Table 5-4

Table 5-3: County-to-County Workers Flows

Worker Flows, Target								
	County	**IM**	**LA**	**OR**	**RIV**	**SB**	**VN**	**Sum**
25	Imperial	91%	2%	1%	5%	1%	0%	100%
37	Los Angeles	0%	91%	6%	1%	2%	1%	100%
59	Orange	0%	16%	81%	2%	1%	0%	100%
65	Riverside	0%	8%	10%	68%	13%	0%	100%
71	San Bernardino	0%	19%	6%	9%	66%	0%	100%
111	Ventura	0%	24%	1%	0%	0%	74%	100%
Worker Flows, 2019 Model Estimate								
	County	**IM**	**LA**	**OR**	**RIV**	**SB**	**VN**	**Sum**
25	Imperial	91%	0%	0%	8%	1%	0%	100%
37	Los Angeles	0%	90%	6%	1%	2%	1%	100%
59	Orange	0%	15%	81%	2%	1%	0%	100%
65	Riverside	0%	8%	11%	67%	14%	0%	100%
71	San Bernardino	0%	19%	7%	9%	65%	0%	100%
111	Ventura	1%	27%	0%	0%	0%	72%	100%
Forecast Difference (%)								
	County	**IM**	**LA**	**OR**	**RIV**	**SB**	**VN**	**Sum**
25	Imperial	0%	2%	1%	-3%	0%	0%	100%
37	Los Angeles	0%	1%	0%	0%	0%	0%	100%
59	Orange	0%	1%	0%	0%	0%	0%	100%
65	Riverside	0%	0%	-1%	1%	-1%	0%	100%
71	San Bernardino	0%	0%	-1%	0%	1%	0%	100%
111	Ventura	-1%	-3%	1%	0%	0%	2%	100%

Table 5-4: Sub-County Work Trip Validation

Sub-county to Sub-county Workflows, Target																
Sub-county name	**ID**	**25**	**71**	**111**	**371**	**372**	**373**	**374**	**375**	**376**	**377**	**378**	**591**	**592**	**651**	**652**
Imperial	25	90%	1%	0%	0%	0%	1%	0%	1%	1%	0%	0%	0%	1%	1%	4%
San Bernardino	71	0%	64%	0%	1%	1%	3%	0%	3%	2%	10%	1%	3%	4%	9%	1%
Ventura	111	0%	1%	71%	2%	1%	3%	5%	1%	10%	1%	2%	1%	1%	0%	0%
Westside Cities	371	0%	0%	1%	42%	9%	29%	1%	3%	11%	2%	0%	1%	2%	0%	0%
South Bay Cities	372	0%	1%	0%	12%	49%	15%	0%	11%	3%	2%	1%	2%	2%	0%	0%
City of Los Angeles	373	0%	1%	1%	15%	6%	47%	0%	9%	11%	5%	1%	1%	1%	0%	0%
Las Virgenes	374	0%	0%	9%	13%	3%	12%	28%	1%	29%	2%	1%	1%	1%	0%	0%
Gateway Cities	375	0%	2%	0%	5%	10%	13%	0%	44%	3%	6%	1%	11%	5%	1%	0%
San Fernando Valley	376	0%	1%	3%	6%	2%	17%	2%	2%	57%	4%	3%	1%	1%	1%	0%
San Gabriel Valley	377	0%	6%	0%	2%	3%	15%	0%	8%	6%	50%	1%	4%	3%	1%	0%
North Los Angeles County	378	0%	2%	2%	3%	2%	10%	1%	3%	21%	3%	51%	1%	1%	1%	0%
Orange County North	591	0%	2%	0%	2%	4%	3%	0%	11%	1%	3%	0%	43%	28%	2%	0%
Orange County South	592	0%	1%	0%	1%	2%	2%	0%	3%	1%	2%	0%	13%	74%	2%	0%
West Riverside	651	0%	16%	0%	1%	1%	2%	0%	2%	1%	3%	0%	6%	7%	59%	2%
Coachella Valley	652	1%	3%	0%	0%	0%	1%	0%	1%	1%	1%	0%	1%	2%	7%	82%

Sub-county to Sub-county Workflows, Model (2019)																
Name	**ID**	**25**	**71**	**111**	**371**	**372**	**373**	**374**	**375**	**376**	**377**	**378**	**591**	**592**	**651**	**652**
Imperial	25	90%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	8%
San Bernardino	71	0%	65%	0%	0%	0%	2%	0%	2%	1%	12%	1%	4%	3%	8%	1%
Ventura	111	1%	0%	70%	3%	1%	4%	3%	1%	14%	1%	2%	0%	0%	0%	0%
Westside Cities	371	0%	0%	1%	38%	9%	31%	1%	5%	9%	3%	1%	1%	1%	0%	0%
South Bay Cities	372	0%	0%	1%	11%	40%	15%	0%	16%	4%	3%	0%	4%	3%	0%	0%
City of Los Angeles	373	0%	1%	1%	12%	7%	47%	1%	9%	11%	7%	1%	2%	1%	0%	0%
Las Virgenes	374	0%	0%	15%	11%	4%	15%	17%	3%	30%	3%	1%	1%	0%	0%	0%
Gateway Cities	375	0%	1%	1%	5%	10%	14%	0%	40%	4%	9%	0%	10%	6%	1%	0%
San Fernando Valley	376	0%	0%	4%	6%	2%	16%	1%	3%	56%	6%	3%	1%	1%	0%	0%
San Gabriel Valley	377	0%	7%	1%	3%	2%	13%	0%	10%	7%	44%	1%	6%	4%	2%	0%
North Los Angeles County	378	0%	2%	3%	4%	1%	8%	0%	1%	21%	4%	54%	0%	0%	0%	0%
Orange County North	591	0%	2%	1%	1%	3%	4%	0%	9%	1%	4%	0%	46%	28%	2%	0%
Orange County South	592	0%	1%	0%	1%	1%	2%	0%	3%	1%	2%	0%	17%	70%	2%	0%
West Riverside	651	0%	17%	0%	0%	0%	1%	0%	2%	0%	6%	0%	6%	7%	58%	1%
Coachella Valley	652	1%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	6%	88%

Sub-county to Sub-county Workflows, Difference																
Name	**ID**	**25**	**71**	**111**	**371**	**372**	**373**	**374**	**375**	**376**	**377**	**378**	**591**	**592**	**651**	**652**
Imperial	25	0%	0%	0%	0%	0%	1%	0%	1%	1%	0%	0%	0%	1%	0%	-4%
San Bernardino	71	0%	-1%	0%	1%	1%	1%	0%	1%	1%	-2%	0%	-1%	1%	1%	0%
Ventura	111	-1%	1%	1%	-1%	0%	-1%	2%	0%	-4%	0%	0%	1%	1%	0%	0%
Westside Cities	371	0%	0%	0%	4%	0%	-2%	0%	-2%	2%	-1%	-1%	0%	1%	0%	0%
South Bay Cities	372	0%	1%	-1%	1%	9%	0%	0%	-5%	-1%	-1%	1%	-2%	-1%	0%	0%
City of Los Angeles	373	0%	0%	0%	3%	-1%	0%	-1%	0%	0%	-2%	0%	-1%	0%	0%	0%
Las Virgenes	374	0%	0%	-6%	2%	-1%	-3%	11%	-2%	-1%	-1%	0%	0%	1%	0%	0%
Gateway Cities	375	0%	1%	-1%	0%	0%	-1%	0%	4%	-1%	-3%	1%	1%	-1%	0%	0%
San Fernando Valley	376	0%	1%	-1%	0%	0%	1%	1%	-1%	1%	-2%	0%	0%	0%	1%	0%
San Gabriel Valley	377	0%	-1%	-1%	-1%	1%	2%	0%	-2%	-1%	6%	0%	-2%	-1%	-1%	0%
North Los Angeles County	378	0%	0%	-1%	-1%	1%	2%	1%	2%	0%	-1%	-3%	1%	1%	1%	0%
Orange County North	591	0%	0%	-1%	1%	1%	-1%	0%	2%	0%	-1%	0%	-3%	0%	0%	0%
Orange County South	592	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	-4%	4%	0%	0%
West Riverside	651	0%	-1%	0%	1%	1%	1%	0%	0%	1%	-3%	0%	0%	0%	1%	1%
Coachella Valley	652	0%	-1%	0%	0%	0%	1%	0%	1%	1%	1%	0%	1%	2%	1%	-6%

USUAL SCHOOL LOCATION

The usual school location model is fully segmented by type of student, as follows: pre-school students, kindergarden to 8th grade school students, 9th grade to 12th grade students, and college/university students. All sub-models take the form of destination choice models. The size term for the grade school and college/university models is the number of enrolled students at the school location; for pre-school students, the model uses a composite term that considers education employment and households. Table 5-5 illustrates the target distance from home to school derived from California Household Travel Survey 2011 which is reweighted for the new base year of 2019 in comparison to the same metric estimated by the model. Figure 5-5 illustrates the frequency distribution of travel time to school by school grade comparing target to the model.

Table 5-5: Average Home to School Distance (miles)

School Segment	Target (CHTS)	Model
Pre-School	2.6	2.7
Grade K to 8th	22.2	2.9
Grade 9th to 12th	3.0	3.8
College/University	9.9	10.0

Figure 5-5: Usual School Location Calibration, Preschool

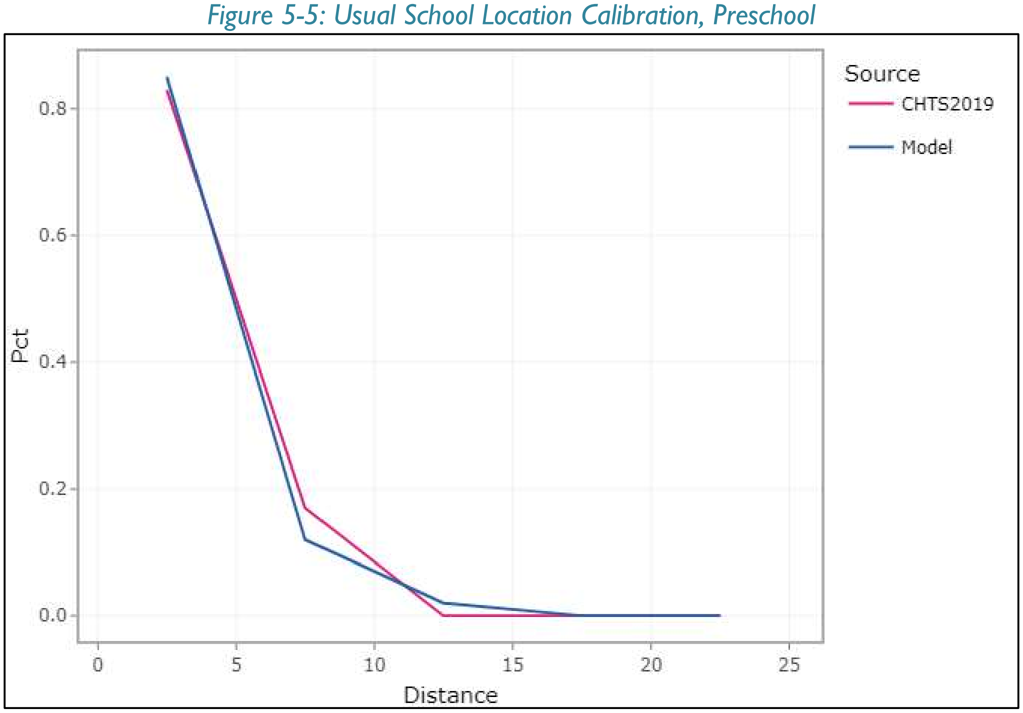


Figure 5-6: Usual School Location, Grade k-8 Students

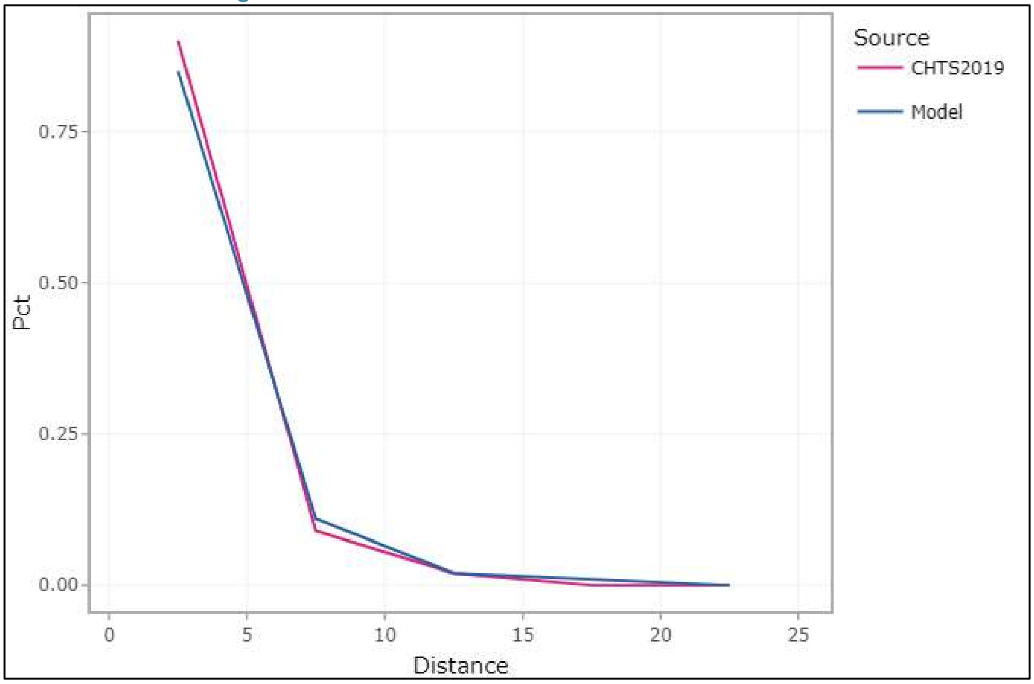


Figure 5-7: Usual School Location, Grade 9-12 Students

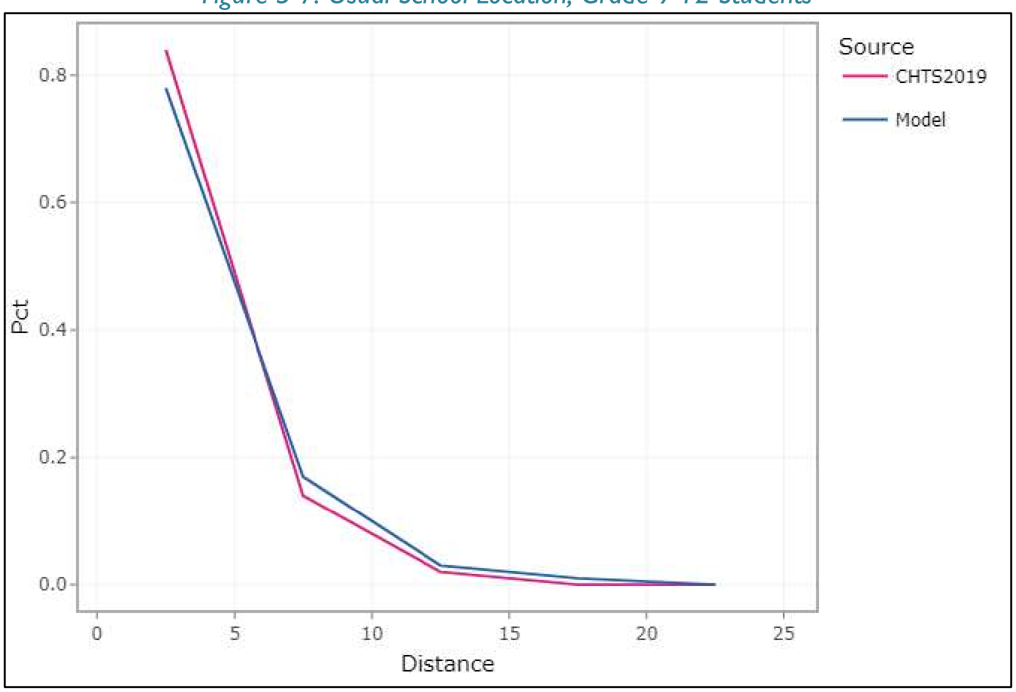
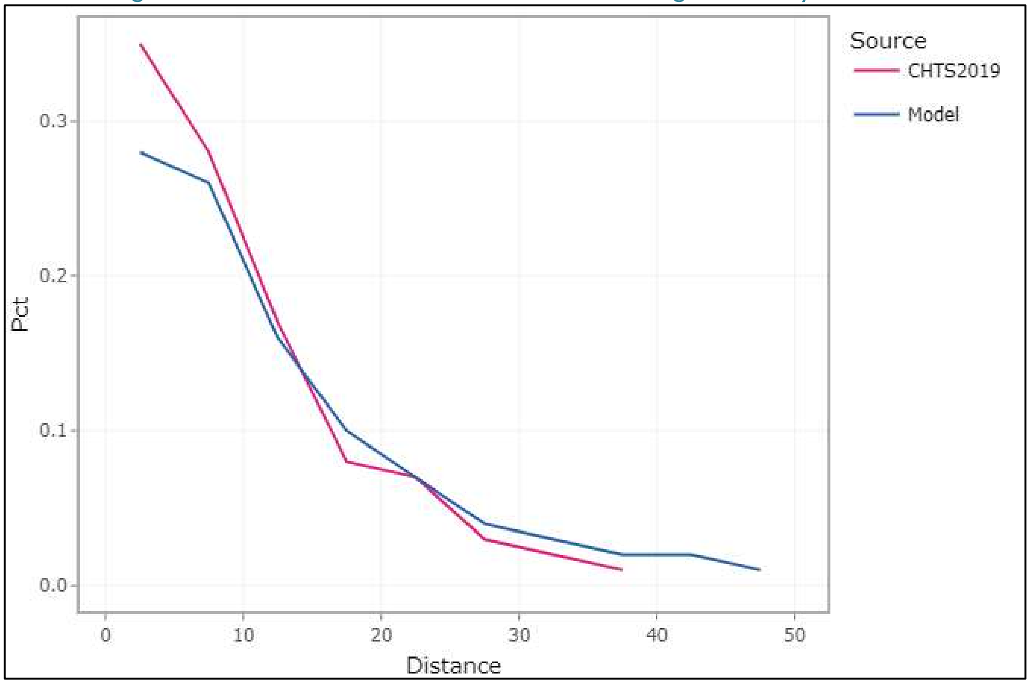


Figure 5-8: Usual School Location Calibration, College/University Students



USUAL WORK SCHEDULE FLEXIBILITY

The usual work schedule flexibility model simultaneously predicts three responses – (i) number of days per week working at primary job, (ii) work flexibility at primary job, and (iii) the availability of compressed week option at primary job. It applies to all the workers in a household, including student workers. This model takes the form of a multinomial logit model, with choice alternatives defined by all possible combinations of the three main response variables. The categories defined for each response variable are shown below. The number of alternatives is the Cartesian product of these categories, for a total of 18 choices (3*3*2).

Number Of Days Per Week	Work Scheduling Flexibility	Compressed Week Option
• Five days per week	• None	• Available
• Less than five days per week	• Moderate	• Not available
• More than five days per week	• High	

The model was calibrated to the proportions exhibited by the 2011 CHTS (weighted to reflect 2019 base year), separately for full-time and part-time workers. The model calibrating results are shown in Figure 5-7 to Figure 5-9.

Figure 5-9: Numbers of Days at Work, Observed and Predicted

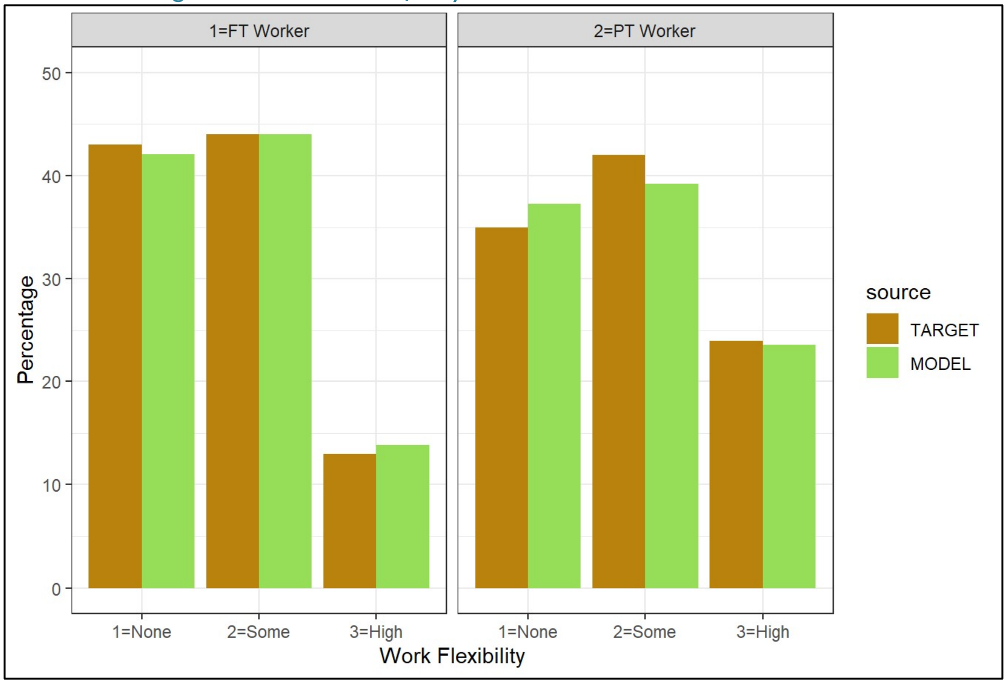


Figure 5-10: Work Schedule Flexibility, Observed and Predicted

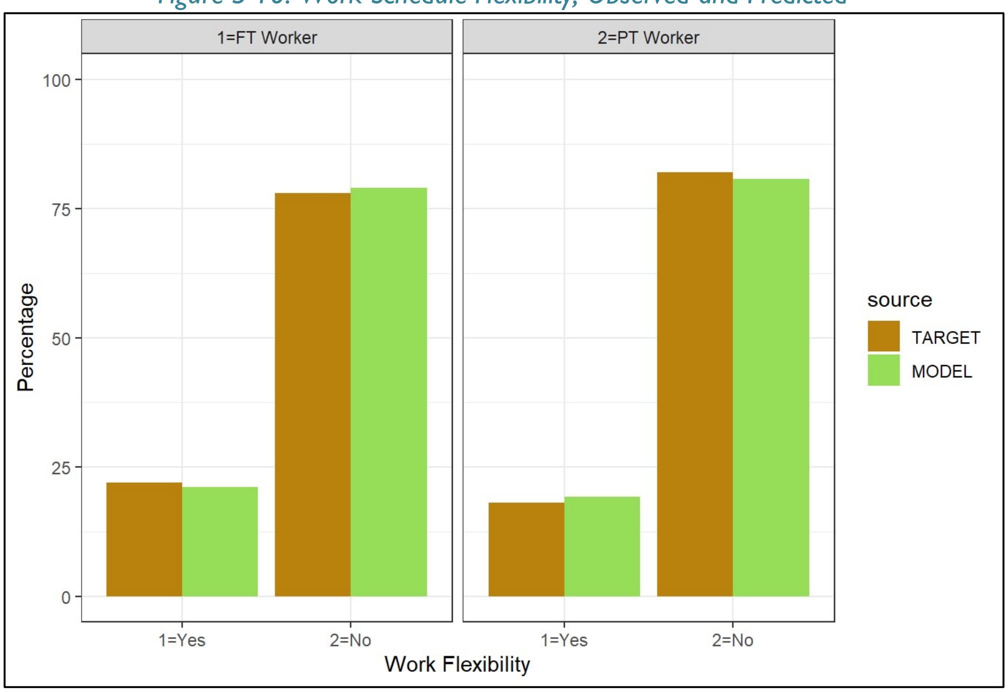
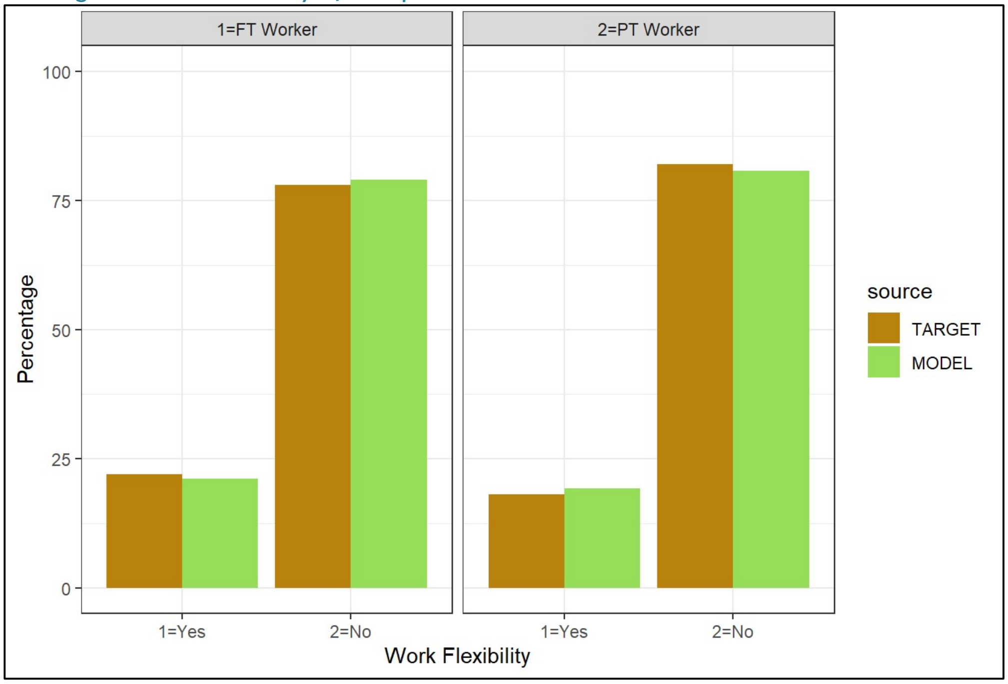


Figure 5-11: Availability of Compressed Work Schedules, Observed and Predicted



Chapter 6 MOBILITY CHOICE

DRIVER LICENSE

The driver license model predicts whether an individual holds a valid driver's license or not. It applies to all persons 16 years old and older. The model takes the form of a binary logit model. The utility of the "no driver license" choice is assumed equal to zero. Variables that explain possession of a driver license include household and individual socio-demographics, land use and built environment characteristics of the home zone, and accessibility from the home zone to non-mandatory opportunities using different modes. A summary of the model results by person type is shown in Figure 6-1 validated based on CHTS, and the validation to Department of Motor Vehicle registrations is shown in Figure 6-2

Figure 6-1: Driver License Holding by Person-Type, Observed and Predicted

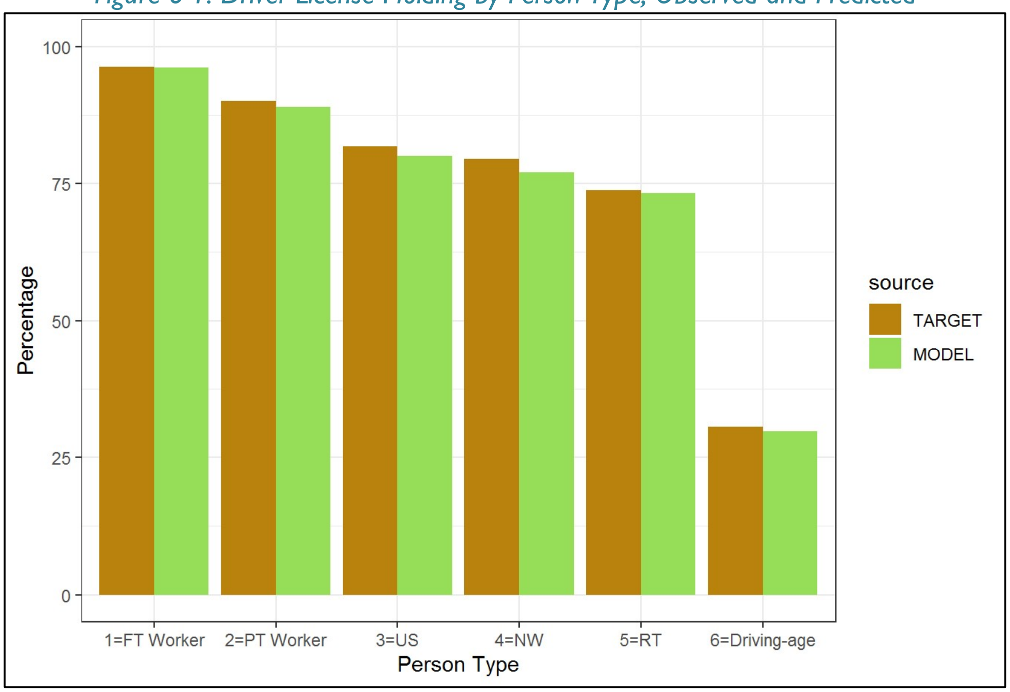
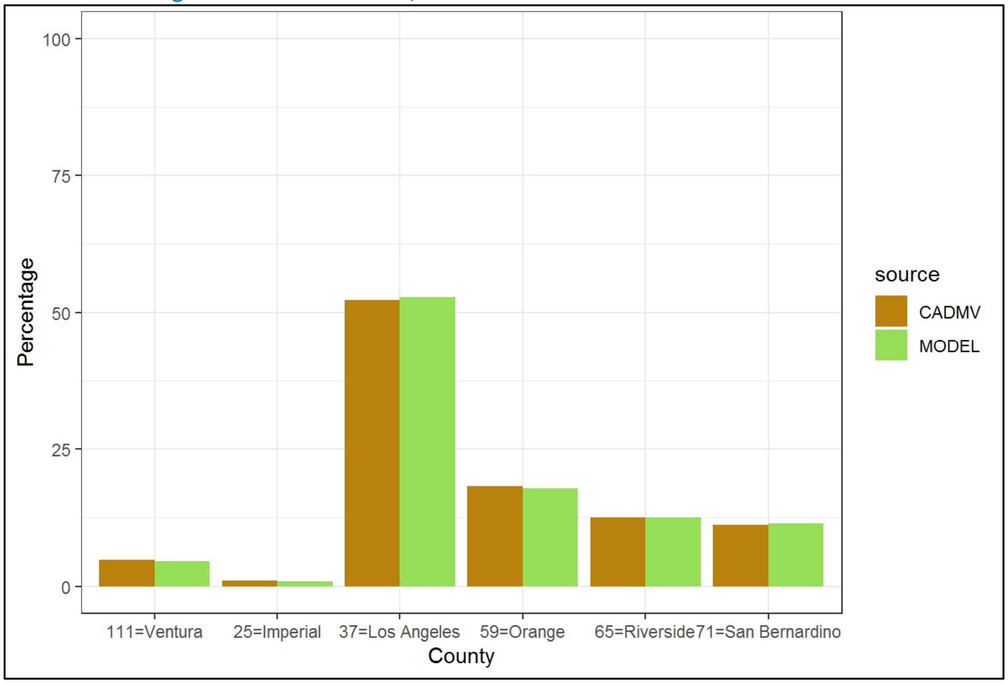


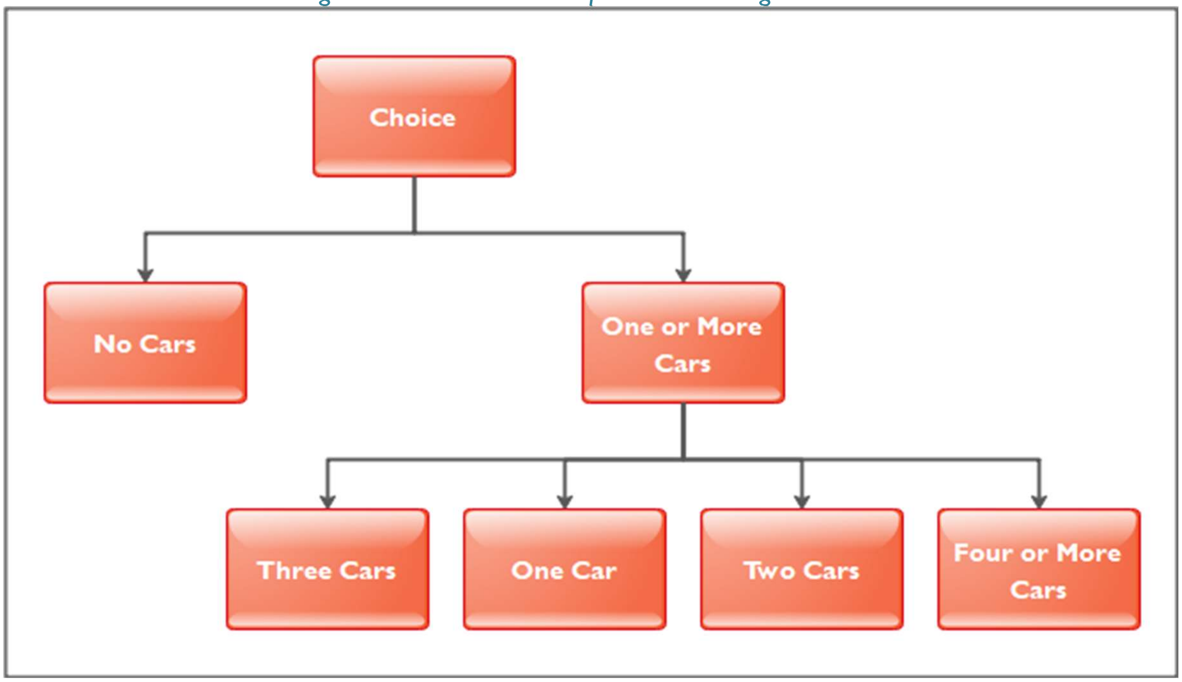
Figure 6-2: Validation of Licensed Drivers Prediction, Year 2019



AUTO OWNERSHIP

The auto ownership model predicts the number of cars, light-duty trucks and motorcycles owned by each household. It applies to all households in the synthetic population. The model was estimated with approximately 20,000 observations (household records) from the 2011 CHTS. The model takes the form of a nested logit model, with nesting structure shown in Figure 6-3.

Figure 6-3: Auto Ownership Model Nesting Structure



In this model auto ownership is explained as a function of household socio-demographics, work and school location of constituent household members, land use and built environment characteristics of home zone, and accessibility using different modes to non-mandatory activities from home zone.

Some of the household composition variables are stratified using car sufficiency. Car sufficiency is calculated as the difference between number of cars owned by the household and the number of people with valid driving license in a household.

Model Calibration and Validation

Table 6-1 shows a comparison of the model predicted car ownership to household auto ownership by county of residence from the 2015-2019 ACS. As shown, the model reproduces well the observed car ownership pattern in each county, and for the region as a whole. The validation of household auto ownership segmented by number of licensed drivers in the household is shown in Figure 6-3 and by income is shown in Figure 6-4. These two comparisons also shows a good correspondence between the observed proportions, which were obtained from the CHTS, and the model predictions.

The model predictions were also compared to vehicle registrations obtained from the Department of Motor Vehicles (DMV). The total number of vehicles owned by households in the region, including motorcycles, is approximately 94% of the vehicles registered at the DMV in 2019. Rental cars and institutional fleets such as police cars are not included in the DMV estimate.

Table 6-1: Year 2019 Auto Availability Forecast – County of Residence Validation

ACS 2015-2019 Auto Availability						
Residence County	**0 Cars**	**1 Car**	**2 Cars**	**3 Cars**	**4+ Cars**	**Total**
Imperial	8.05%	28.42%	36.86%	17.06%	9.60%	100.0%
Los Angeles	8.63%	33.86%	33.53%	15.14%	8.85%	100.0%
Orange	4.63%	28.77%	40.59%	16.18%	9.83%	100.0%
Riverside	4.18%	28.54%	37.57%	16.79%	12.92%	100.0%
San Bernardino	5.22%	28.02%	35.13%	18.36%	13.28%	100.0%
Ventura	4.42%	26.65%	41.37%	16.91%	10.65%	100.0%
Total	6.86%	31.36%	35.78%	15.95%	10.06%	100.0%
2019 Model						
Residence County	**0 Cars**	**1 Car**	**2 Cars**	**3 Cars**	**4+ Cars**	**Total**
Imperial	8.05%	28.45%	36.83%	17.07%	9.60%	100.0%
Los Angeles	8.63%	33.86%	33.52%	15.14%	8.85%	100.0%
Orange	4.64%	28.80%	40.55%	16.17%	9.84%	100.0%
Riverside	4.19%	28.54%	37.57%	16.78%	12.92%	100.0%
San Bernardino	5.23%	28.03%	35.11%	18.36%	13.27%	100.0%
Ventura	4.42%	26.68%	41.34%	16.91%	10.65%	100.0%
Total	6.86%	31.37%	35.76%	15.95%	10.06%	100.0%
Forecast Difference (%), County Normalized						
Residence County	**0 Cars**	**1 Car**	**2 Cars**	**3 Cars**	**4+ Cars**	**Total**
Imperial	0.00%	-0.03%	0.03%	-0.01%	0.00%	0.00%
Los Angeles	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%
Orange	-0.01%	-0.03%	0.04%	0.01%	-0.01%	0.00%
Riverside	-0.01%	0.00%	0.00%	0.01%	0.00%	0.00%
San Bernardino	-0.01%	-0.01%	0.02%	0.00%	0.01%	0.00%
Ventura	0.00%	-0.03%	0.03%	0.00%	0.00%	0.00%
Total	0.00%	-0.01%	0.02%	0.00%	0.00%	0.00%

Figure 6-4: Auto Ownership by Number of Drivers in the Household, Observed & Predicted

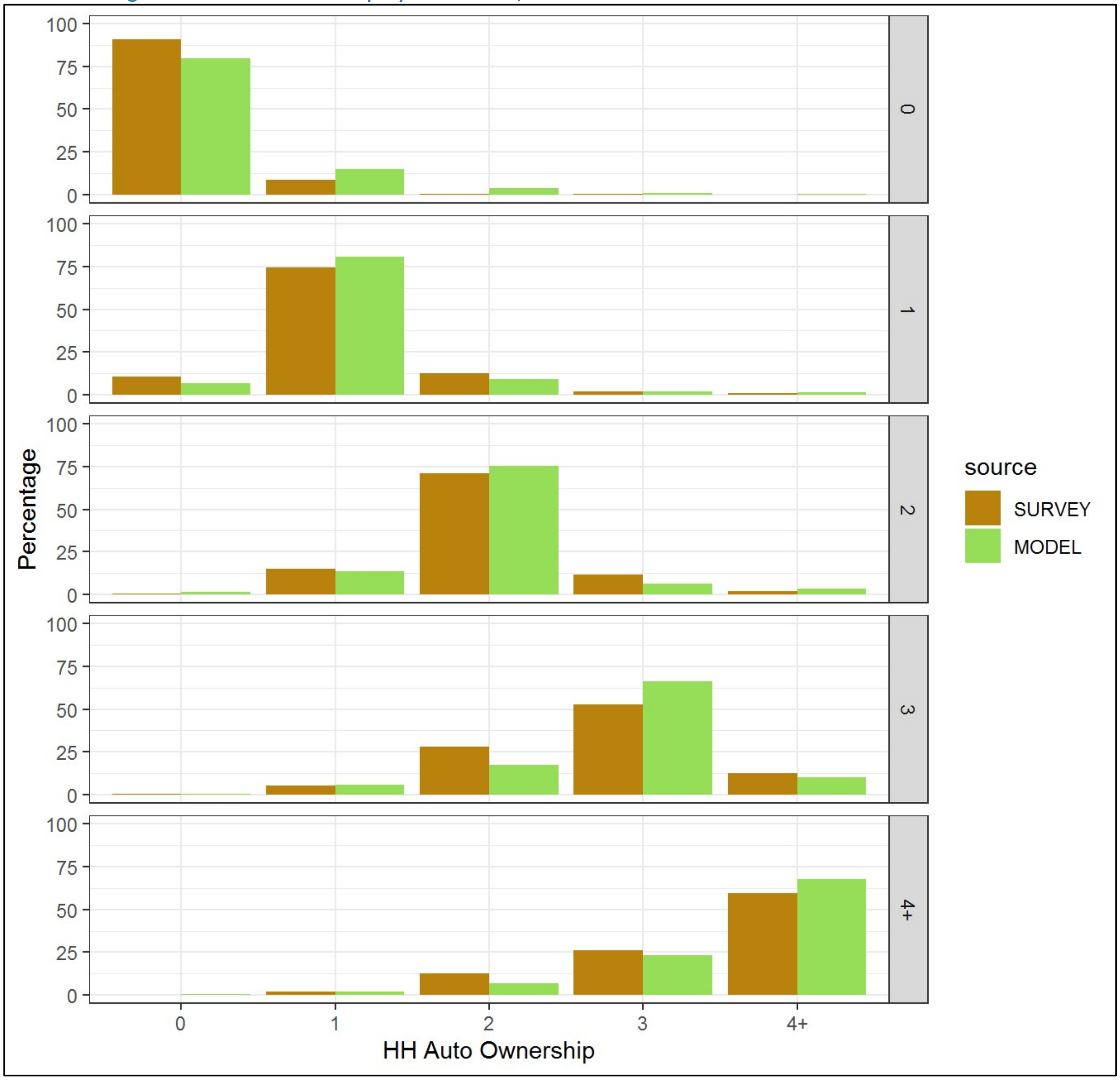


Figure 6-5Auto Ownership by Household Income, Observed & Predicted

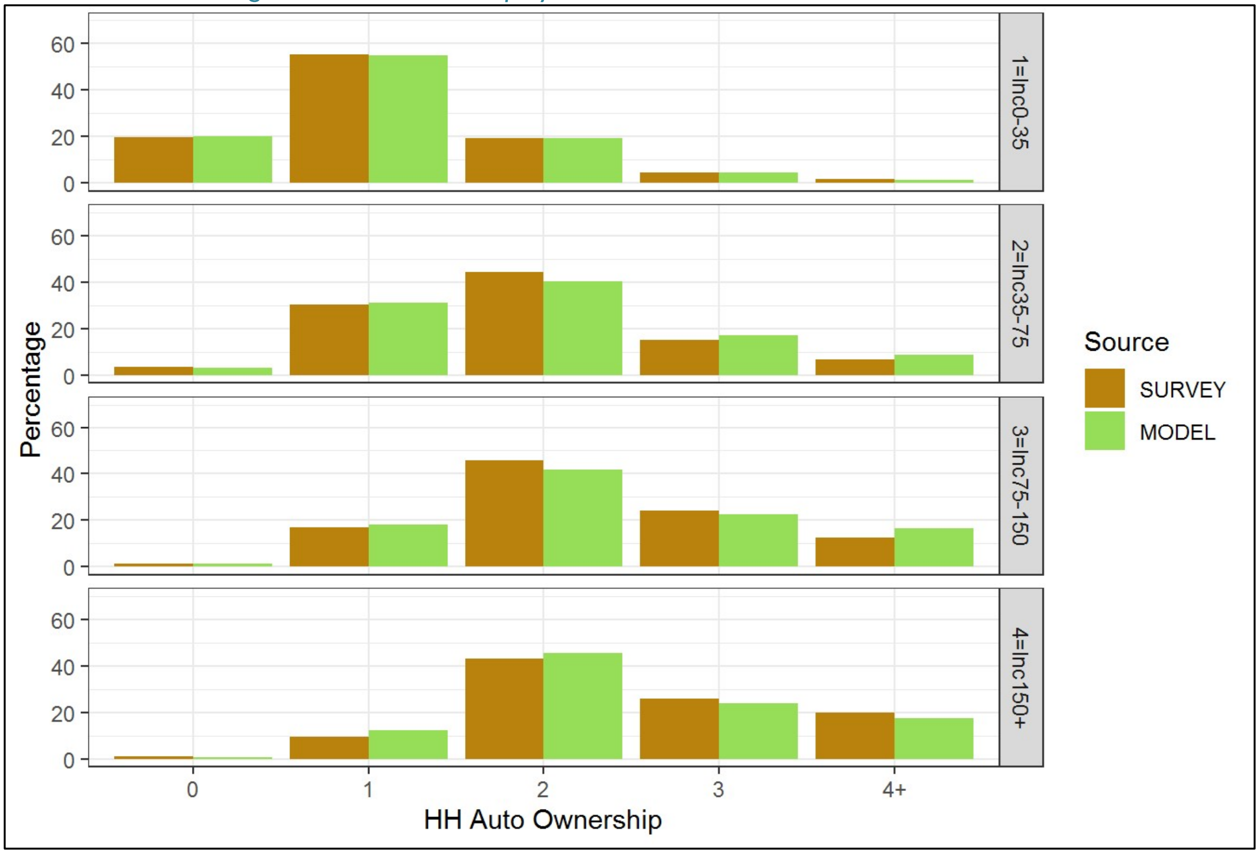


Table 6-2: Household Car Holdings Validation, Year 2019

Residence County	Registered Vehicles, CA Department of Motor Vehicles	Predicted Household Vehicles	Difference
Imperial	131,116	121,010	-8%
Los Angeles	6,567,187	423,521	-2%
Orange	2,341,100	2,203,170	-6%
Riverside	1,489,204	1,598,816	7%
San Bernardino	1,341,914	1,379,174	3%
Ventura	605,961	565,746	-7%
Total	**12,476,482**	**12,291,438**	**-1%**

Chapter 7 COORDINATED DAILY ACTIVITY PATTERN

DESCRIPTION

In the CT-RAMP3 structure each person is assigned a daily activity pattern (DAP). The DAP predicts whether the person will stay home all day or travel, and in the case that some travel is predicted, whether it is for work or school. The DAP also indicates whether the household generates fully joint trips. The following DAPs are possible:

Mandatory pattern (M) that includes at least one of the three mandatory activities—work, university or school. This constitutes either a workday or a university/school day, and may include additional non-mandatory activities such as separate home-based tours or intermediate stops on the mandatory tours.

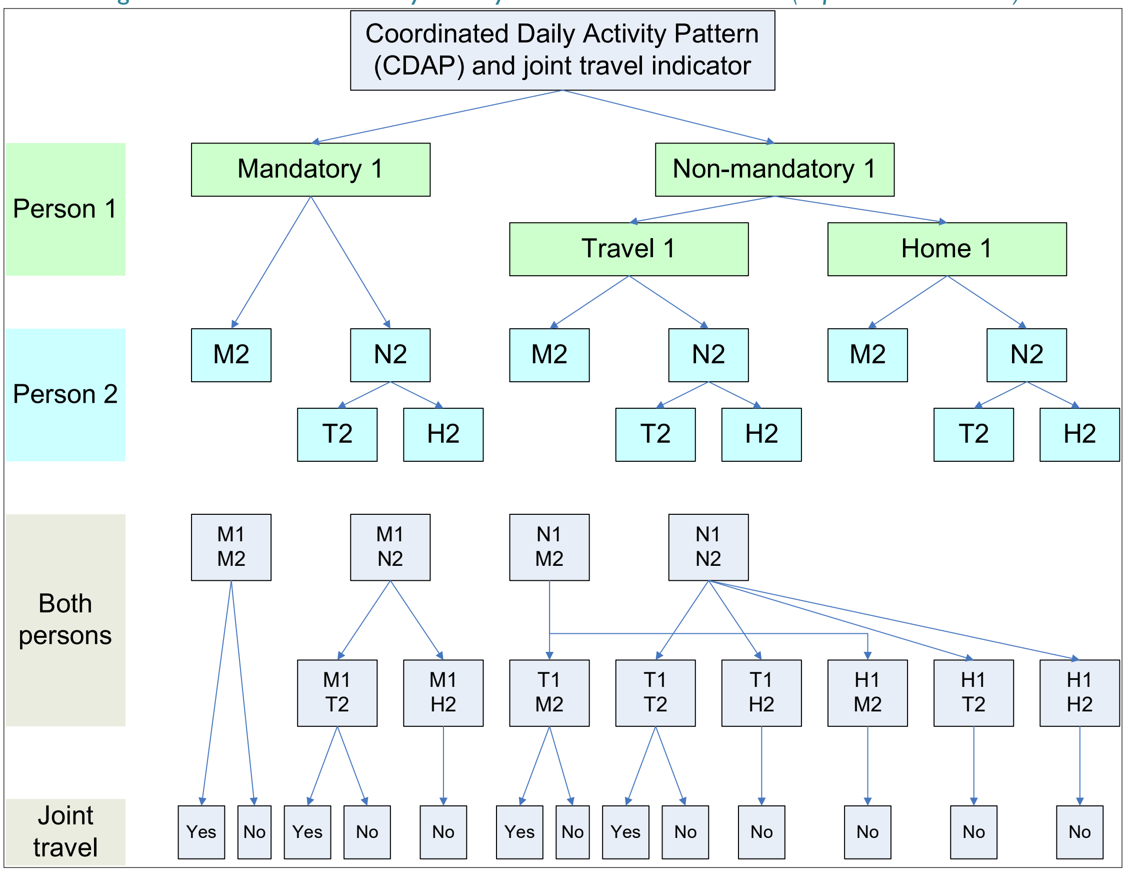
Non-mandatory pattern (NM) that includes only maintenance and discretionary activities and tours. By virtue of the tour primary purpose definition, maintenance and discretionary tours cannot include travel for mandatory activities.

Home pattern (H) that includes only in-home activities. At-home patterns are not distinguished by any specific activity (e.g., work at home, take care of child, being sick, etc.). Cases of complete absence from the model area (e.g., business travel) are included in this category.

The DAP is predicted simultaneously for all members of a household. Along with the indicator for fully-joint travel, this simultaneity is what gives rise to the "coordinated" aspect of this submodel. The model takes the form of a nested logit model, with number of choices that depend on household size. The Coordinated Daily Activity Pattern (CDAP) model in the CT-RAMP3 design features simultaneous modeling of these trinary pattern alternatives for all household members with the subsequent modeling of individual alternatives, as shown in Figure 7-1.

The explanatory variables include person and household attributes, accessibility measures, and density/urban form variables. Since the model features intra-household interactions, several model parameters are specified as interaction terms. These terms are based on the contribution to the total utility of an alternative from either a two-person interaction, a three-person interaction, or an entire-household interaction. For example, the contribution of a two-worker interaction to the utility for each worker to stay home on the simulation day is positive, indicating that it is more likely that both workers will attempt to coordinate their days off to engage in recreational opportunities together. Similarly, the contribution of a pre-school child to a worker mandatory pattern is negative, indicating the likelihood that if a pre-school child stays at home, a worker also is more likely to stay at home with the child.

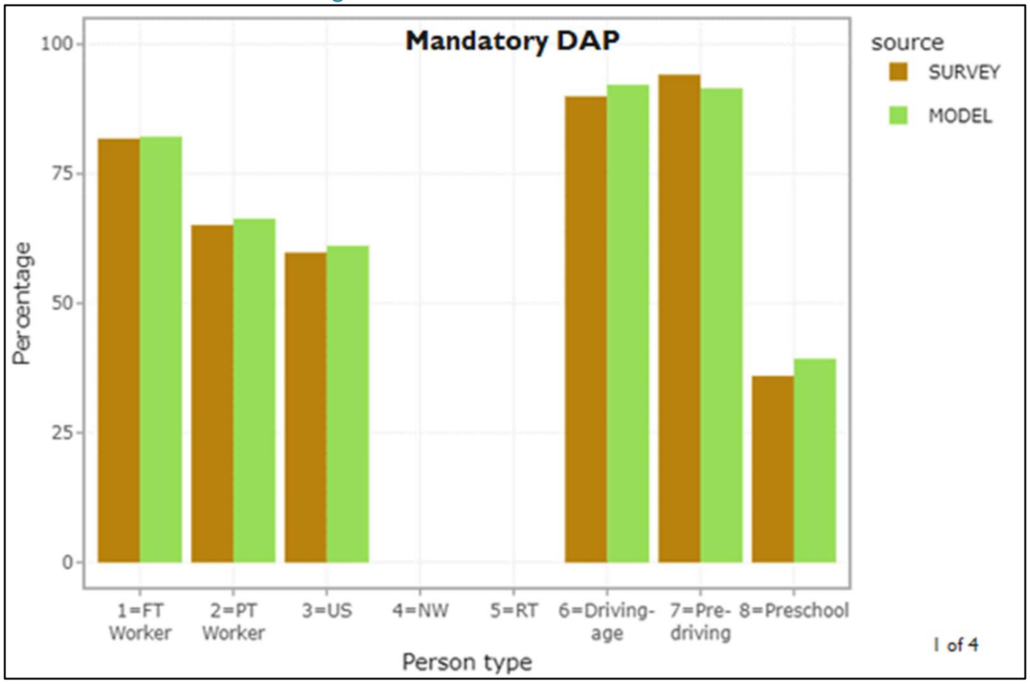
Figure 7-1: Coordinated Daily Activity Pattern Choice Structure (2-person household)

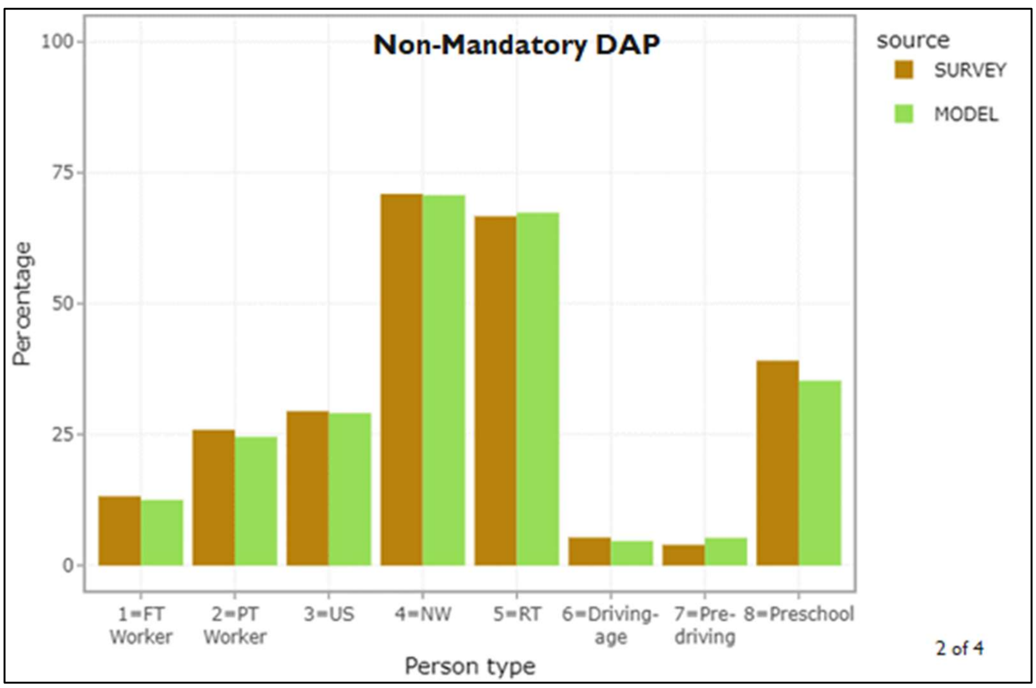


Model Calibration

The model was calibrated by adjusting the person-type constants so that the aggregate proportions of DAPs by person-type matched the calibration targets. The targets were derived based on data from the 2011 CHTS. The model calibration results are shown in the following figures.

Figure 7-2: CDAP Calibration Results





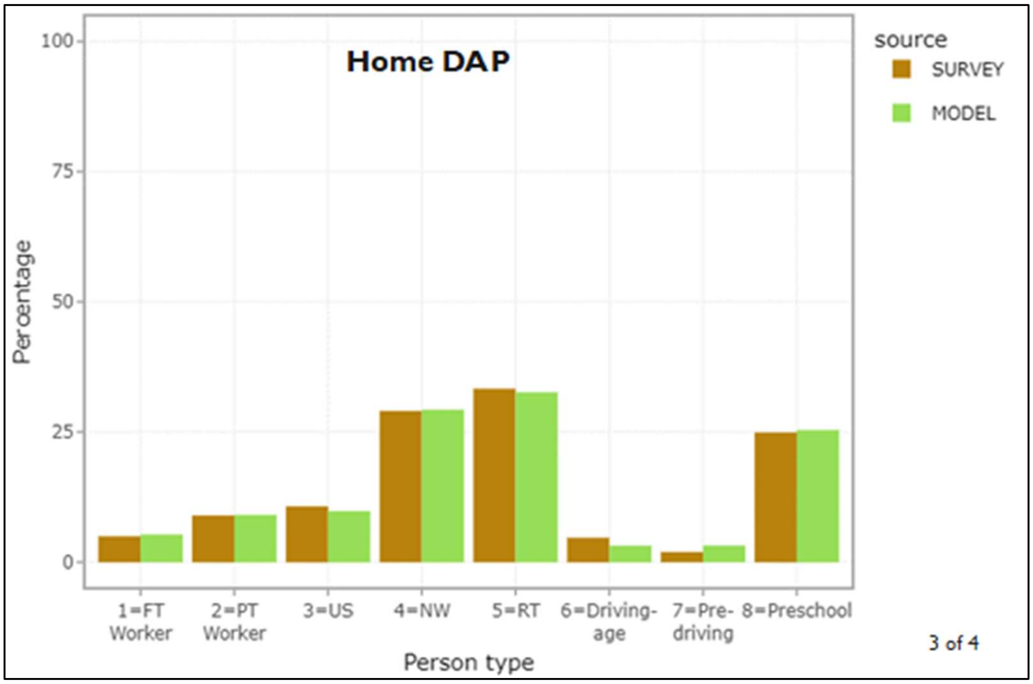
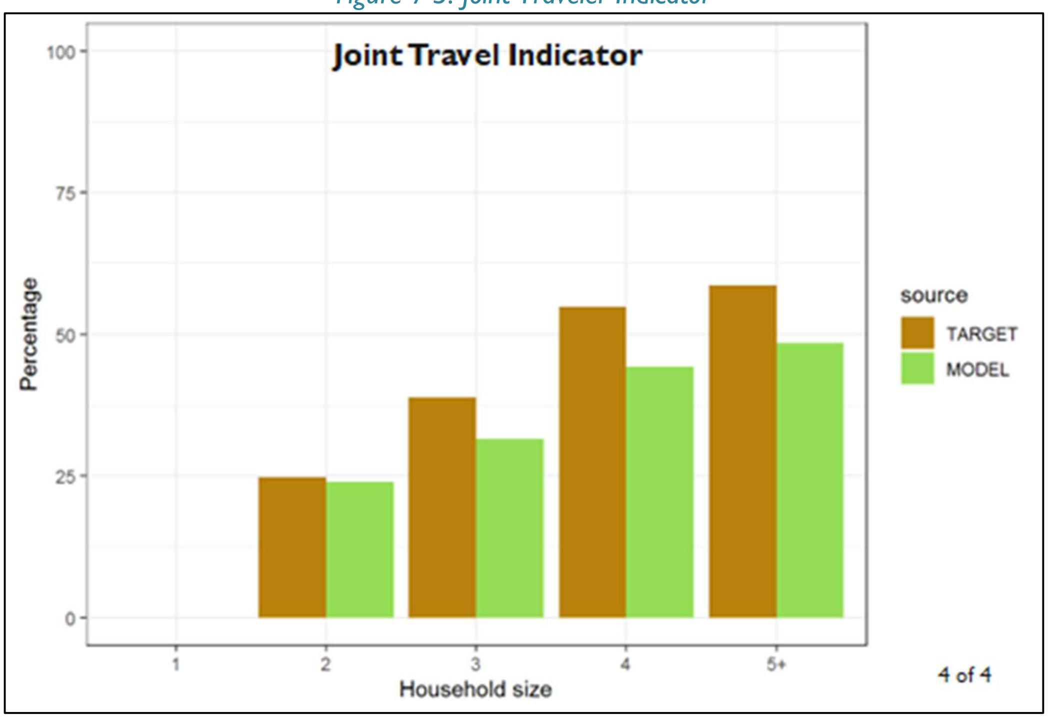


Figure 7-3: Joint Traveler Indicator



Chapter 8 MANDATORY ACTIVITY GENERATION AND TOUR FORMATION

OVERVIEW OF TOUR FORMATION APPROACH

In the activity-based travel demand modeling approach, travel is derived from activities; that is, the central unit of modeling is the activity in which an individual intends to participate during the day. However, most ABMs, in practice and research, do not entirely incorporate this central idea. The most frequently used ABMs generate travel tours up-front and subsequently add details on intermediate stops in each tour. Other ABMs generate the activities that a traveler intends to participate in, but they still involve a series of tour frequency and stop-insertion models to model daily travel. This framework is largely borrowed from tour-based travel demand models, where the basic unit for travel analysis is the tour.

It can be reasonably hypothesized that an individual makes a preliminary decision to participate in a certain set of activities. His or her scheduling decisions are then driven by the associated temporal and spatial constraints and differential priorities. For example, a worker who goes to work on the modeled day will generally have a higher priority associated with work activities relative to an individual shopping or discretionary activity. However, these priorities can change if, for example, the shopping activity is undertaken jointly (assuming a major shopping trip such as buying a car or furniture) or a discretionary activity is a special "ticketed" event such as a football game.

The modeling approach applied in the SCAG ABM builds on the idea that certain activities are inflexible or less flexible (referred to as *prioritized activities*) relative to other activities. The traveler plans the schedule of these prioritized activities first and then schedules other activities around them. The four main steps that predict activity generation and form tours from the activity participation decisions are the following:

Model for mandatory activity tour skeletons (frequency of mandatory activities, TOD)

Chapter 8 Mandatory Activity Frequency and Time of Day

Chapter 9 School Escorting and Scheduling Consolidation

Model for fully-joint tours for intra-household shared non-mandatory activities –Chapter 10

Individual Tour Formation

Individual Non-mandatory Activity Frequency and Time of Day- Chapter 11

Model for activity sequencing and within-segment tour formation - 12

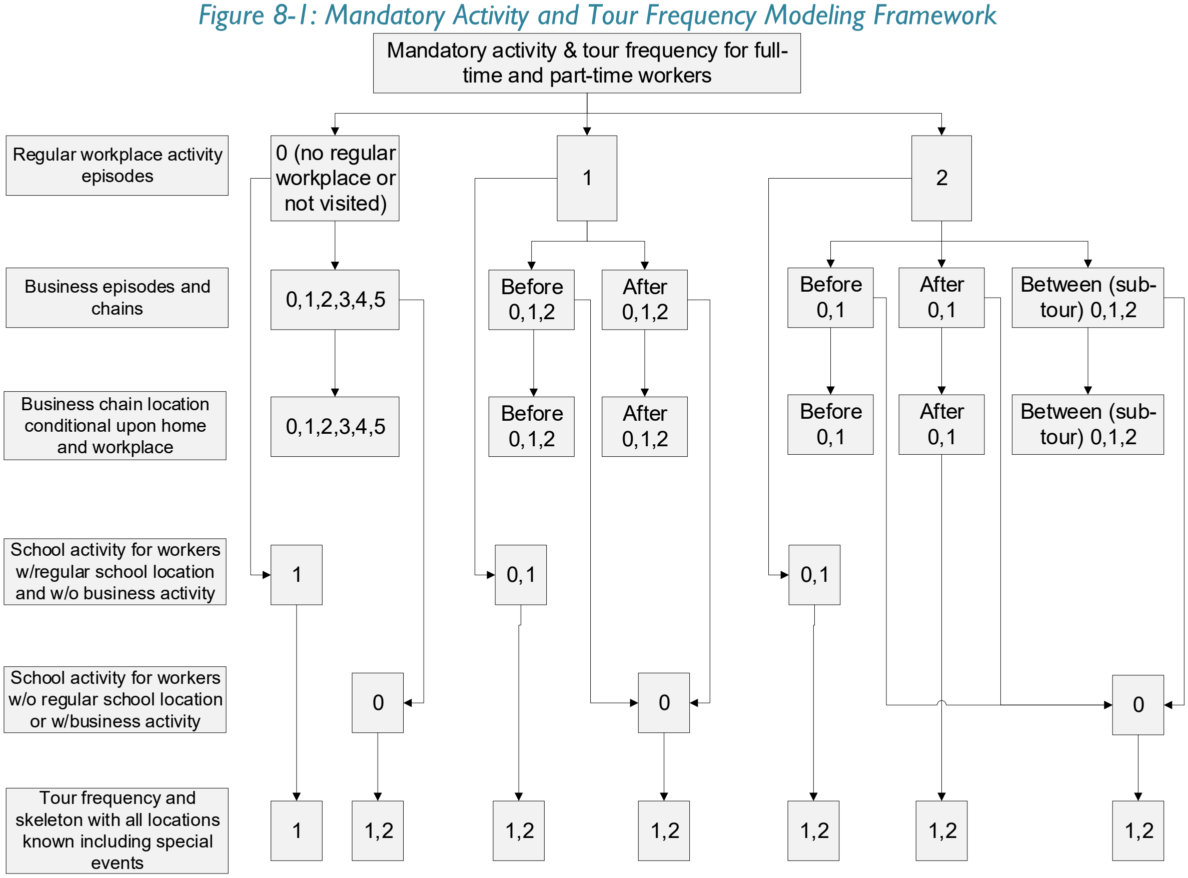
For a more detailed description, please refer to the Model Specification Report.

Mandatory Activity Tour Skeleton

Mandatory Activity Frequency and Order for Worker

The first sub-model (5.2.1.1) predicts mandatory activity frequency and order. The alternatives are defined by the number of workplace episodes, the number of business activities, and the relative ordering of business activities with respect to workplace episodes. Business episodes are not further distinguished by type; adjacent business activities implemented one after another are considered as a "business chain". These chains could be placed before, after or between workplace episodes depending on the number of workplace episodes in the alternative. Based on the observed frequency distribution, this model has a total of 43 alternatives.

Figure 8-1: Mandatory Activity and Tour Frequency Modeling Framework



Business Chain Location

Once the mandatory activity chain (including workplace and other business stops) for a worker has been predicted, the next step is to assign a location to each of the non-workplace (business) stops. A business stops chain can start and end at home or at the usual workplace. The number of business stops in each chain ranges from one to five.

Business stops share the same size variable. This attraction variable is specific to the worker industry and occupation and is computed as the sum of total employment for the worker's industry and total number of households. Since a sequential choice does not guarantee a logical non-zigzag spatial pattern, business stop locations are chosen simultaneously as an entire chain out of the generated sample of chains.

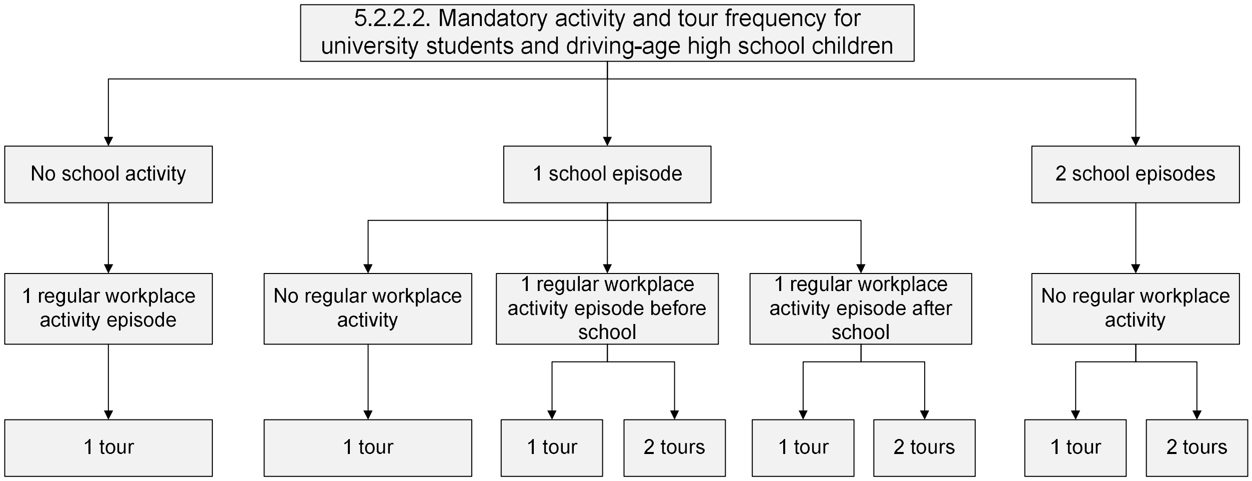
Mandatory Tour Skeleton Choice

After the mandatory activity pattern and locations have been decided, a worker has a choice to pursue these activities as part of a single tour or in multiple tours. A worker has an option to break the tour and return home after each mandatory activity, except for the last one. For example, in case of six mandatory activities, there are 5 positions at which the tour could be broken, resulting in 5 alternatives. The base alternative is always not to break the chain and pursue all mandatory activities as part of a single tour, resulting in a total of six alternatives. Availability of the other five alternatives is identified based on the number of activities being implemented by the worker.

Mandatory Activity and Tour Frequency Choice for Students

University students and driving-age children can participate in school and work activities. The number of school and work episodes, and their chronological order, is predicted simultaneously. The alternatives are defined by the number of school episodes, number of work episodes, and the relative ordering of work and school activities (Figure 8-2). This model has a total of 10 alternatives. The model predicts one school episode and one mandatory tour for pre-driving age students and pre-school age children when their DAP is mandatory, and no school episodes otherwise.

Figure 8-2: Mandatory activity & tour frequency modeling framework for students



Preliminary Mandatory Activity Schedule

After the mandatory tour skeletons are generated, the arrival time to and departure time from the primary mandatory activity are chosen simultaneously. The tour time of day choice model is a discrete-choice construct that operates with arrival time and departure time combinations as alternatives. The utility structure is based on "continuous shift" variables and represents an analytical hybrid that combines the advantages of a discrete-choice structure (flexible in specification and easy to estimate and apply) with the advantages of a duration model (a simple structure with few parameters, and which supports continuous time). The model has a temporal resolution of 15-minute arrival/departure time alternatives.

Model Application and Calibration

The mandatory activity frequency sub-model was calibrated by adjusting the frequency choice-specific constants, which are stratified by person type. These models are applied to workers and students with a mandatory DAP only. The work and business episode frequency for the worker person-types is shown in Figure 8-3 and Figure 8-4. The school episode activity frequency is shown in Figure 8-5.

Figure 8-3: Mandatory Work Episode Frequency, Workers

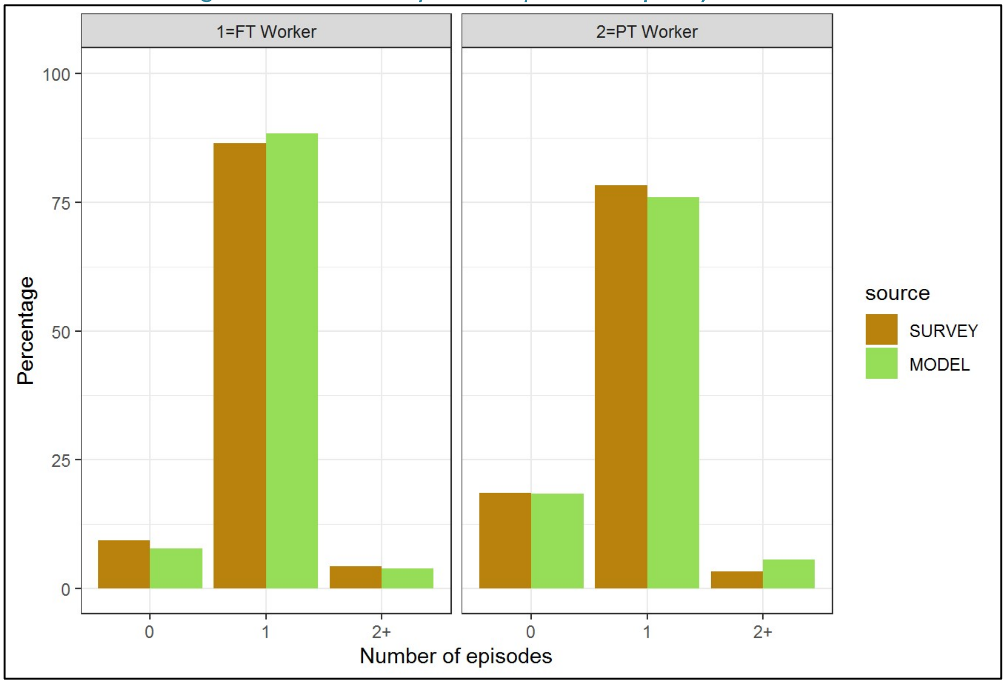


Figure 8-4: Mandatory Business Episode Frequency, Workers

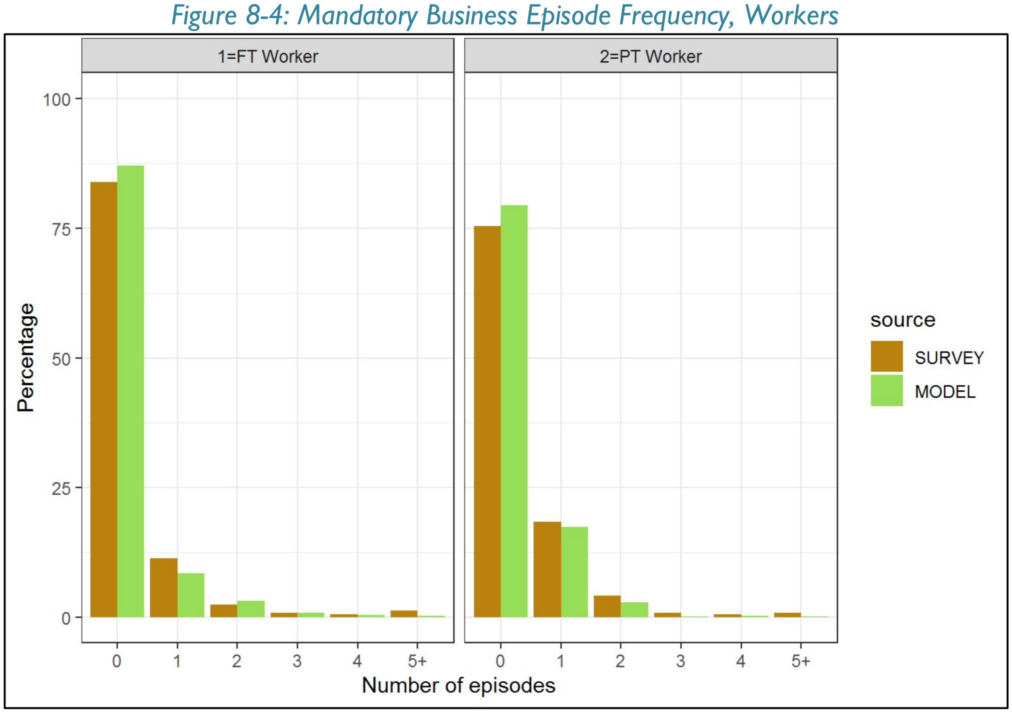
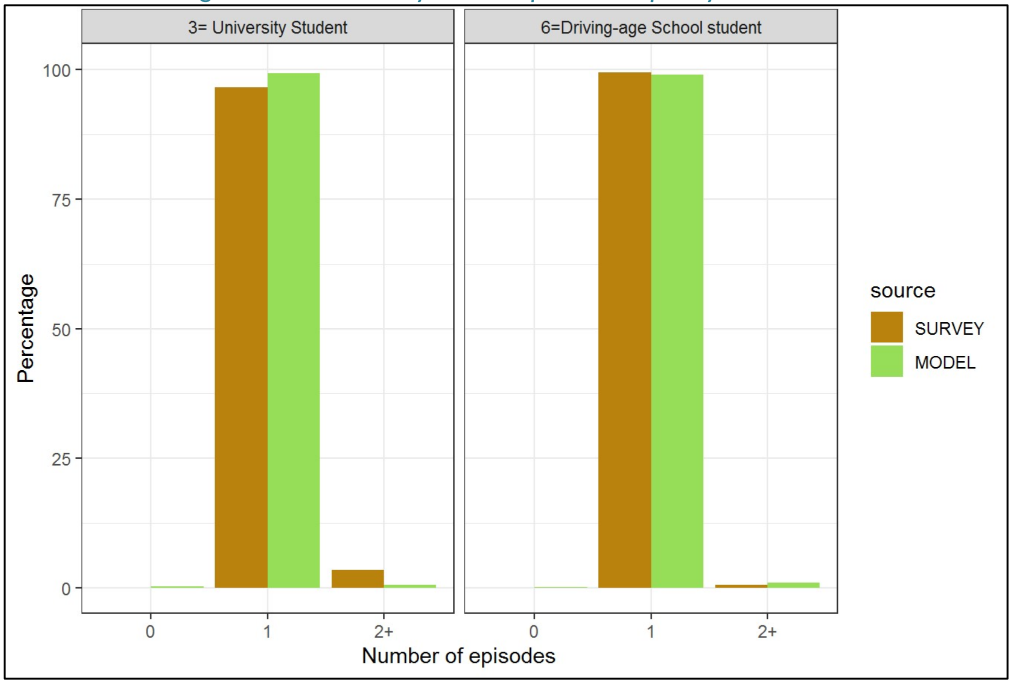
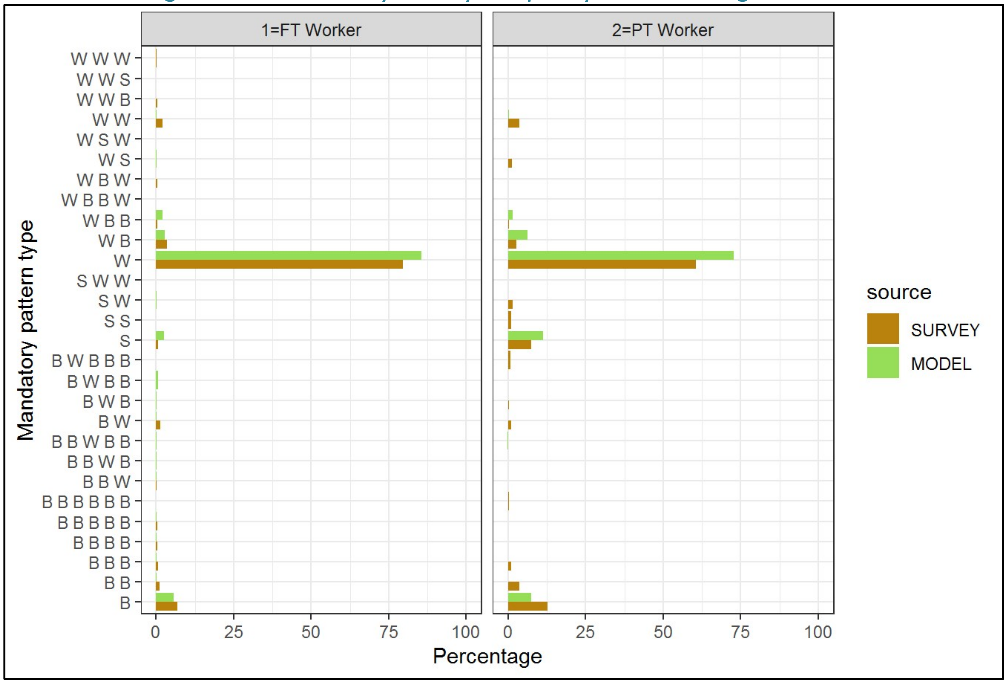


Figure 8-5: Mandatory School Episode Frequency, Students



A comparison of the frequency and ordering of work and business episodes is shown in Figure 8-6. Although many combinations of these types of activities are observed in the household survey, the simplest patterns predominate. Nonetheless, all patterns are considered because the low frequency business chains can be quite long (distance-wise).

Figure 8-6: Mandatory Activity Frequency and Ordering, Workers



The calibration of the mandatory activity time of day choice is shown in Figure 8-5 to Figure 8-12. These figures depict arrival time to the mandatory activity (work/school), departure time from the mandatory activity, and activity duration (exclusive of travel time). The model was calibrated to exhibit somewhat larger share of mandatory activity arrivals during the peak periods than observed in the CHTS. This is because the traffic count data for the region shows a more pronounced AM peak than the household survey.

Figure 8-7: Preliminary Work Episode Time of Day Choice, Full-time Workers

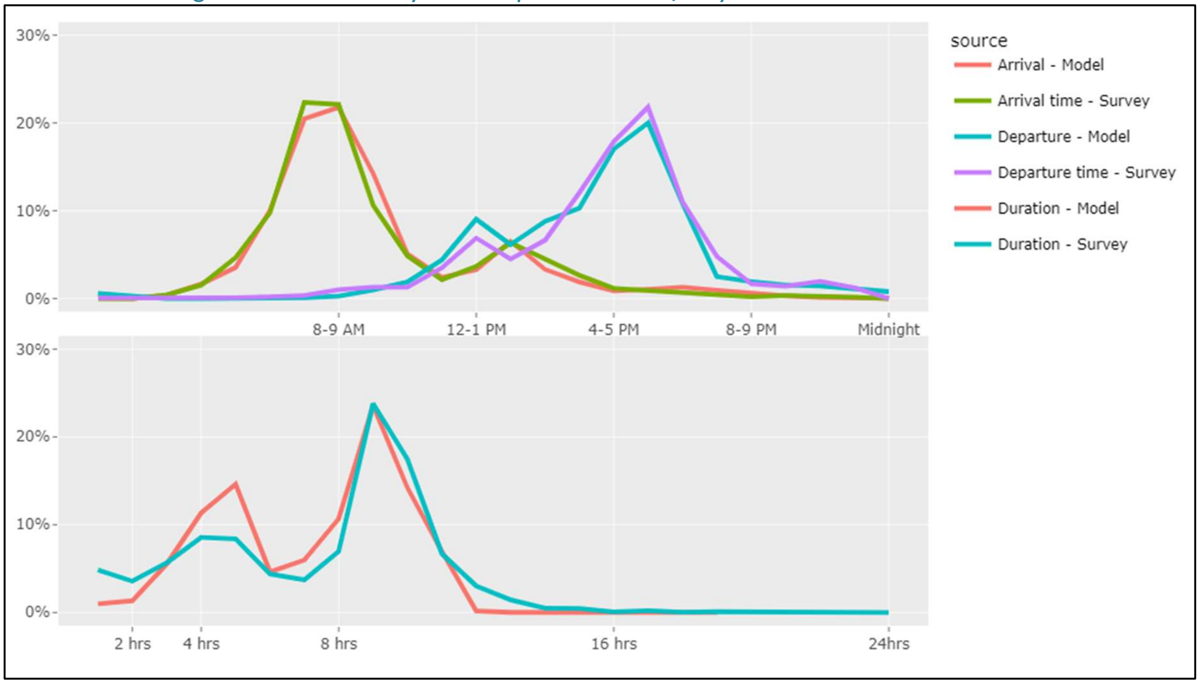


Figure 8-8: Preliminary Work Episode Time of Day Choice, Part-time Workers

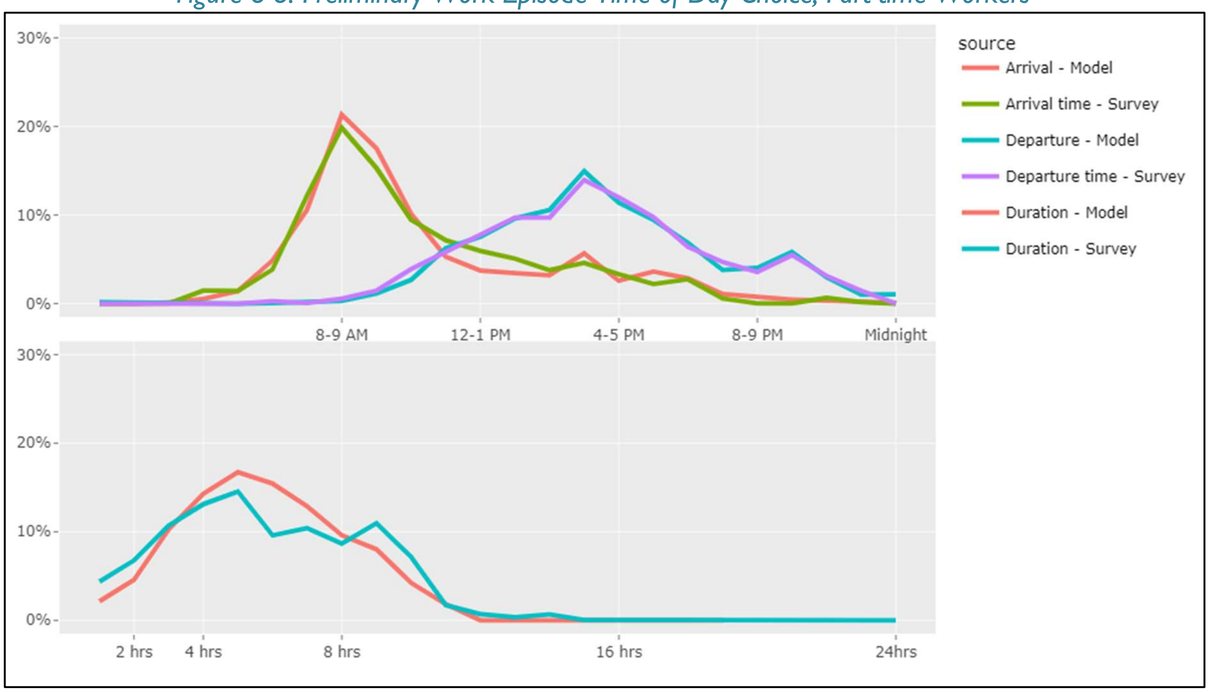


Figure 8-9: Preliminary School Episode Time of Day Choice, College Students

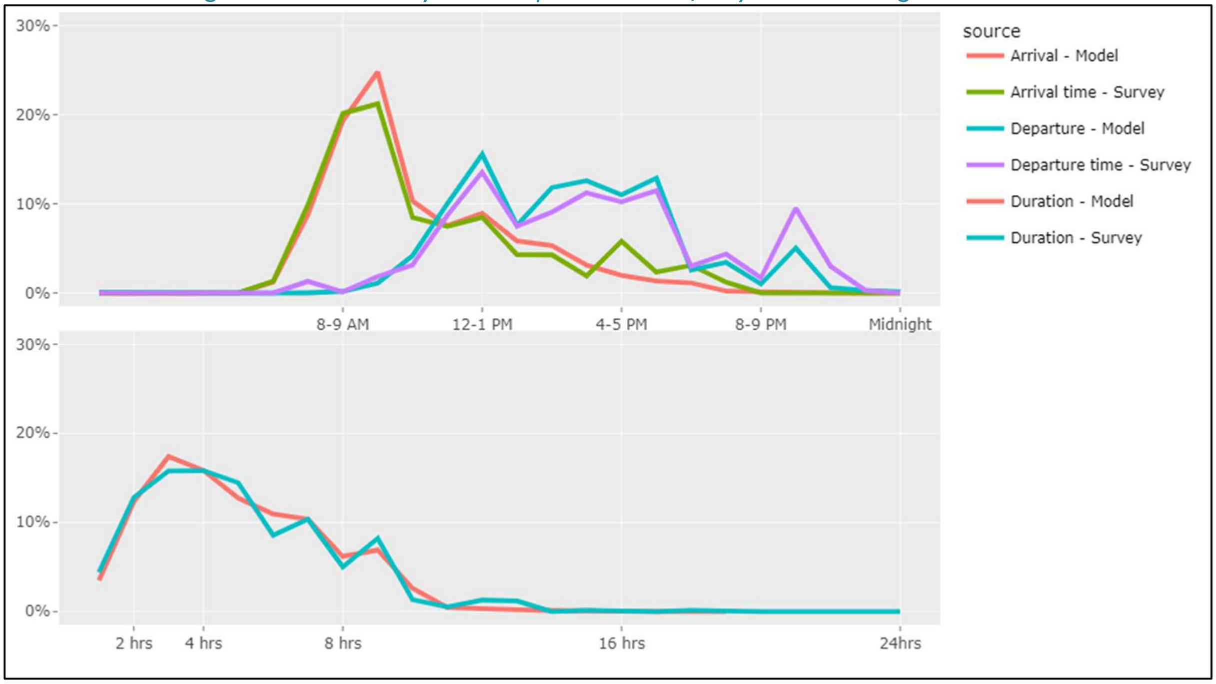


Figure 8-10: Preliminary School Episode Time of Day Choice, Driving-Age Children

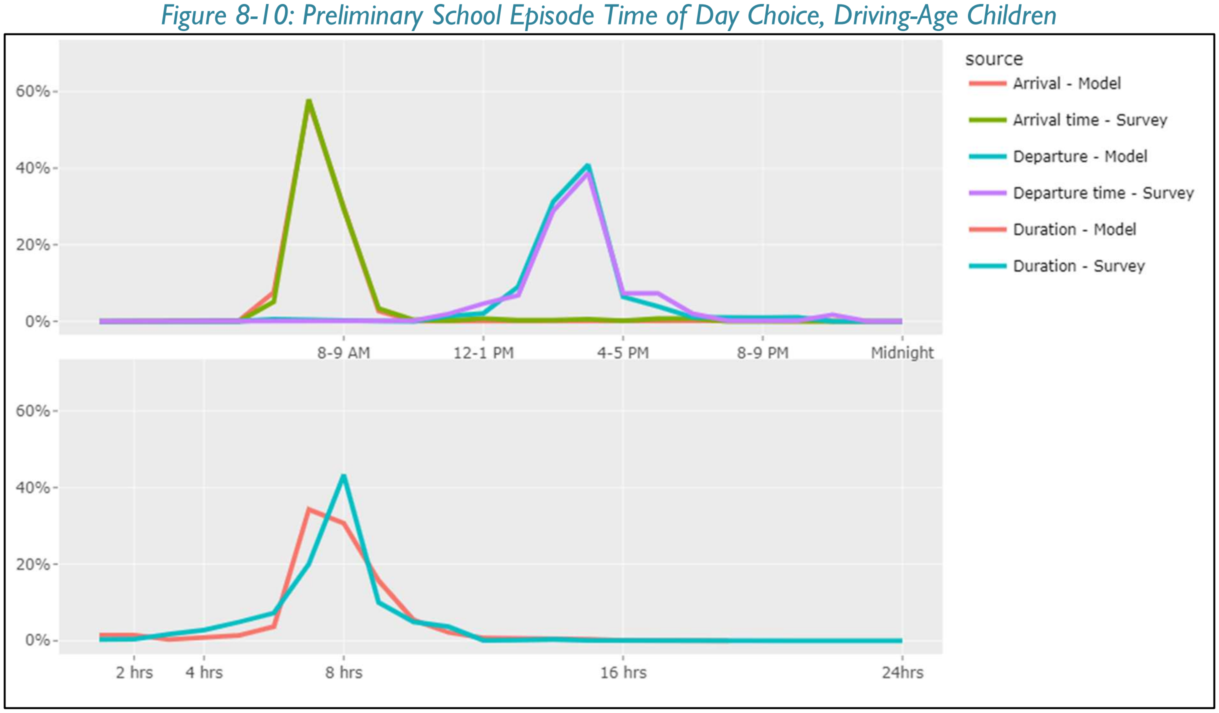


Figure 8-11: Preliminary School Episode Time of Day Choice, Pre-Driving Age Children

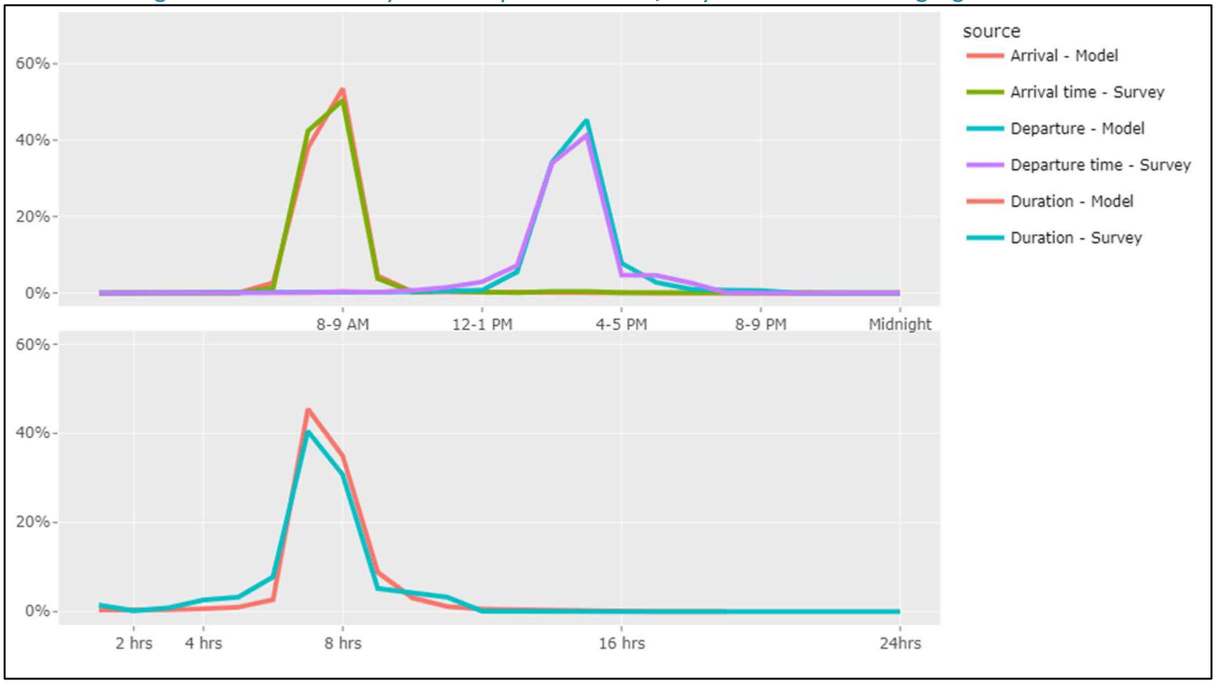
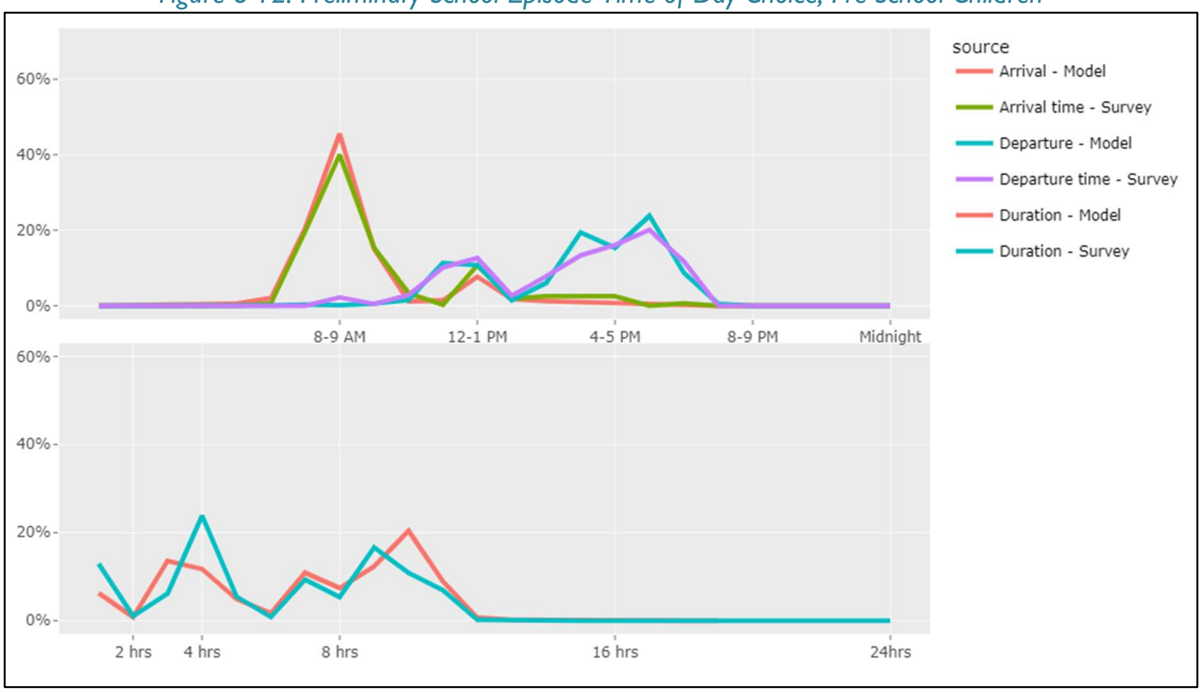


Figure 8-12: Preliminary School Episode Time of Day Choice, Pre-School Children



Chapter 9 School Escorting and Schedule Consolidation

Introduction

The school escorting model predicts which children are escorted to school and by whom. This model is applied after the generation, primary destination choice, and usual time-of-day choice for mandatory activities for all household members. Thus, at this modeling stage, it is known for each child if he/she goes to school, the location of school, and the school arrival and departure times. It is also known for each household adult if he/she goes to work or university, the location of workplace or university, and the work arrival and departure time. From this perspective, the escorting model can be thought of as a matching model that predicts whether escorting occurs, and if so which adult household members are chauffeurs and which children are escorted to school.

Children within the household are ordered and modeled by age from youngest to oldest. The behavioral assumption behind this decomposition rule is that, all else being equal, a younger child has more limited individual mobility than an older child; thus, in a household with more than one child, escorting the younger children is considered first in the household decision making process.

Choice Alternatives

The modeled choice alternatives for each school tour are shown in Figure 9-1 below. For each individual school tour, there are at most 7 outbound alternatives and 7 inbound alternatives including ride-sharing with one of the 3 potential chauffeurs, pure escorting by one of the 3 potential chauffeurs, and a non-escort option. At the level of entire school tour this gives 7×7=49 escort alternatives. If less than 3 chauffeurs are available for either outbound or inbound half-tour, the alternatives that correspond to non-available chauffeurs are blocked out in the choice model.

If the household has only one child, this model is used directly to generate the escorting arrangement for this child. However, if there are several children in the household implementing school school activity episodes, then an additional "bundling" model is applied to predict the probability that several children are escorted by the same adult on the same tour.

Model Application

When applied to the SCAG region, the model under-estimated the share of Pure Escorting while over-estimating both Shared Ride and No Escort options. The choice-specific constants were adjusted accordingly. The observed and estimated escorting proportions for the three children person-types are shown in Figure 9-1. As shown in Figure 9-2, the chauffer most often escorting children as shared-ride is a worker (as part of the work commute), while pure escort is most often associated with a non-working adult.

Figure 9-1: School Escorting Mode Shares

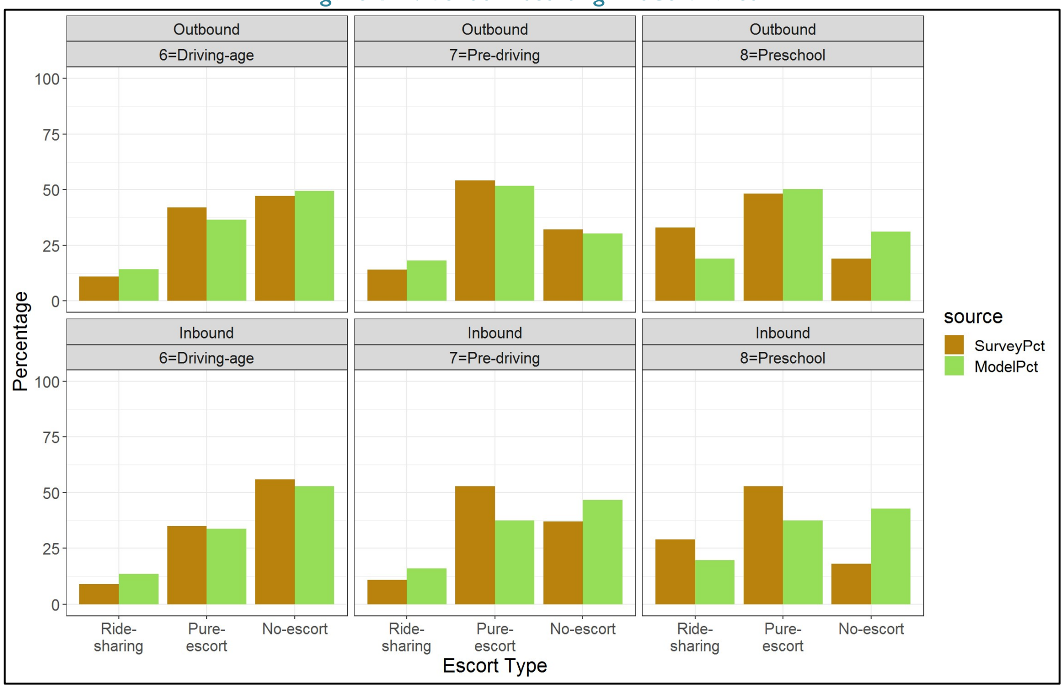
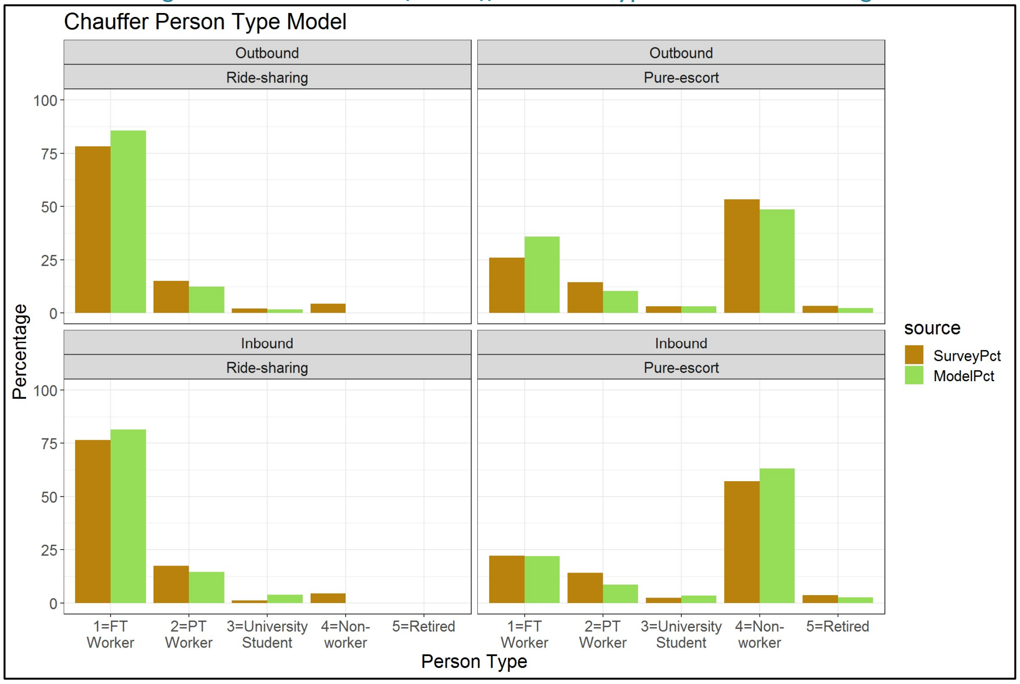


Figure 9-2: Allocation of Chauffer Person-Type to School Escorting



Chapter 10 FULLY JOINT TOUR ACTIVITY GENERATION AND SCHEDULING

INTRODUCTION

In the SCAG ABM, joint travel for non-mandatory activities is modeled explicitly in the form of fully joint tours. A fully joint tour occurs when all members of the travel party travel together from the very beginning to the end of the tour and participate in the same activities along the way. Each fully joint tour is considered a unit of modeling with group-wise decision-making for primary destination, mode, frequency, time-of-day, and location of stops. Joint tours are only modeled for households that include at least one joint activity predicted by the CDAP model.

Generation of joint activities

The generation of joint tour activities involves two linked stages:

A tour generation stage that generates the number of joint tours by purpose/activity type made by the entire household.

A tour participation stage at which the decision whether to participate or not in each joint tour is made for each household member.

Activity Location and Sequence

This model simultaneously predicts three choices: (a) the sequence of activities within each tour, (b) the location of all activities, and (c) whether to end the tour and go home. The location of the primary purpose of the fully joint tour is modeled first, followed by the sequence and location of additional stops within the tour relative to the primary destination. For each stop, there are two alternatives, "go directly" or "go through primary destination". Choosing the "go directly" alternative creates stops in the outbound direction while "go through primary destination" create stops in the inbound direction. The decision to end the tour and go back home is represented as the alternative corresponding to "not choosing any combination of purpose and location".

Tour Time of Day

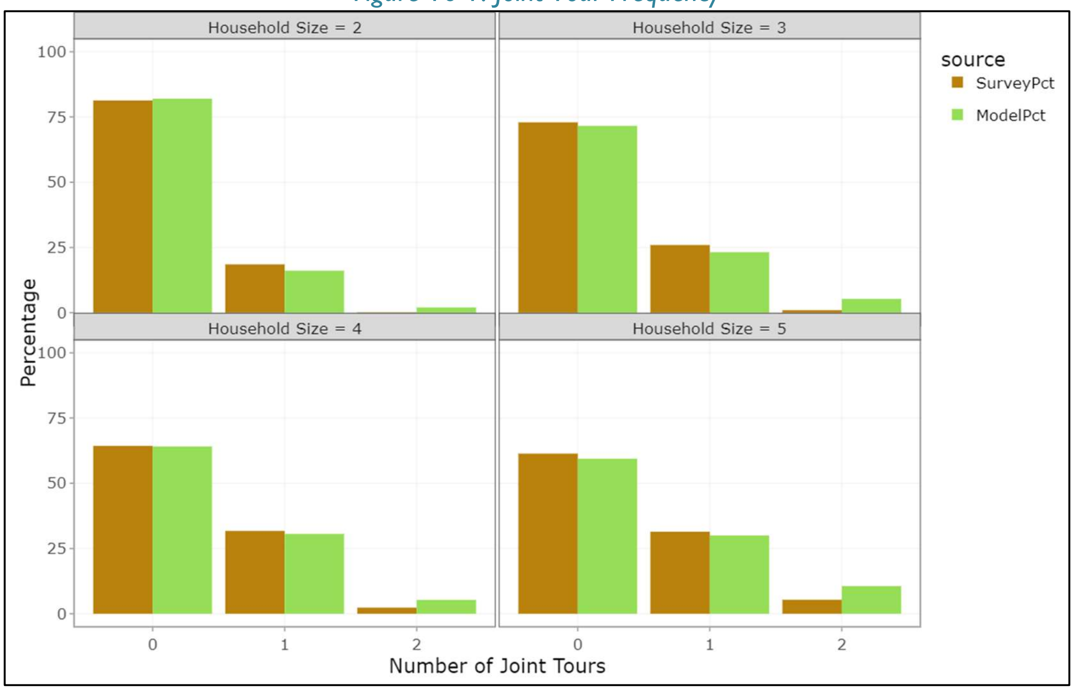
The arrival and departure times for the primary joint activities are chosen simultaneously after fully joint activities have been generated, assigned a primary location, and the party composition is known. The model is conceptually like the mandatory activity time of day model described in Chapter 9. However, a unique condition applies when applying the time-of-day choice model to joint tours. That is, the arrival /

departure interval combinations are restricted to only those available to all participants on the tour, after scheduling mandatory activities. Once the joint activity schedule is chosen, it is applied to all participants on the tour.

MODEL CALIBRATION

Joint tour frequency was calibrated for household size segments. The observed and predicted proportions of households making zero, one and two joint tours is shown in Figure 10-1.

Figure 10-1: Joint Tour Frequency



The propensity to participate in joint tours is shown in Figure 10-2 for each person-type and party composition. Children are primarily involved in "mixed party" tours, while retired adults are primarily involved in "adult-only" joint tours. Among all other adults, the split is approximately 25% to 40% mixed-party joint tours, and 60% to 75% adult-only joint tours.

The distribution of joint tour party composition for each tour purpose is shown in Figure 10-3. Other model calibration results include the average distance from home to the primary joint tour destination (Figure 10-4), and the number of intermediate stops on joint tours (Figure 10-5). The total number of joint tours predicted for 2019 is shown in Table 10-1.

Figure 10-2: Joint Tour Participation by Person-Type

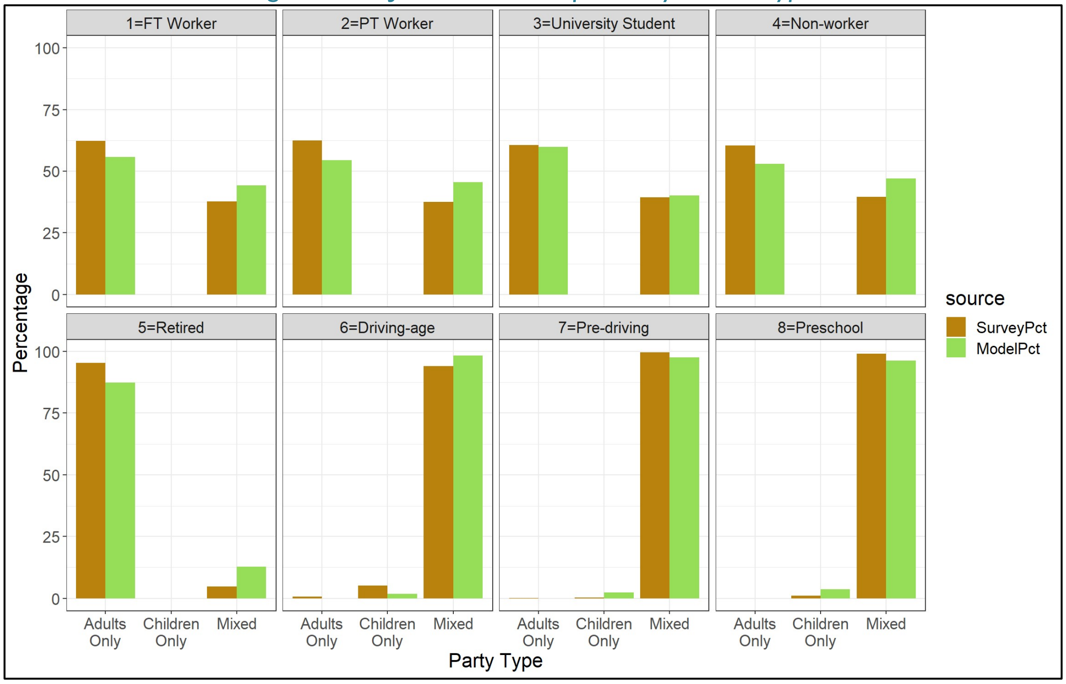


Figure 10-3: Joint Tour Purpose and Party Composition

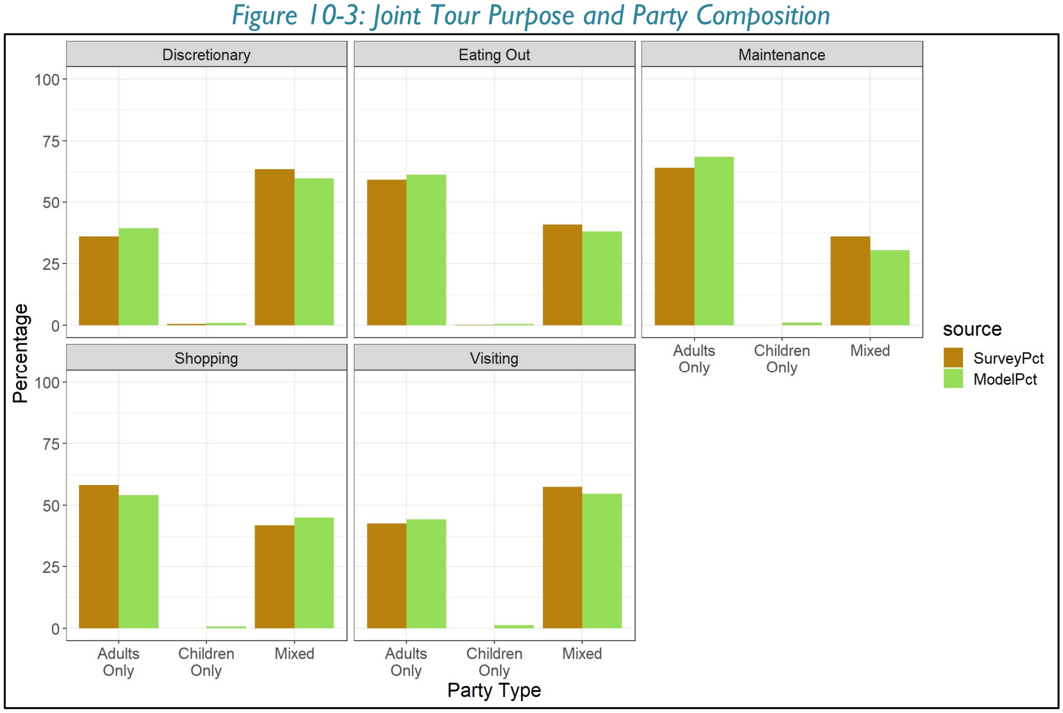


Figure 10-4: Joint Tour Average Trip Length

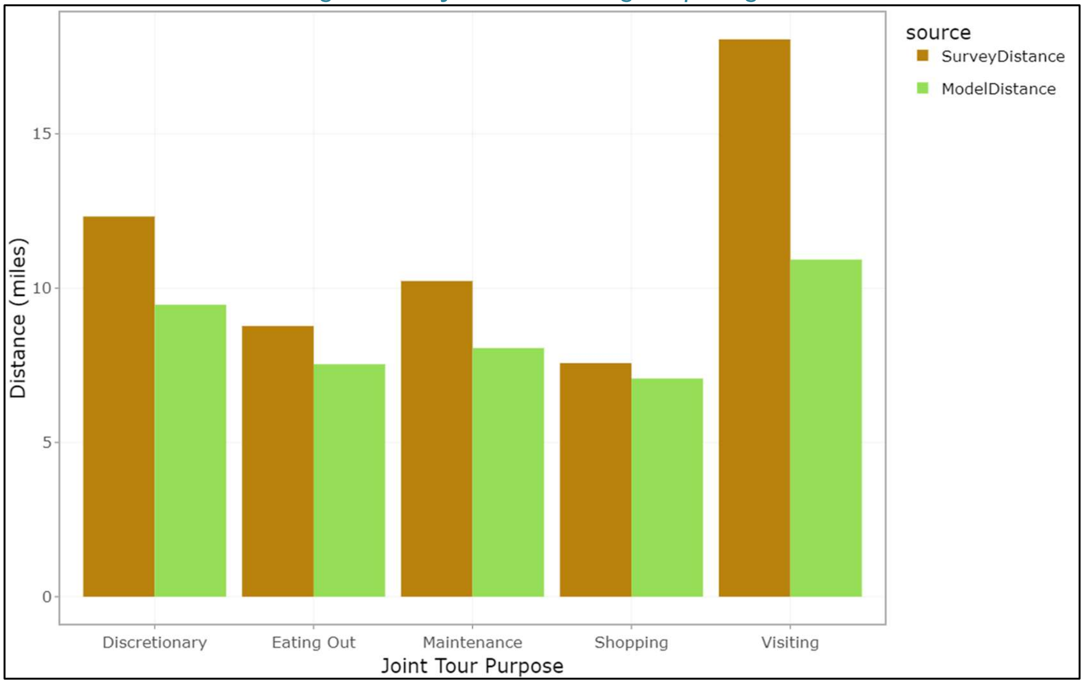


Figure 10-5: Joint Tour Stop Frequency

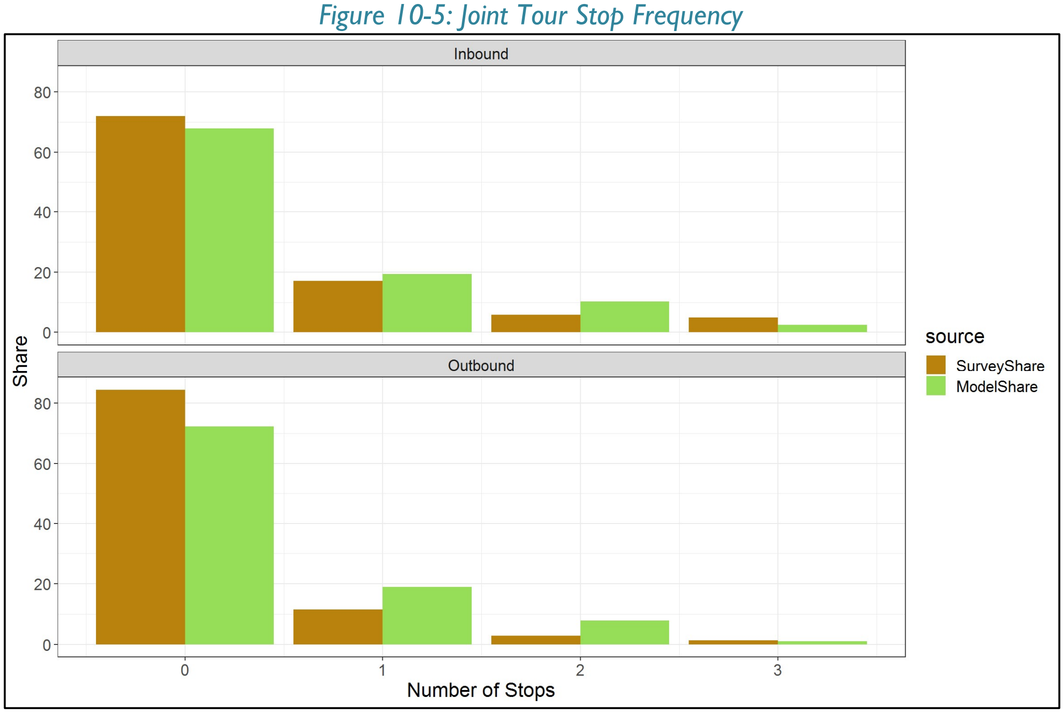


Table 10-1: Number of Joint Tours & Trips on Joint Tours, 2019

Observed			
Tour Purpose	**Number of Tours**	**Number of Trips**	**Trips per Tour**
Shopping	1,296,653	3,823,858	2.9
Maintenance	893,949	2,654,975	3.0
Eating Out	611,072	1,361,035	2.2
Visiting	542,454	1,403,096	2.6
Discretionary	1,098,004	2,743,875	2.5
Total	4,442,132	11,986,839	2.7

2019 Model			
Tour Purpose	**Number of Tours**	**Number of Trips**	**Trips per Tour**
Shopping	1,215,656	3,608,710	3.0
Maintenance	810,545	2,373,580	2.9
Eating Out	727,115	1,875,382	2.6
Visiting	333,782	1,019,170	3.1
Discretionary	1,284,729	3,554,367	2.8
Total	**4,371,827**	**12,431,209**	**2.8**

Chapter 11 Individual Non-mandatory Activity Generation

Introduction

In the SCAG ABM, household maintenance tasks are generated at the entire-household level and then allocated to household members for individual implementation. These tasks do not include joint maintenance activities and tours that are modeled earlier in the model system chain. Discretionary activities are generated at the individual level by model.

Household Maintenance Activity Frequency and Allocation

The *maintenance task frequency* model predicts the frequency of allocated maintenance tasks such as household errands, grocery shopping and escorting. These tasks are generated at the household-level and then allocated to one or more household members depending on their availability and schedule.

The propensity to participate in non-mandatory activities is a function of the time available. The model uses residual time windows as an explanatory variable, to measure time availability. Residual time windows are the time slots during the active time window available to carry out more activities, once the time dedicated to higher priority activities is blocked out. The active time frame for each person is determined after excluding sleep time from the 24-hour day. Once maintenance activities have been generated at the household level they are allocated to persons within the household.

Discretionary Activity Generation

The *discretionary activity generation* model predicts frequency of individual discretionary activity episodes for each person in the synthetic population. It treats five activity types in one integrated framework: 1=eating out/breakfast, 2=eating out/lunch, 3=eating out/dinner, 4=visiting relatives and friends, and 5=other discretionary activity. Each activity type has its own upper frequency bound, established based on observed frequencies. No more than six total discretionary activities are predicted for each person. The discretionary activity generation model takes the form of a MNL model. Utilities are a function of household attributes, person attributes, residual time windows, accessibilities and urban form.

At-home Non-mandatory Activity Choice

The SCAG ABM-CT-RAMP2 now incorporates a new sub-model called the at-home non-mandatory activity choice. This sub-model aims to account for the growing trend of non-mandatory activities being carried out at home. With the increasing popularity of online shopping and telemedicine, there has been a decrease in the frequency of physical shopping and maintenance activities, respectively. The sub-model addresses these issues by being flexible enough to be applied to other non-mandatory activities such as discretionary or eat-out, in the future.

The at-home activity choice sub-model is positioned between the discretionary task frequency sub-model and the tour formation sub-model. Its purpose is to identify a portion of the individual discretionary tasks generated by the discretionary task frequency model as at-home activities. These at-home activities are then excluded from the tour formation process. This approach is expected to result in a reduction in trips and vehicle miles traveled (VMT).

The at-home activity model was developed using a simple lookup table-based approach, instead of an econometric approach. This was because predicting trip substitution due to factors such as online shopping and telemedicine is beyond the scope of a travel demand model. Instead, external quantification of the substitution effect was required, and this sub-model directly incorporates these factors. Therefore, it is essentially a policy-oriented sub-model.

To identify activity substitution in shopping (due to online shopping) and maintenance (due to telemedicine), SCAG staff conducted internal research and shared the factors with WSP. The reduction factors for these two activities were segmented by age group categories, with different age groups for shopping and maintenance. WSP expanded this segmentation by person type, allowing for future extension of the model to incorporate person type segmentations, if required. Currently, all person types within a given age group have the same at-home activity factor for a specific purpose.

The final lookup table for this sub-model is shown in appendix A. The first field is the person type of the person, second and third fields are the age range for which the factor is applied (both inclusive), purpose is the purpose category, and the last field is the at home activity factor. An at home activity factor of 0.21 means that 21% of that activity will be undertaken as at-home activity and hence not scheduled as part of any tour.

Following the implementation of the sub-model, testing was conducted to ensure that the model outputs were functioning as intended. The testing aimed to confirm whether the reduction in trips for activities that have positive at-home factors in the lookup table aligned with the expected reduction based on probabilities. The results of the ABM simulation revealed that the realized at-home factor closely matched the input factors in the lookup table. This outcome demonstrated that the model is performing as designed.

Model Application

Frequency of household shopping, maintenance and escorting tasks as well as allocation of those tasks to person types in the households are illustrated in Figures 11-1, 11-2, 11-3, 11-4, 11-5, and 11-6 comparing model estimation to the target coming from the CHTS. Additionally, the frequency of individual task frequency is presented in figure 11-7 by person type comparing target to the model output.

Figure 11-1: Frequency of Allocated Household Shopping Tasks

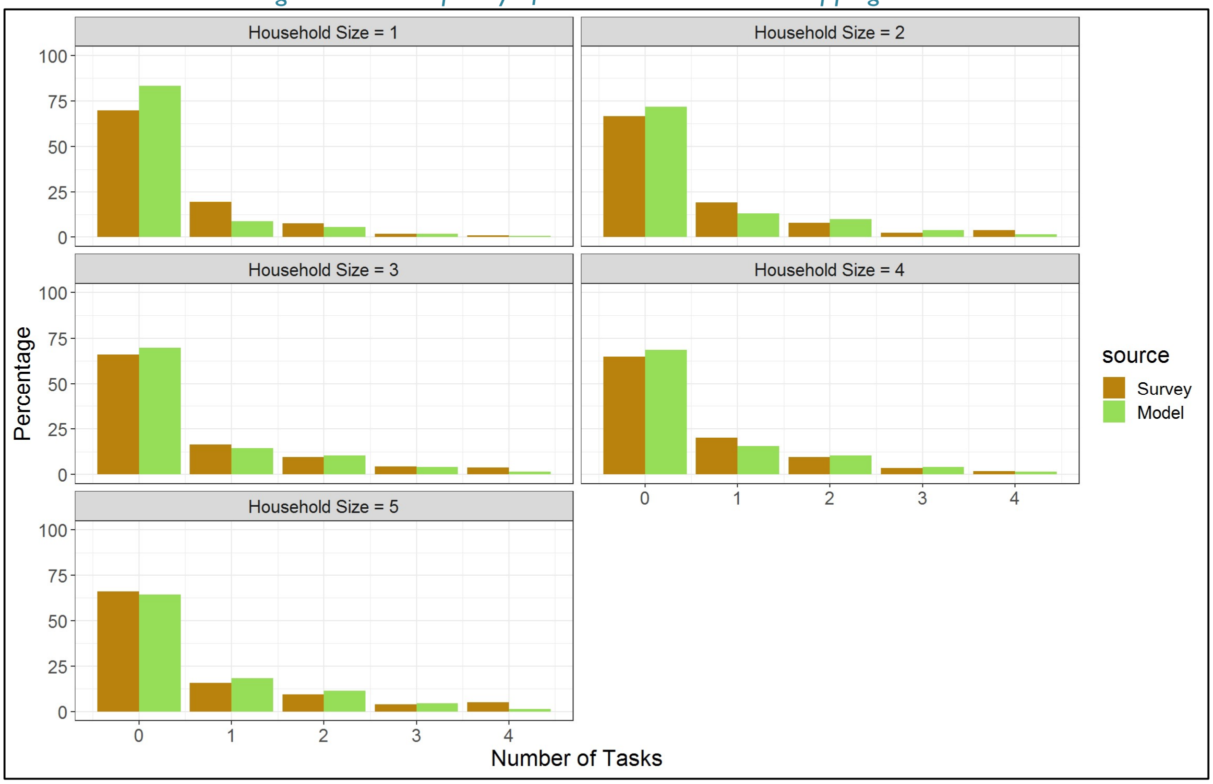


Figure 11-2: Allocation of Shopping Tasks to Household Members

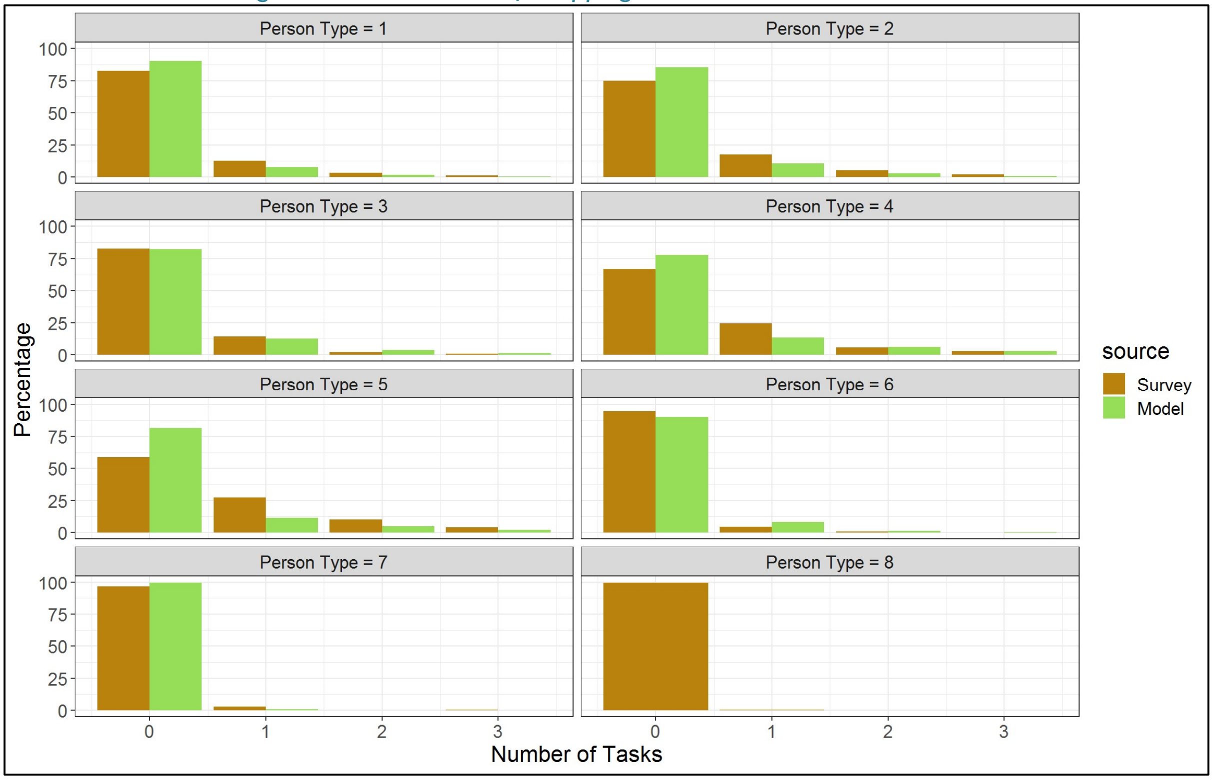


Figure 11-3: Frequency of Allocated Household Errands

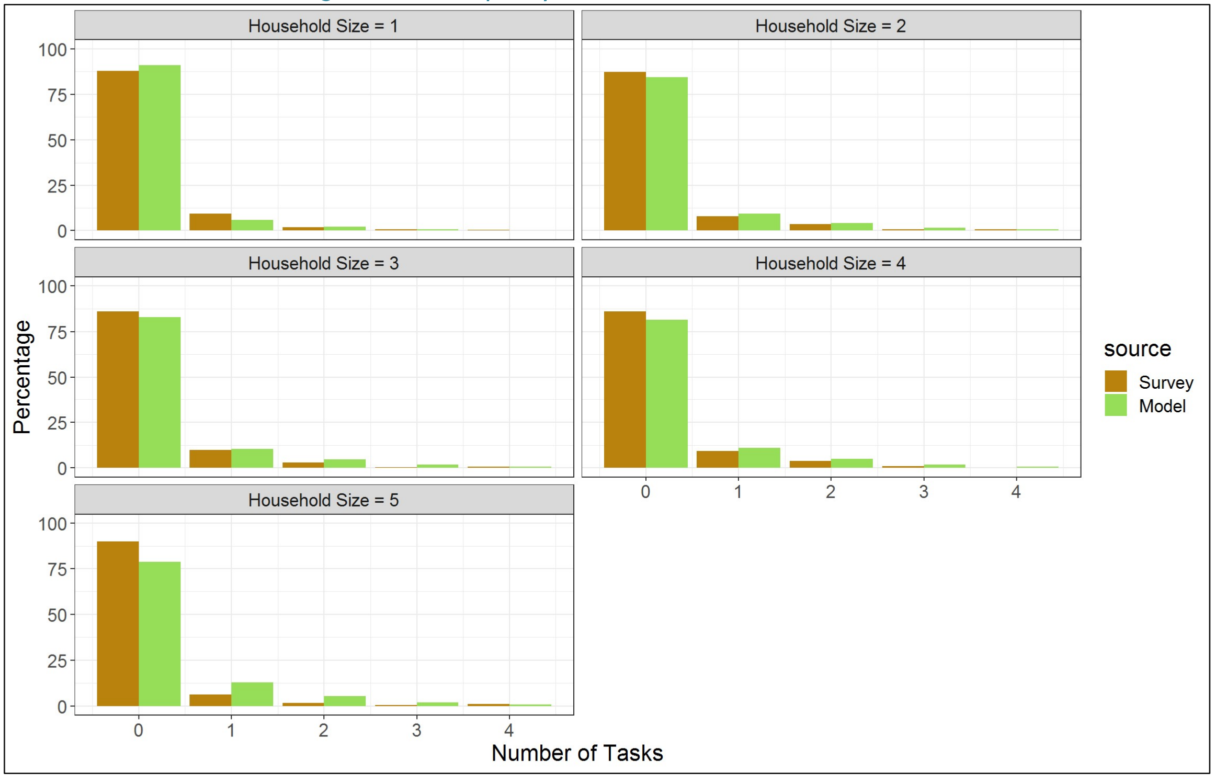


Figure 11-4: Allocation of Household Errands Tasks to Household Members

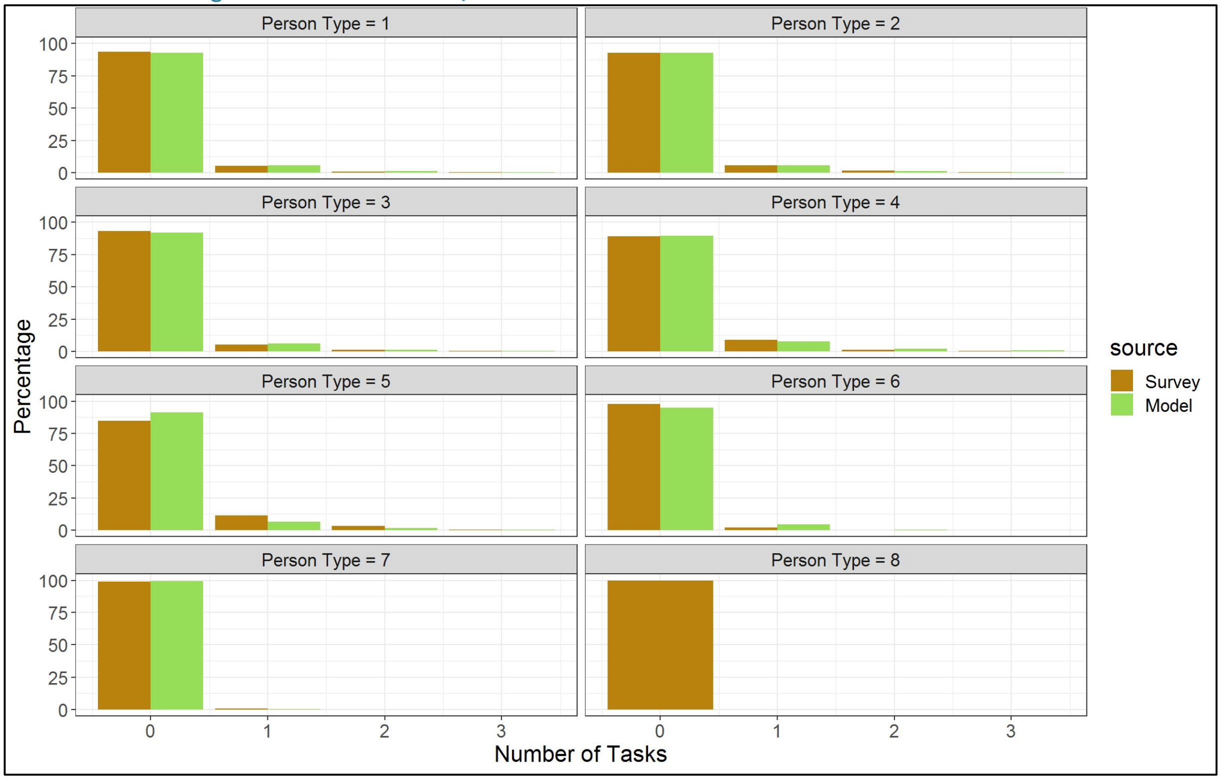


Figure 11-5: Frequency of Allocated Household Escorting Tasks

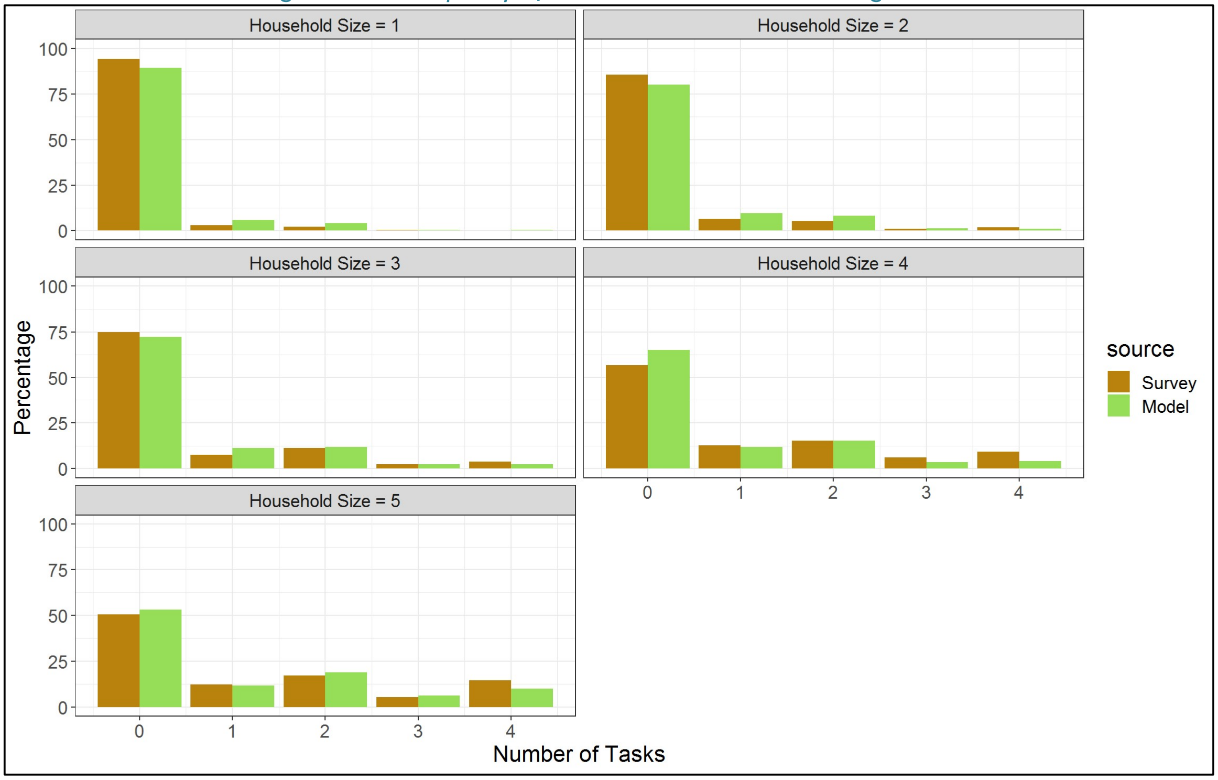


Figure 11-6: Allocation of Escorting Tasks to Household Members

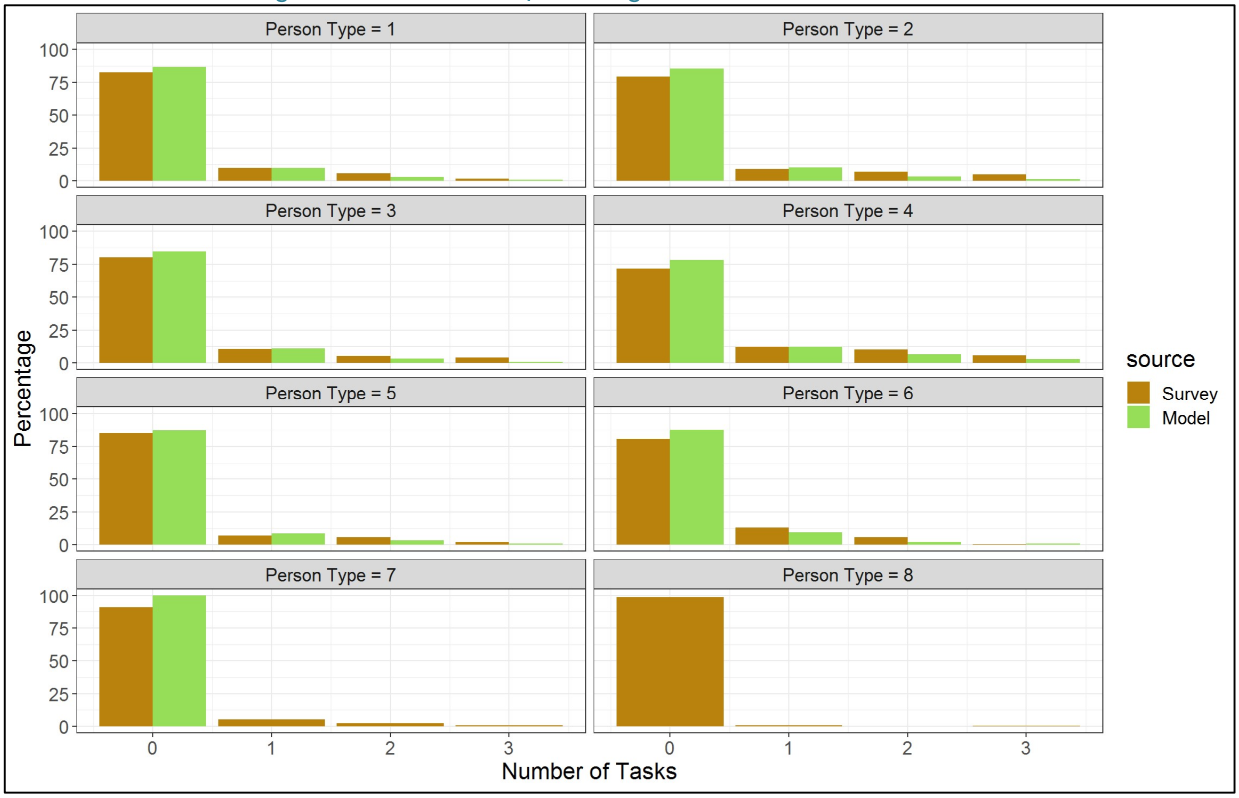
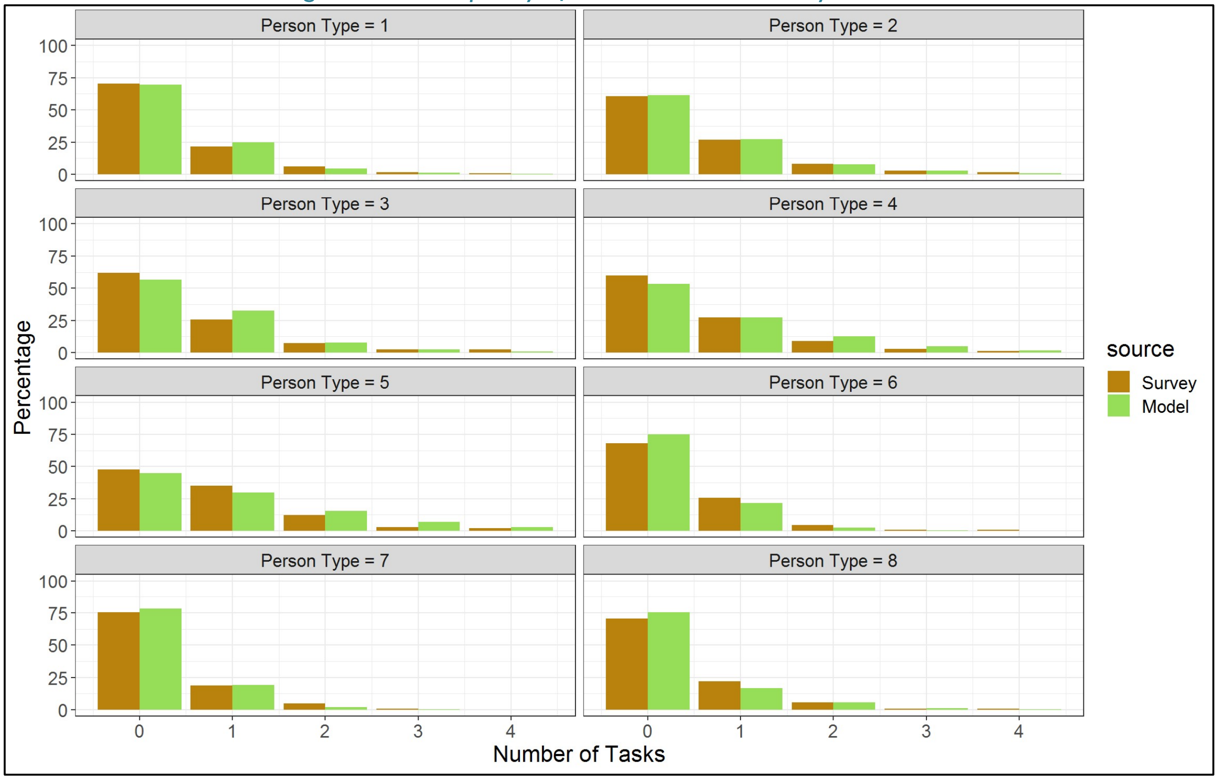


Figure 11-7: Frequency of Individual Discretionary Activities



Chapter 12 Tour Formation

Introduction

A preliminary schedule of the prioritized activities and associated tours has already been predicted at this stage of the model chain. Given this preliminary schedule, the entire day can be characterized as consisting of day segments created by the prioritized activities. This approach of creating day segments is important because different day segments are associated with different temporal and spatial constraints.

Allocation of Individual Non-Mandatory Activities to Day Segments

The day segments to which non-prioritized activities are allocated can be classified into the following four types:

Type 0: Any segment during the day without any prioritized tours.

Type 1: Segment between the prioritized activity tours. These allocations generate individual non-mandatory tours.

Type 2: Outbound and inbound legs of prioritized tours. These allocations do not result in any new tours but increase the number of stops in the prioritized tours. For multiple commute tours, Type 2 refers to the outbound leg of first commute tour and inbound leg of last commute tour.

Type 3: This category corresponds to at-work sub-tours that start and end at the workplace. For example, a worker going out for lunch during office hours is categorized as a Type 3 allocation.

Model Application and Calibration

The tour formation model was calibrated to match the observed activity segment allocation by person type and the observed tour frequency and observed stop frequency by segment type. Since this model interacts significantly with the immediate upstream model, the non-mandatory activity frequency model, during calibration, both the models were updated. Higher number of activities generated by the non-mandatory activity frequency model can lead to more tours and stops and vice-versa. Similarly, more tour breaks can lead to more tours but with fewer stops per tour. The final output from the model that was compared to the survey target is the tour frequency distribution by segment type and stop frequency distribution by segment type, shown in Figure 12-1 and Figure 12-2.

Figure 12-1: Non-mandatory Tour Frequency by Day-Segment (Brown: Target, Green: Model)

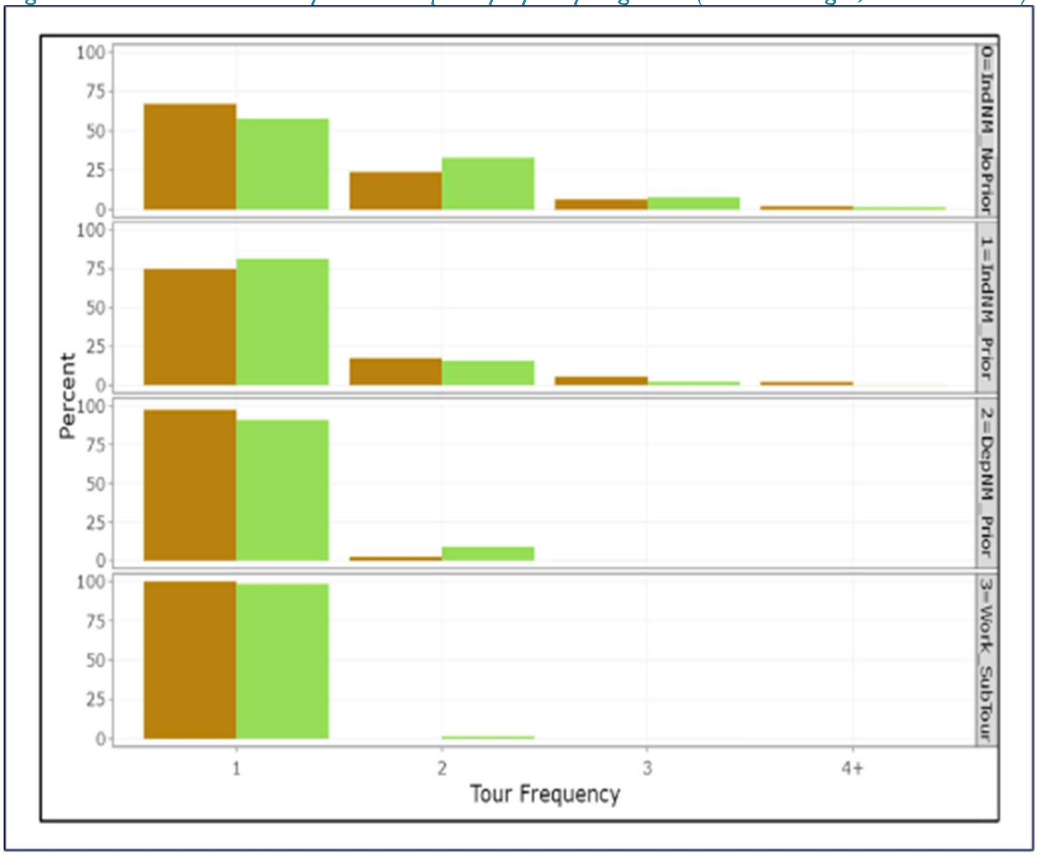


Figure 12-2: Stop Frequency on Non-mandatory Tours by Day-Segment (Brown: Target, Green: Model)

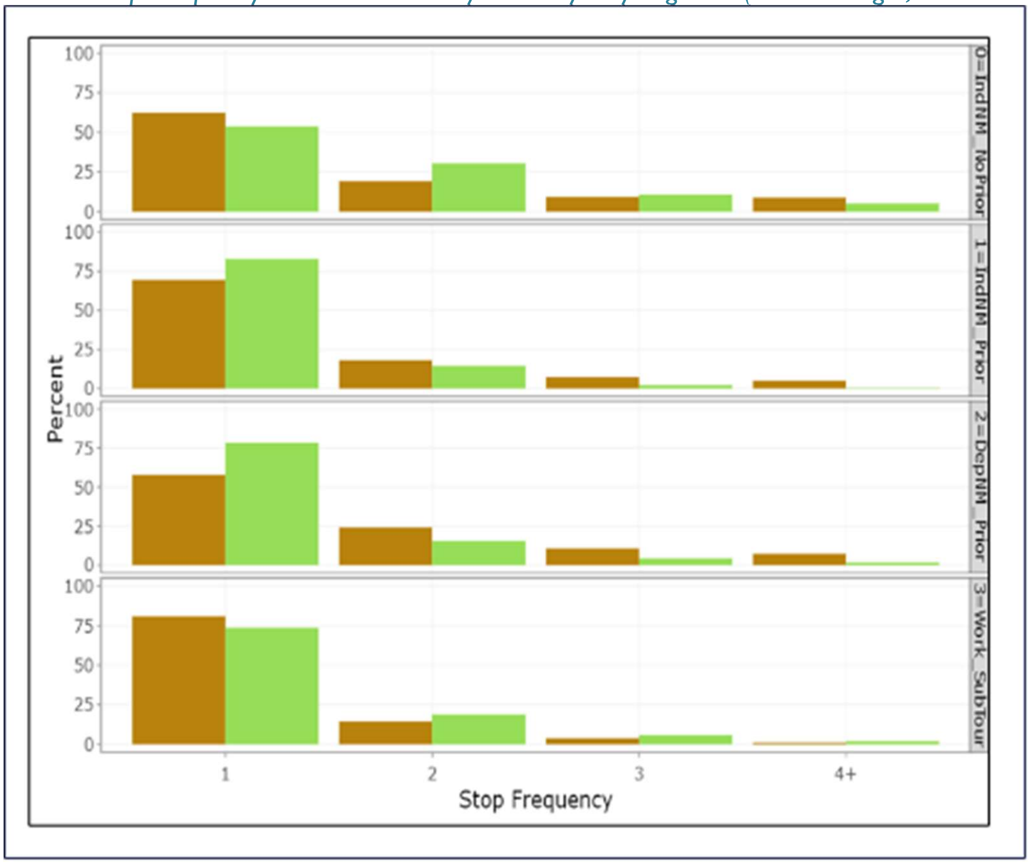


Table 12-1: Average Number of Tours per Person

Observed	Work	School	HH Maintenance	Ind Non-mandatory	Total
1-Full Time Worker	0.87	0.00	0.30	0.22	1.39
2- Part Time Worker	0.62	0.08	0.51	0.41	1.61
3- University Student	0.11	0.50	0.42	0.38	1.42
4- Non Working Adult	-	0.02	0.81	0.62	1.45
5- Retiree (Non-working elderly)	-	0.00	0.37	0.72	1.09
6- Driving Age School Child (16-18)	0.05	0.87	0.15	0.24	1.31
7- Pre-driving Age School Child (6-15)	-	0.94	0.29	0.17	1.40
8- Preschool Child (U5)	-	0.35	0.63	0.25	1.23

Predicted	Work	School	HH Maintenance	Ind Non-mandatory	Total
1-Full Time Worker	0.86	0.03	0.32	0.23	1.43
2- Part Time Worker	0.66	0.08	0.44	0.38	1.56
3- University Student	0.01	0.60	0.40	0.46	1.47
4- Non Working Adult	-	-	0.92	0.70	1.62
5- Retiree (Non-working elderly)	-	-	0.42	0.82	1.23
6- Driving Age School Child (16-18)	0.01	0.92	0.17	0.24	1.35
7- Pre-driving Age School Child (6-15)	-	0.91	0.23	0.18	1.33
8- Preschool Child (U5)	-	0.39	0.32	0.28	1.00

Difference	Work	School	HH Maintenance	Ind Non-mandatory	Total
1-Full Time Worker	(0.01)	0.03	0.02	0.01	0.04
2- Part Time Worker	0.05	(0.00)	(0.07)	(0.03)	(0.05)
3- University Student	(0.10)	0.10	(0.02)	0.08	0.06
4- Non Working Adult	-	(0.02)	0.11	0.07	0.17
5- Retiree (Non-working elderly)	-	(0.00)	0.05	0.09	0.14
6- Driving Age School Child (16-18)	(0.04)	0.06	0.02	(0.00)	0.04
7- Pre-driving Age School Child (6-15)	-	(0.03)	(0.05)	0.01	(0.07)
8- Preschool Child (U5)	-	0.04	(0.31)	0.03	(0.23)

Table 12-2: Total Tours by Person Type

Person type	Tour Purpose (Observed)			
	Mandatory (Work/School)	Household Maintenance	Other Non-Mandatory	Total
1 Full-time worker	5,615,628	1,949,467	1,440,463	9,005,558
2 Part-type worker	1,026,604	753,129	609,081	2,388,813
3 College student	619,679	426,776	385,045	1,431,500
4 Non-worker	60,365	2,724,732	2,101,691	4,886,788
5 Retired	2,689	838,751	1,657,137	2,498,577
6 Driving age child	561,468	92,660	146,896	801,024
7 Pre-driving age child	2,487,784	753,459	442,991	3,684,233
8 Pre-school child	459,739	828,908	326,498	1,615,145
Total Tours	**10,833,956**	**8,367,880**	**7,109,802**	**26,311,638**

Person type	Tour Purpose (2019 Model)			
	Mandatory (Work/School)	Household Maintenance	Other Non-Mandatory	Total
1 Full-time worker	6,098,499	2,181,993	1,621,624	9,895,918
2 Part-type worker	938,956	564,829	485,445	1,994,767
3 College student	613,052	405,172	463,242	1,482,385
4 Non-worker	-	2,790,117	2,122,204	4,912,321
5 Retired	-	923,194	1,812,360	2,735,554
6 Driving age child	556,969	103,651	140,912	801,274
7 Pre-driving age child	2,288,390	584,177	449,257	3,322,164
8 Pre-school child	455,645	374,961	327,540	1,158,458
Total Tours	**10,951,511**	**7,928,094**	**7,422,584**	**26,302,841**

Table 12-3: Total Trips by Person Type

Person type	Trip Purpose (Observed)		
	Mandatory (Work/School)	Non-Mandatory	Total
1 Full-time worker	17,760,067	7,879,364	25,639,431
2 Part-type worker	3,620,081	2,949,952	6,570,033
3 College student	1,877,225	1,983,128	3,860,353
4 Non-worker	-	12,673,483	12,673,483
5 Retired	-	6,931,405	6,931,405
6 Driving age child	1,366,890	556,015	1,922,906
7 Pre-driving age child	6,409,373	2,469,398	8,878,771
8 Pre-school child	1,722,423	2,341,004	4,063,427
Total Trips	**32,756,060**	**37,783,747**	**70,539,807**

Person type	Trip Purpose (2019 Model)		
	Mandatory (Work/School)	Other Non-Mandatory	Total
1 Full-time worker	16,217,837	9,483,655	25,701,492
2 Part-type worker	2,547,700	2,694,906	5,242,606
3 College student	1,558,589	2,204,931	3,763,520
4 Non-worker	-	13,058,959	13,058,959
5 Retired	-	7,419,093	7,419,093
6 Driving age child	1,400,237	565,736	1,965,973
7 Pre-driving age child	5,777,281	2,458,444	8,235,725
8 Pre-school child	1,093,656	1,710,033	2,803,689
Total Trips	**28,595,300**	**39,595,757**	**68,191,057**

Chapter 13 Final Time of Day

Introduction

The time-of-day choice model is a hybrid discrete-choice and duration construct that operates with tour departure-from-home and arrival-back-home time combinations as alternatives. The utility structure is identical to the structure of the mandatory activity time-of-day model. The model utilizes direct availability rules for each subsequently scheduled tour, to be placed in the residual time window left after scheduling tours of higher priority. This conditionality ensures full consistency of the individual entire-day activity and travel schedule as an outcome of the model.

The model uses household, person, and zonal characteristics, most of which are generic across time alternatives. Network LOS variables vary by time of day, and are specified as alternative-specific based on each alternative's departure and arrival time. By using generic coefficients and variables associated with the departure period, arrival period, or duration, a compact structure of the choice model is created, where the number of alternatives can be arbitrarily large depending on the chosen time unit scale, but the number of coefficients to estimate is limited to a reasonable number. Duration variables can be interpreted as "continuous shift" factors that parameterize the termination rate. Positive coefficients mean that duration tends to increase, while negative coefficients shift the time-of-day distributions toward shorter durations.

The tour-scheduling model is placed after destination choice (tour formation) and before mode choice. Thus, the destination of the tour and all related destination and origin-destination attributes are known and can be used as explanatory variables.

For work and school activities, the time-of-day choice model is applied twice. It is first applied to define start and end times of the work and school activity episodes (see Chapter 9). At this stage, the details of work and school tours (and details of the other activities of the person day) are not known except for possible participation in a fully joint tour. If there are several activity episodes allocated to several tours, the start time of the first one and the end time of the last one is modeled. Once all the details of the tours are known (except for trip mode), then the entire work and school tour time of day choice is modeled conditional upon the work / school activity schedule, other intermediate stops assigned to the work / school tour, and other activities and tours planned by the person.

The final time-of-day model predicts start and end time for each tour from the departure from home for the first activity until arrival back home after the last activity. The model has a 15-minute temporal resolution and ensures that the time of day choices for any person are consistent throughout the day (i.e., without gaps or overlaps).

New Sub-model: Trip Departure Time Choice

This sub-model is designed to predict the duration of non-mandatory activities when there is more than one activity in any given tour segment. If there is only one activity in the tour segment, the activity duration is directly determined by segment's constraint pegs and travel time to/from activities. For example, in a non-mandatory tour with two activities, we know the trip departure from origin of the first trip and the trip arrival time home of the third trip. We also know the total tour duration as well as the trip travel time for the three trips. What we don't know is the activity duration of the two activities. The allocation of available time to the activities within the tour, after subtracting travel time, is what this sub-model would predict. Once the activity durations are predicted we can compute the trip departure times for all the trips within the tour segment.

To inform the activity duration allocation between activities, an analysis of CHTS 2012 was undertaken by SCAG. CHTS trip data was summarized using two different segmentations and the segmentation that showed better variation across segments was selected for the model design. The segmentation by person type, tour type and trip purpose were found to have more variation and thus expected to better represent the observed data.

Sub-model Implementation

This section will describe how the lookup table was used in implementing the activity duration sub-model. This will be described using an example. Assume there is a non-mandatory tour made by a non-worker with two activities: shopping (activity 1) and visit (activity 2). The activity duration sub-model gets applied after the tour formation sub-model in the modeling sequence. `

> As mentioned in the introduction, at this point in the modeling sequence, we know the following attributes. Tour departure from home and arrival back home time. Assume these values are departure at 10:15 AM and arrival at 1:45 PM. The total tour duration is 210 minutes.
>
> We know the destination locations of activity 1 and activity 2. From this information and the *reserved* travel time for the three trips, the total activity durations can be obtained. CT-RAMP2 reserves 2 minutes of travel time for every mile of travel distance at this stage of the model. Assume that these reserved travel times are 13 minutes for first trip, 25 minutes for trip 2 and 30 minutes for trip 3, for a total of 68 minutes of travel time.
>
> From the total tour duration and total trip travel duration we can get the total activity duration as 210-68 = 142 minutes.
>
> These 142 minutes need to be allocated between shopping and visit activities. In order to do that we lookup the average duration for the non-worker person type and independent non-mandatory tour from the lookup table. These are:

Shop = 48 mins

Visit = 162 mins

This implies shopping activity fractional time share = 48/(48+162) = 0.229, visit activity fractional time share = 162/(48+162) = 0.771

These shares are applied to the available activity time obtained in step 3 (142 minutes) to get the activity durations.

Shop = 0.229*142 = 32 minutes

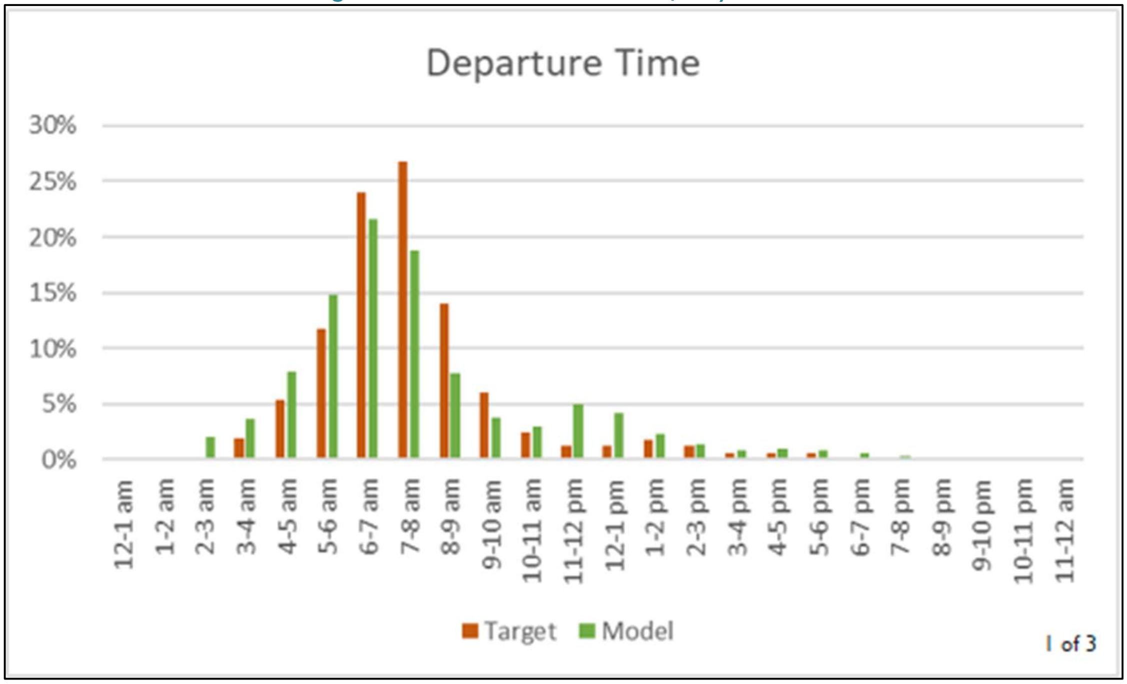
Visit = 0.771*142 = 110 minutes.

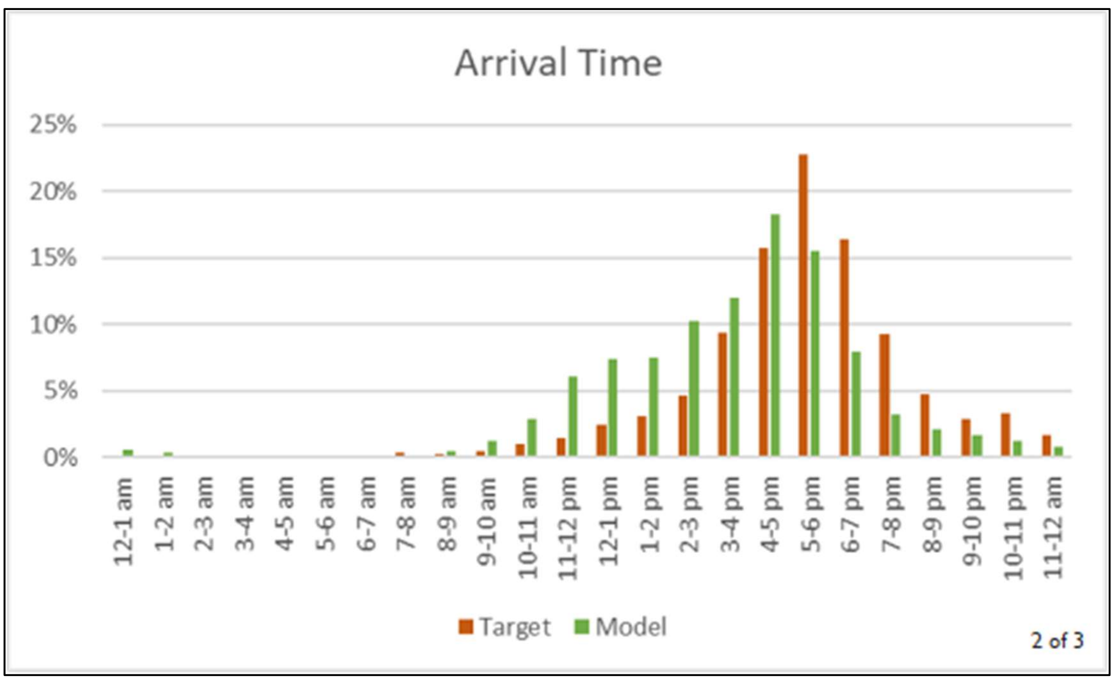
After the implementation, tests were performed to ensure that the model outputs are as expected and that there are no bugs. The activity duration outputs and resulting trip departure times in the model outputs were consistent with the sub-model design and the inputs.

Model Calibration and Application

The model was calibrated by adjusting the time-specific constants and/or shift variables, based on comparisons of the tour departure, tour arrival and tour duration predictions to diurnal distributions obtained from the 2011 CHTS. A top-down check was also applied, which consisted of verifying the trip time-of-day shares (aggregated for the five highway assignment periods) to targets from the 2011 CHTS. Some adjustments to the time of day distributions were also made to improve the overall traffic assignment by time period. The final time of day distributions are shown in Figure 13-1 to Figure 13-8, aggregated to one-hour intervals to smooth out lumpiness due to small sample size.

Figure 13-1: Work Tour Time of Day Choice





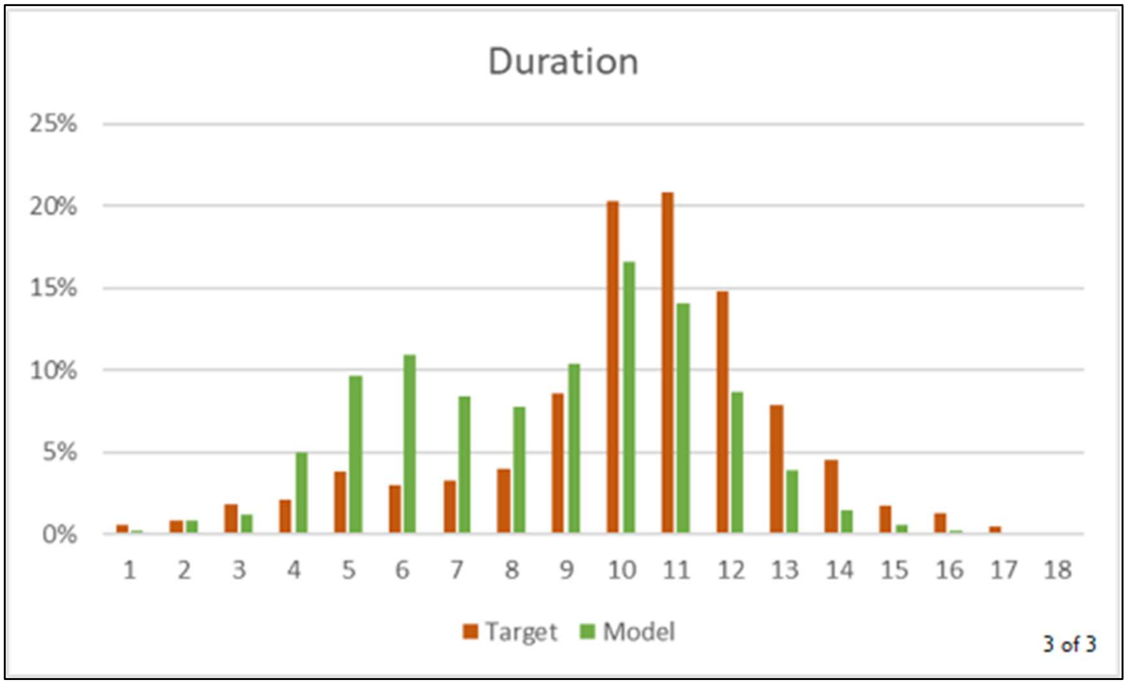
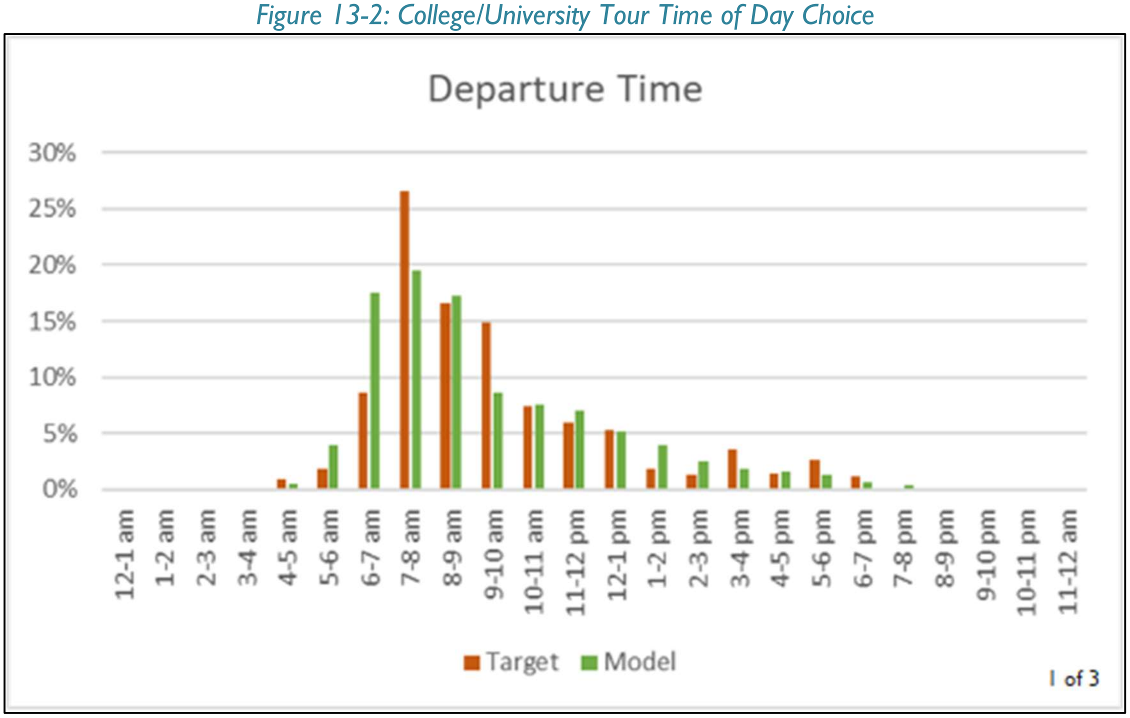
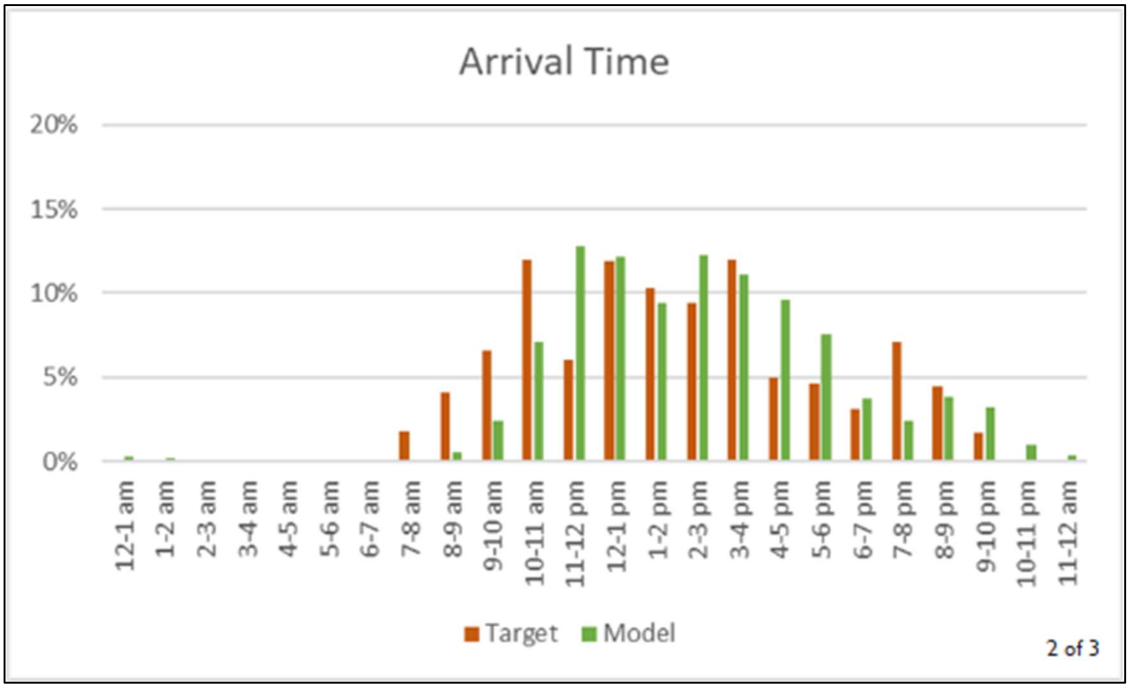


Figure 13-2: College/University Tour Time of Day Choice




Arrival Time
20%
15%
10%
5%
0%
12-1 am
1-2 am
2-3 am
3-4 am
4-5 am
5-6 am
6-7 am
7-8 am
8-9 am
9-10 am
10-11 am
11-12 pm
12-1 pm
1-2 pm
2-3 pm
3-4 pm
4-5 pm
5-6 pm
6-7 pm
7-8 pm
8-9 pm
9-10 pm
10-11 pm
11-12 am
Target
Model
2 of 3

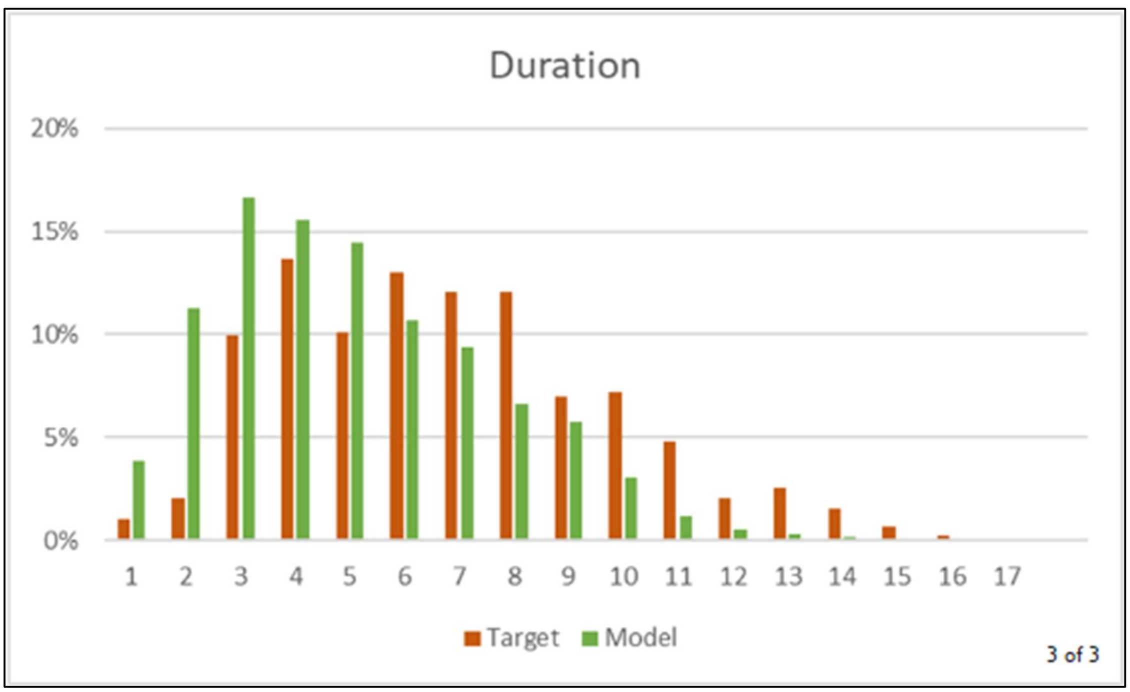
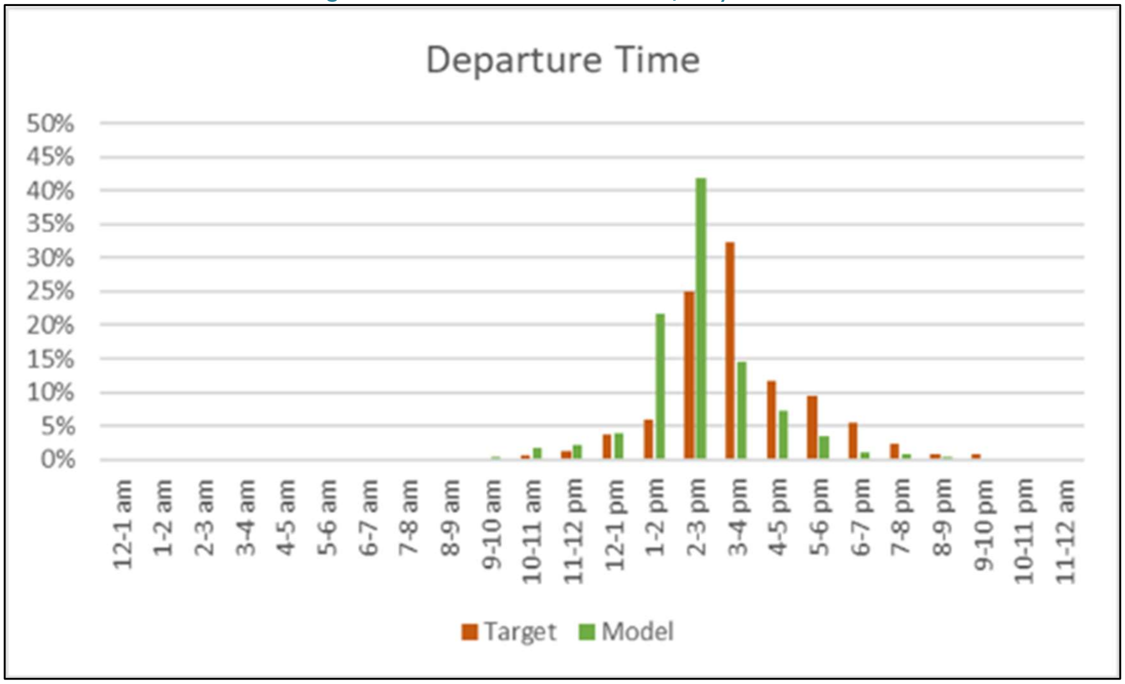
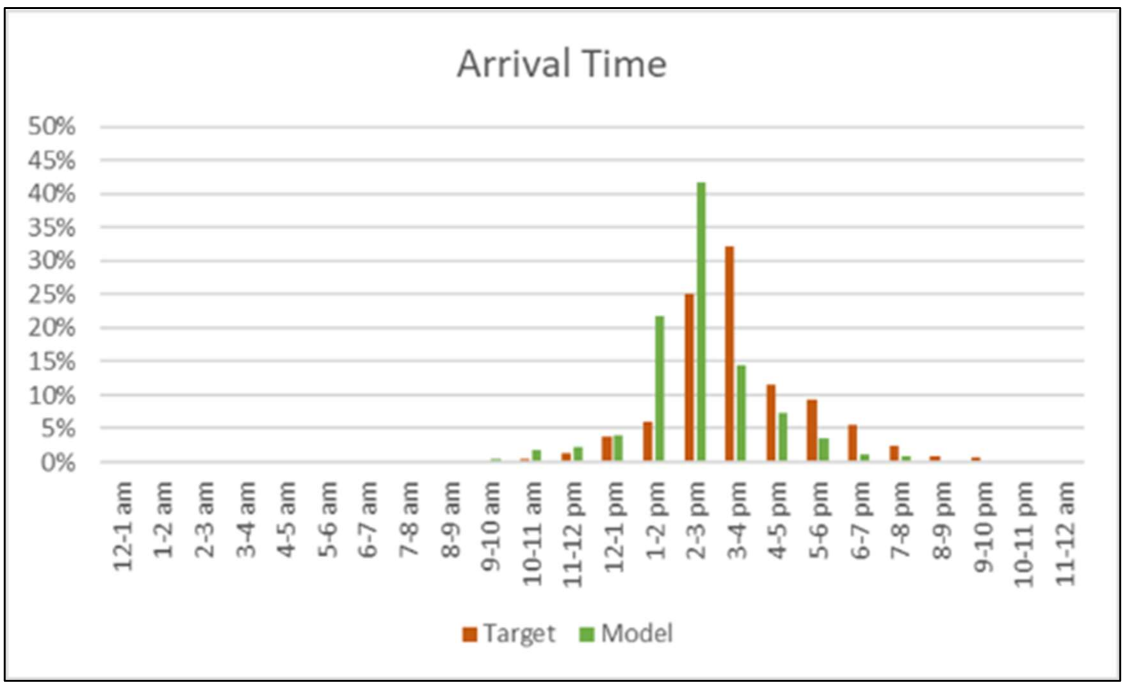

Duration
20%
15%
10%
5%
0%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
Target
Model
3 of 3

Figure 13-3: School Tour Time of Day Choice





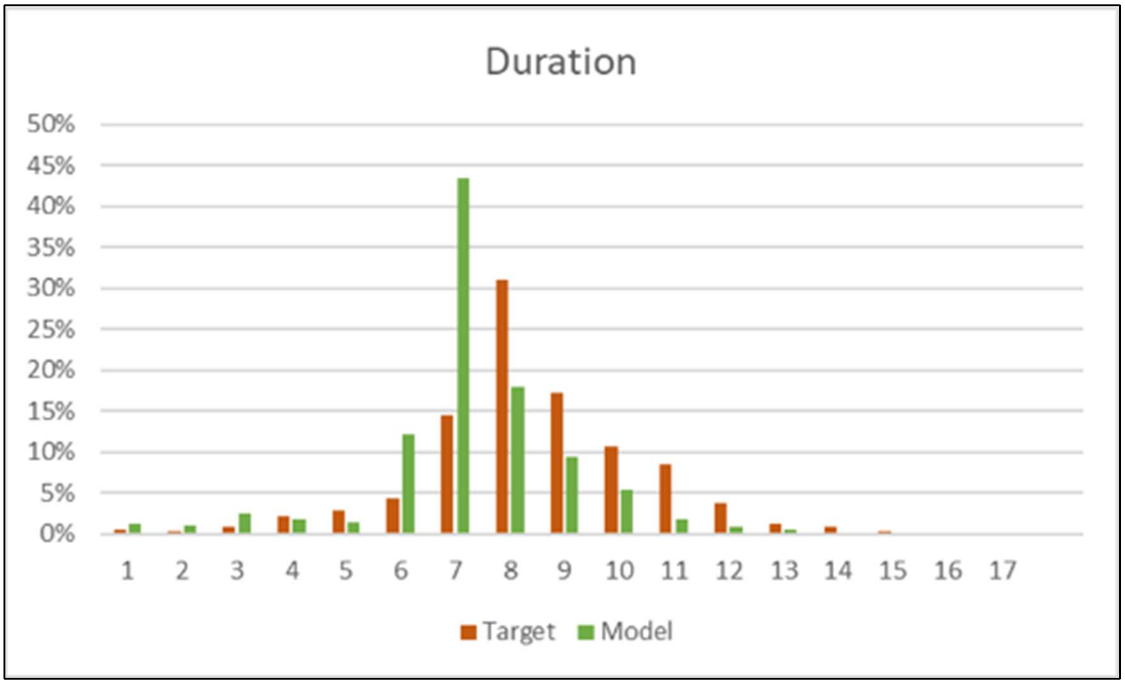
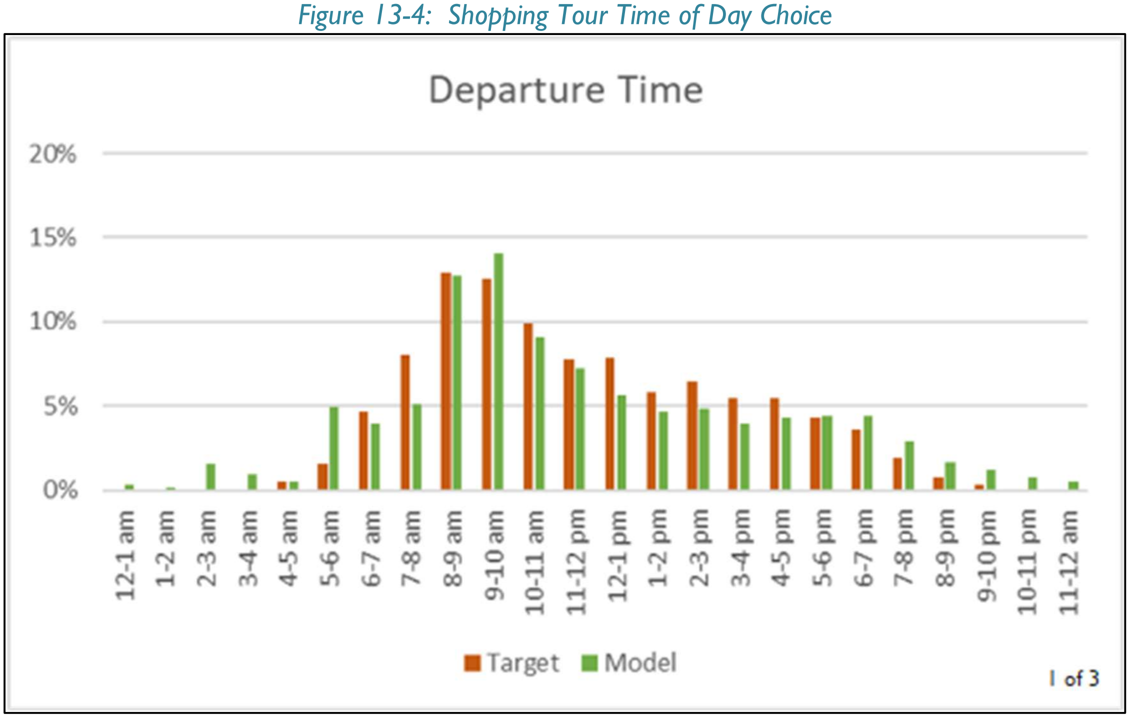
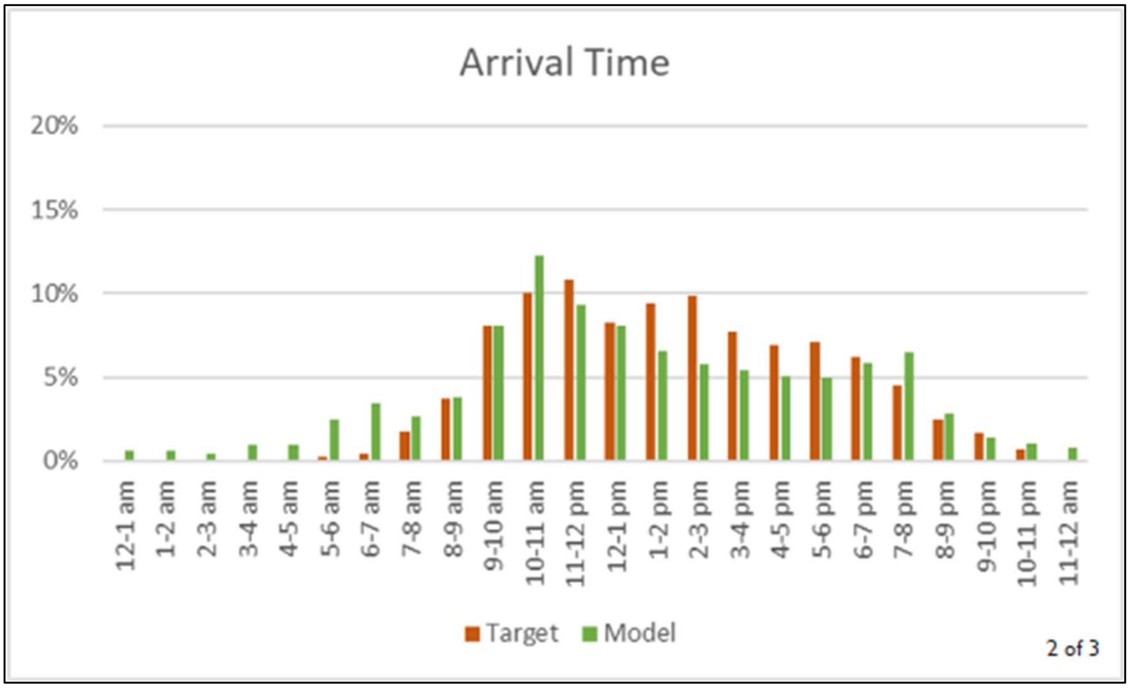


Figure 13-4: Shopping Tour Time of Day Choice




Arrival Time
20%
15%
10%
5%
0%
12-1 am
1-2 am
2-3 am
3-4 am
4-5 am
5-6 am
6-7 am
7-8 am
8-9 am
9-10 am
10-11 am
11-12 pm
12-1 pm
1-2 pm
2-3 pm
3-4 pm
4-5 pm
5-6 pm
6-7 pm
7-8 pm
8-9 pm
9-10 pm
10-11 pm
11-12 am
Target
Model
2 of 3

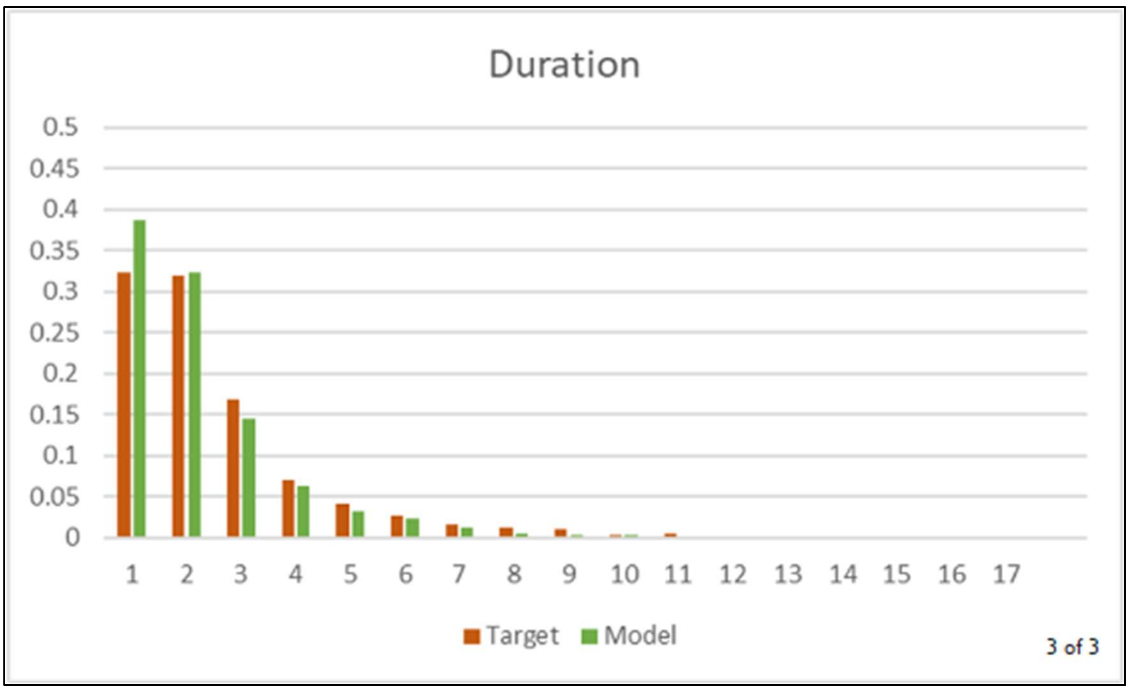
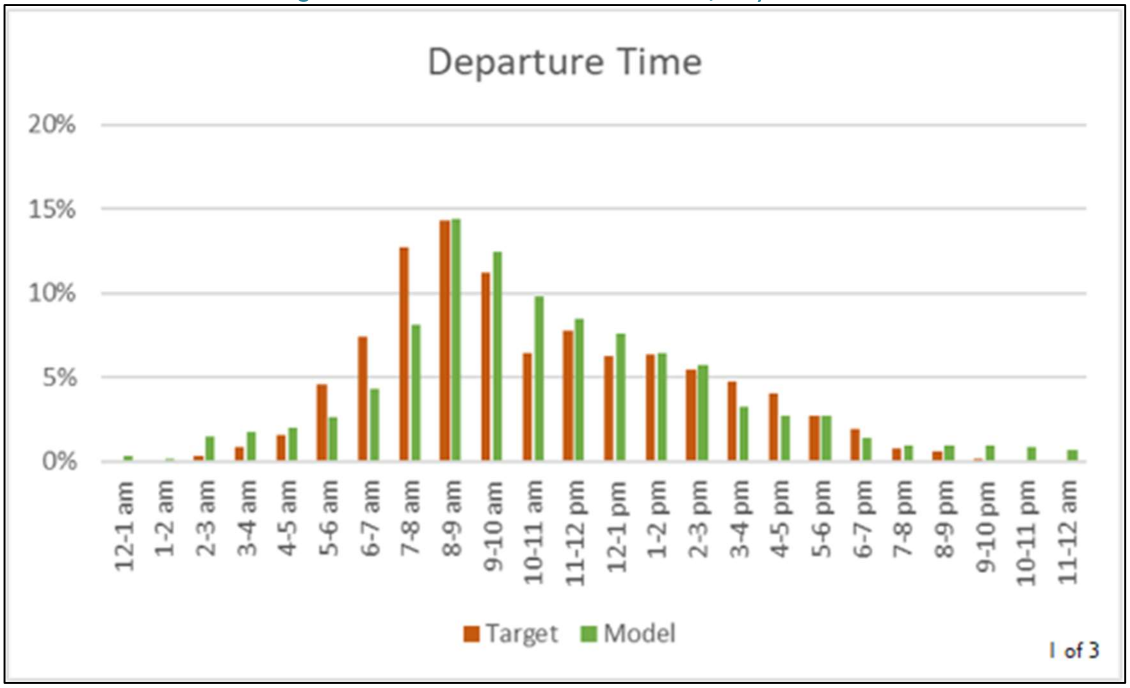
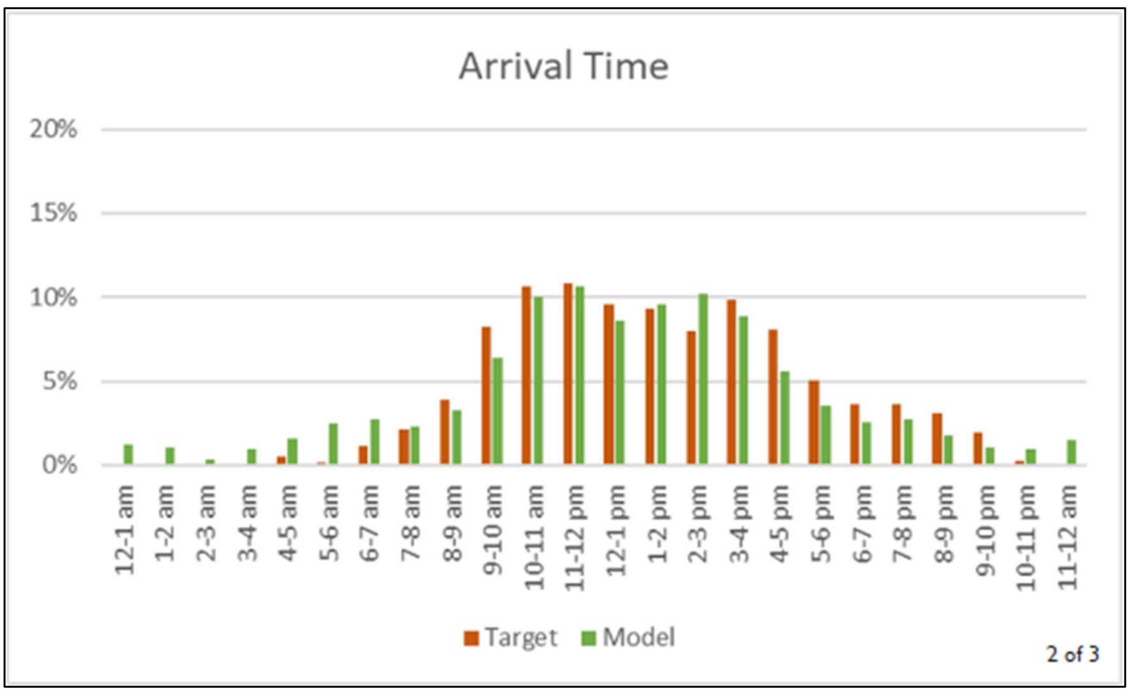

Duration
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
Target
Model
3 of 3

Figure 13-5: Maintenance Tour Time of Day Choice





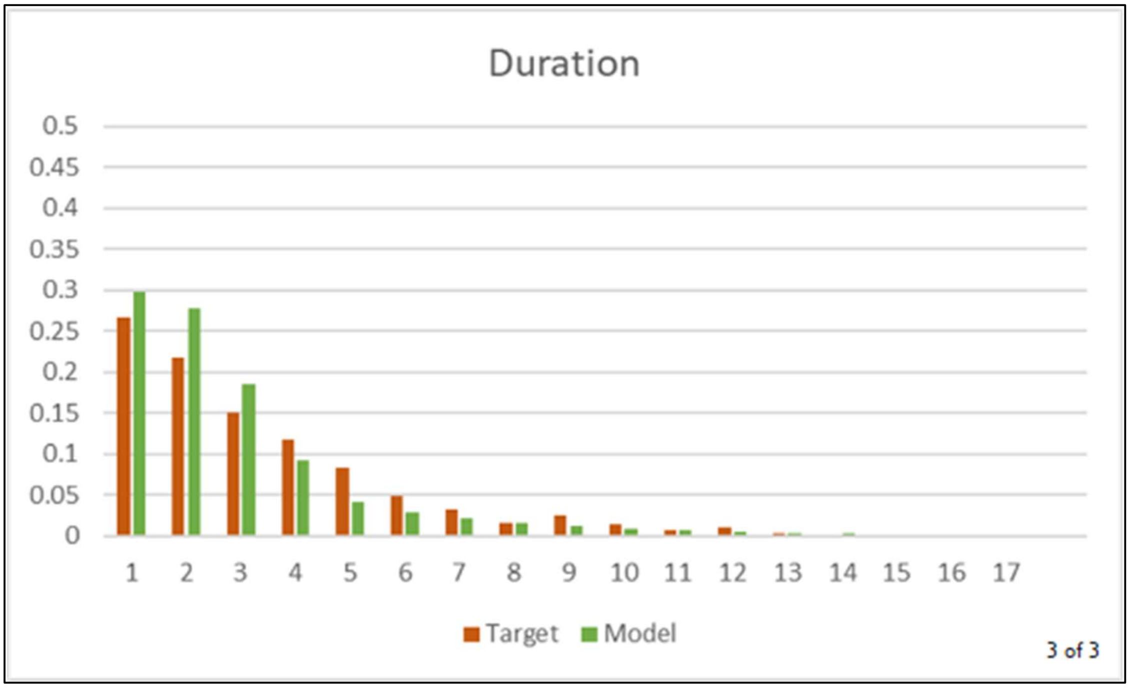
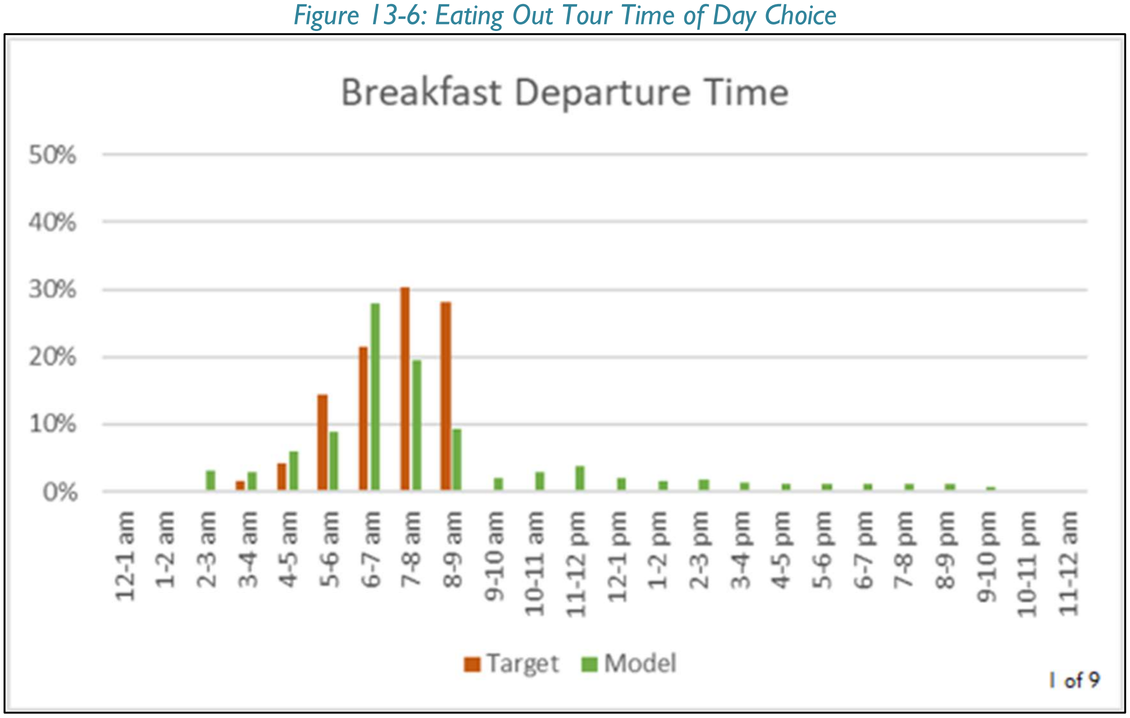
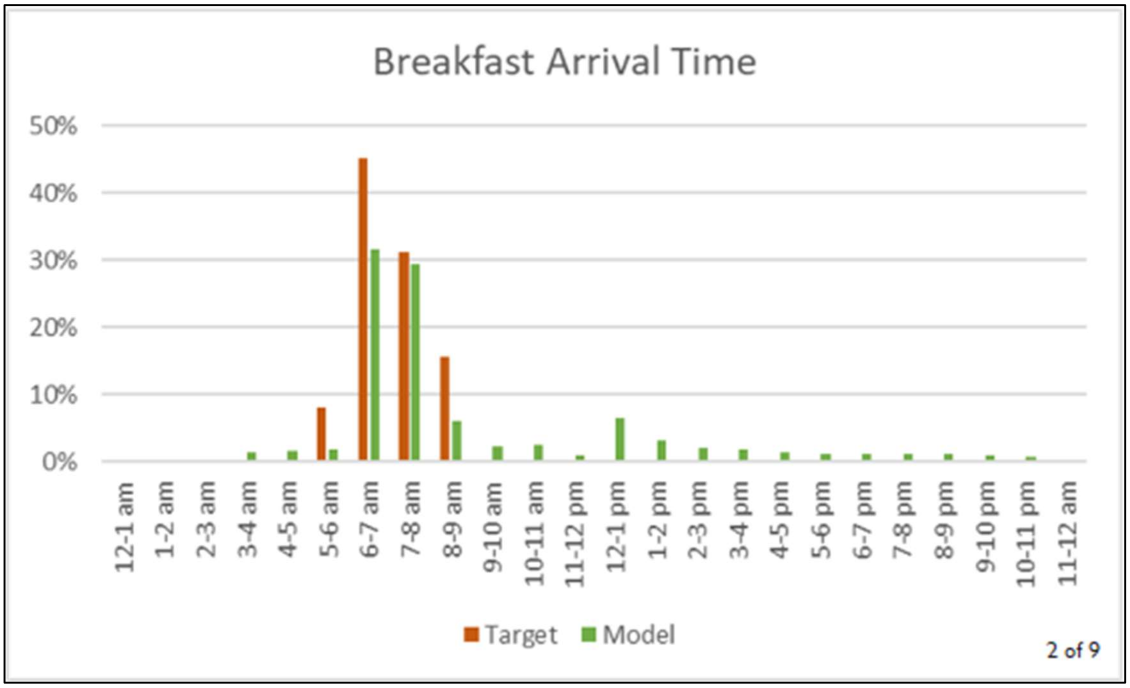
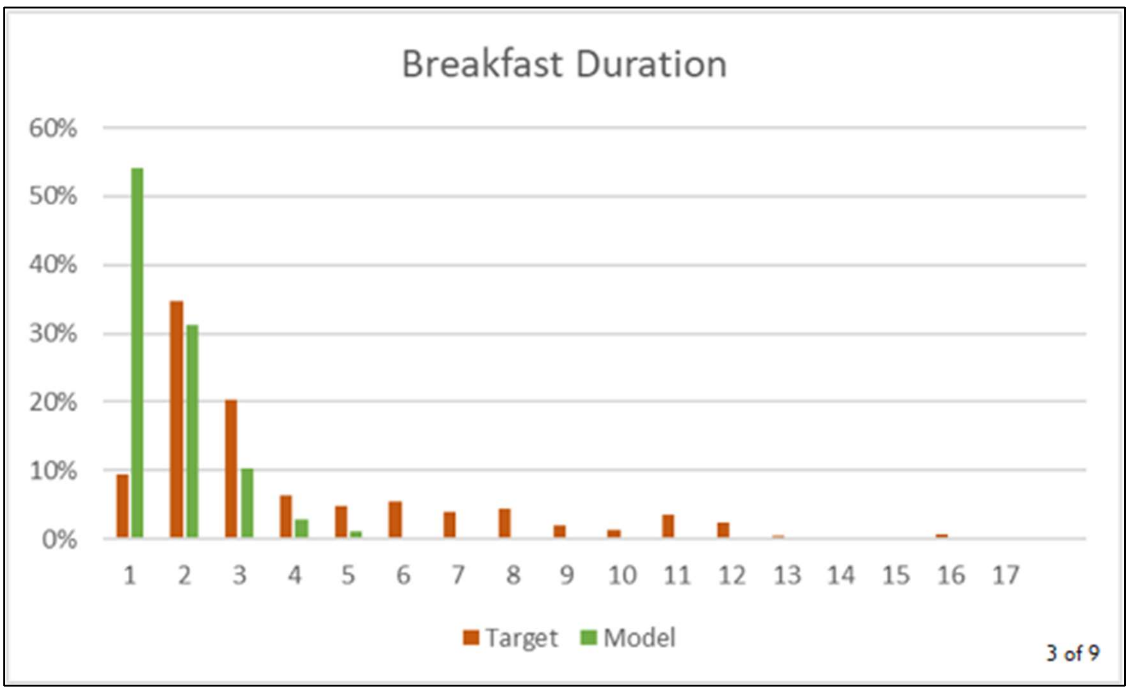
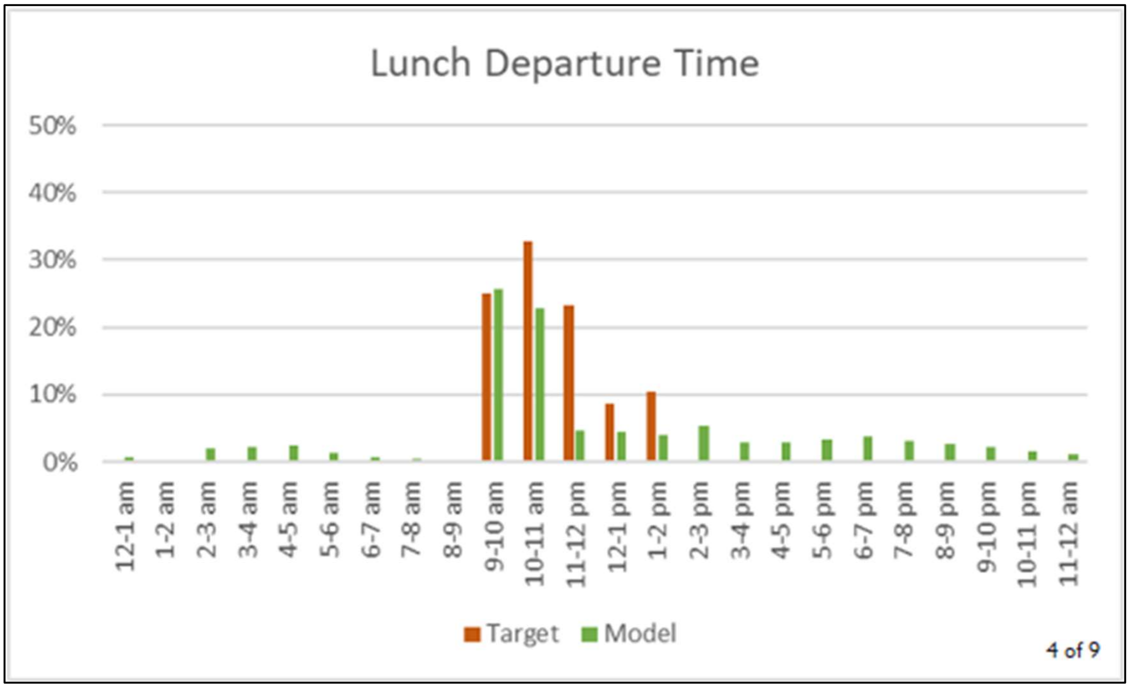


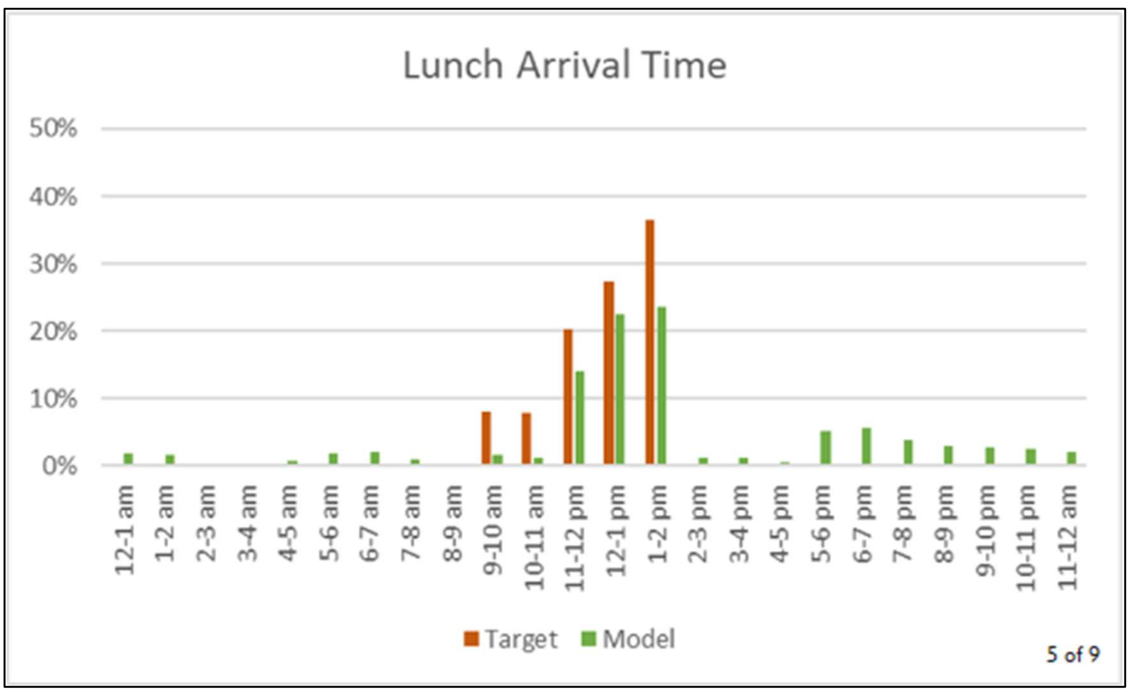
Figure 13-6: Eating Out Tour Time of Day Choice

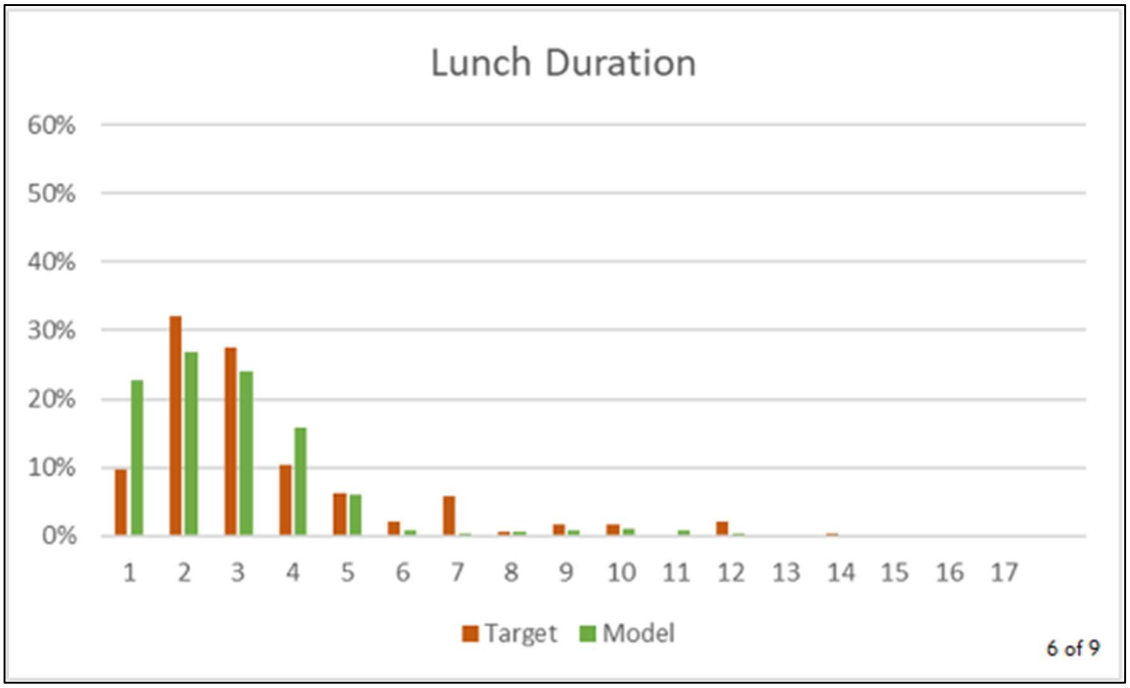


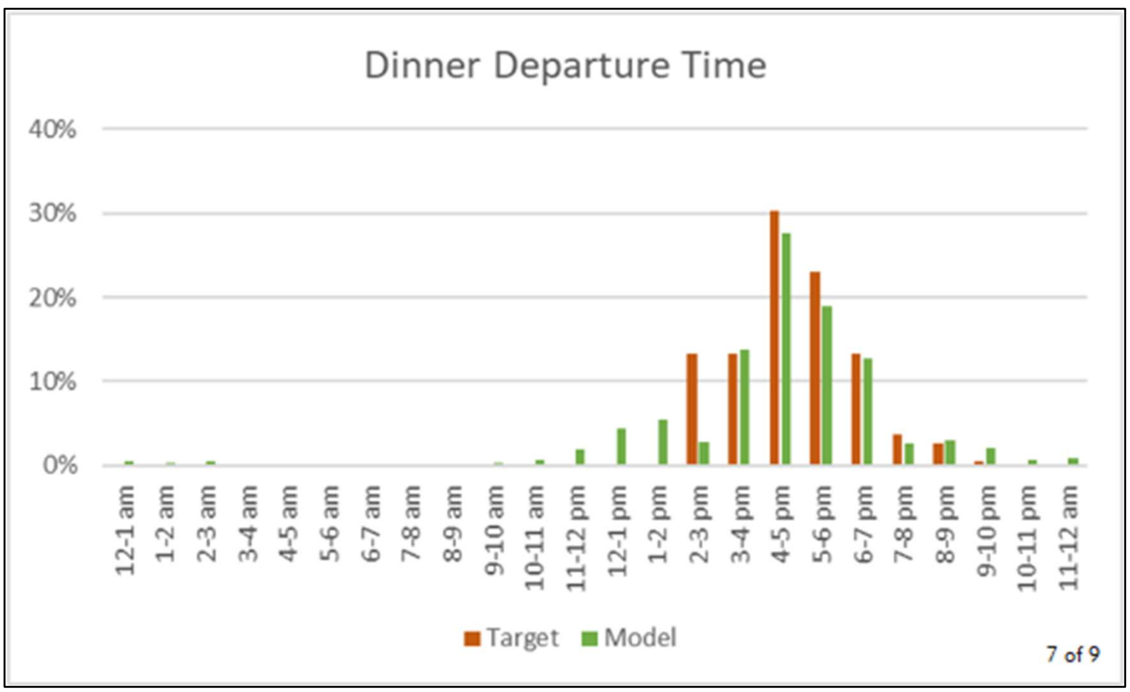

Breakfast Arrival Time
50%
40%
30%
20%
10%
0%
12-1 am
1-2 am
2-3 am
3-4 am
4-5 am
5-6 am
6-7 am
7-8 am
8-9 am
9-10 am
10-11 am
11-12 pm
12-1 pm
1-2 pm
2-3 pm
3-4 pm
4-5 pm
5-6 pm
6-7 pm
7-8 pm
8-9 pm
9-10 pm
10-11 pm
11-12 am
Target
Model
2 of 9

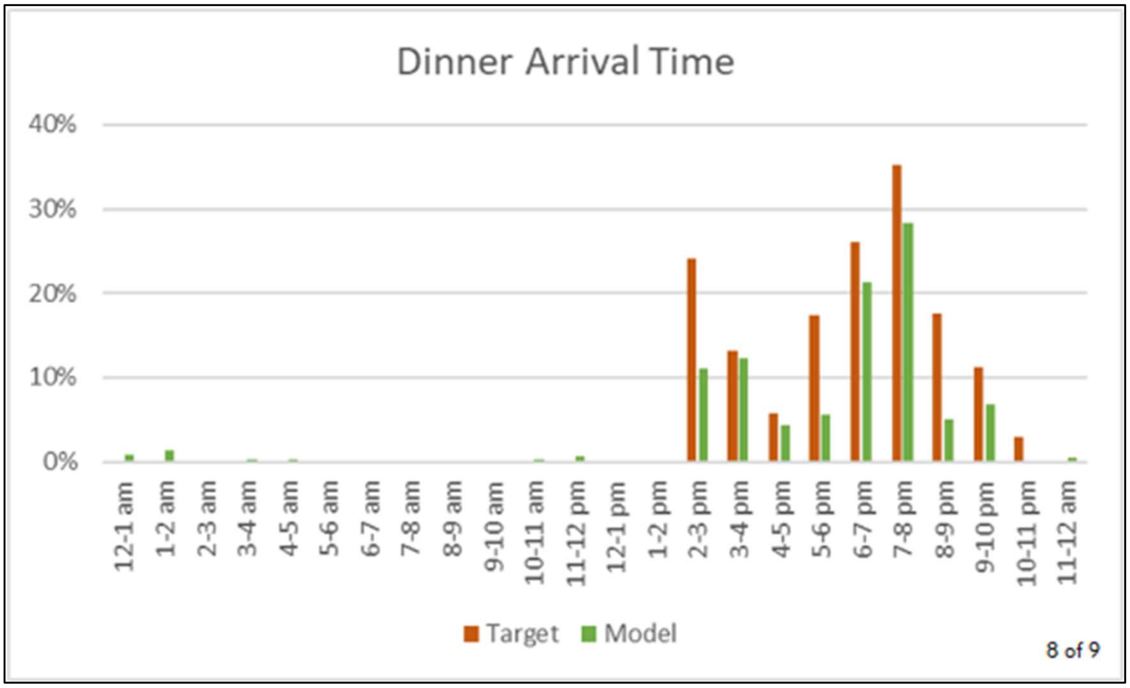

Breakfast Duration
60%
50%
40%
30%
20%
10%
0%
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
Target
Model
3 of 9


Lunch Departure Time
50%
40%
30%
20%
10%
0%
12-1 am
1-2 am
2-3 am
3-4 am
4-5 am
5-6 am
6-7 am
7-8 am
8-9 am
9-10 am
10-11 am
11-12 pm
12-1 pm
1-2 pm
2-3 pm
3-4 pm
4-5 pm
5-6 pm
6-7 pm
7-8 pm
8-9 pm
9-10 pm
10-11 pm
11-12 am
Target
Model
4 of 9


Lunch Arrival Time
50%
40%
30%
20%
10%
0%
12-1 am
1-2 am
2-3 am
3-4 am
4-5 am
5-6 am
6-7 am
7-8 am
8-9 am
9-10 am
10-11 am
11-12 pm
12-1 pm
1-2 pm
2-3 pm
3-4 pm
4-5 pm
5-6 pm
6-7 pm
7-8 pm
8-9 pm
9-10 pm
10-11 pm
11-12 am
Target
Model
5 of 9


Lunch Duration
60%
50%
40%
30%
20%
10%
0%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
Target
Model
6 of 9


Dinner Departure Time
40%
30%
20%
10%
0%
12-1 am 1-2 am 2-3 am 3-4 am 4-5 am 5-6 am 6-7 am 7-8 am 8-9 am 9-10 am 10-11 am 11-12 pm 12-1 pm 1-2 pm 2-3 pm 3-4 pm 4-5 pm 5-6 pm 6-7 pm 7-8 pm 8-9 pm 9-10 pm 10-11 pm 11-12 am
Target
Model
7 of 9


Dinner Arrival Time
40%
30%
20%
10%
0%
12-1 am
1-2 am
2-3 am
3-4 am
4-5 am
5-6 am
6-7 am
7-8 am
8-9 am
9-10 am
10-11 am
11-12 pm
12-1 pm
1-2 pm
2-3 pm
3-4 pm
4-5 pm
5-6 pm
6-7 pm
7-8 pm
8-9 pm
9-10 pm
10-11 pm
11-12 am
Target
Model
8 of 9

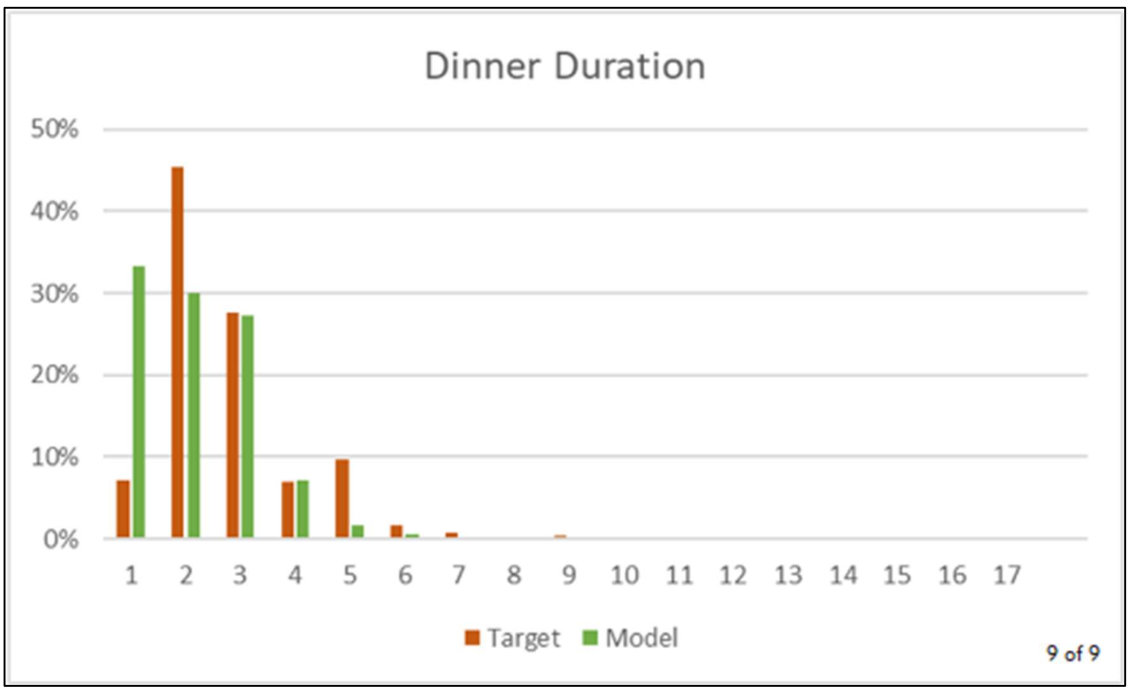
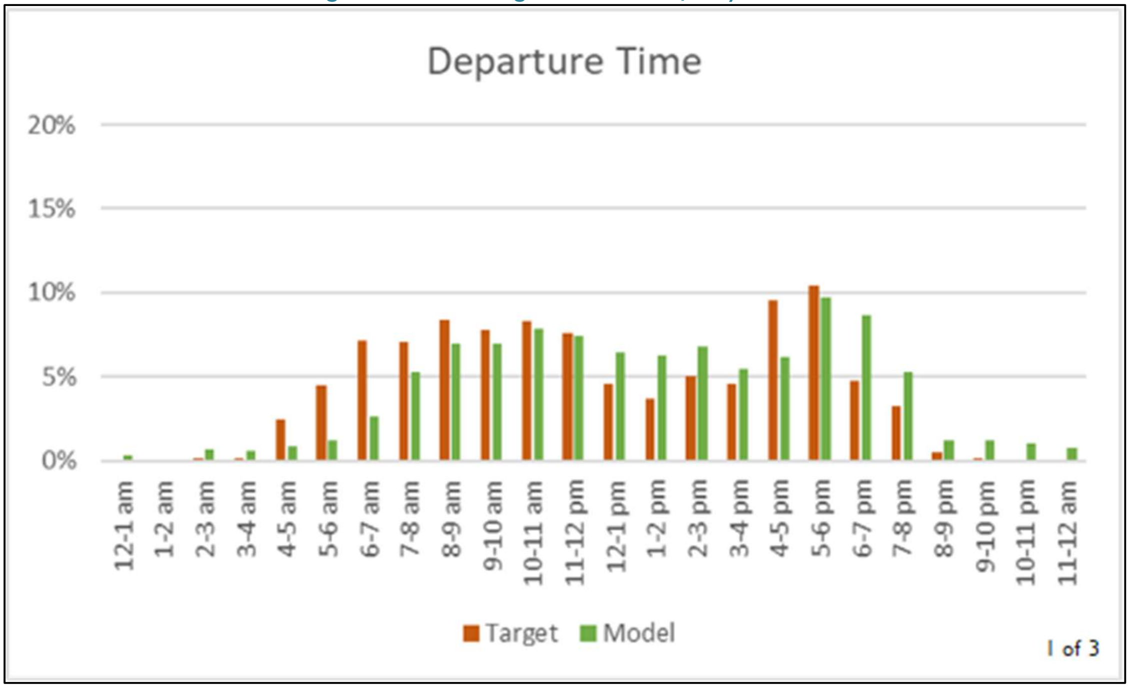
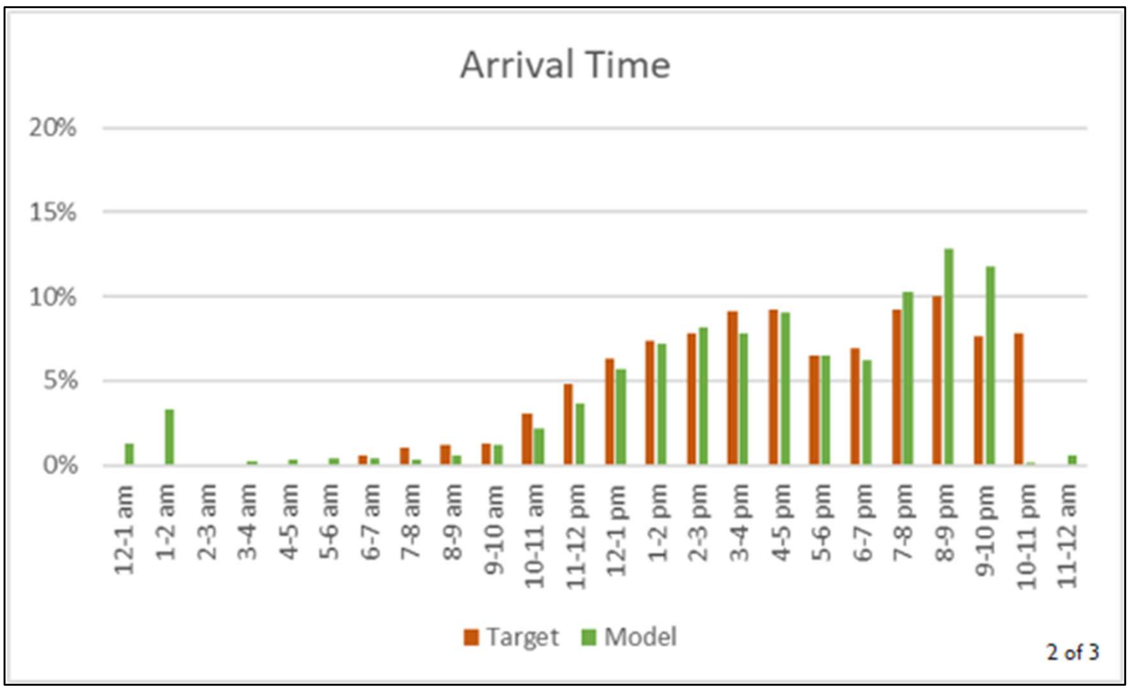

Dinner Duration
50%
40%
30%
20%
10%
0%
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
Target
Model
9 of 9

Figure 13-7: Visiting Tours Time of Day Choice





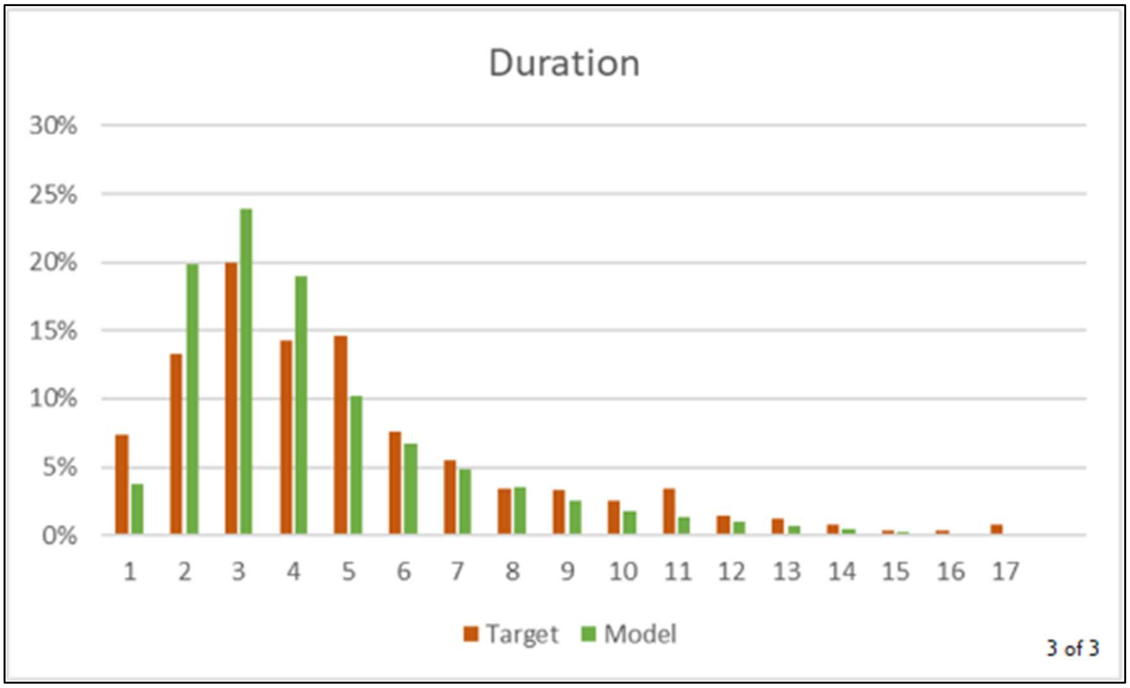
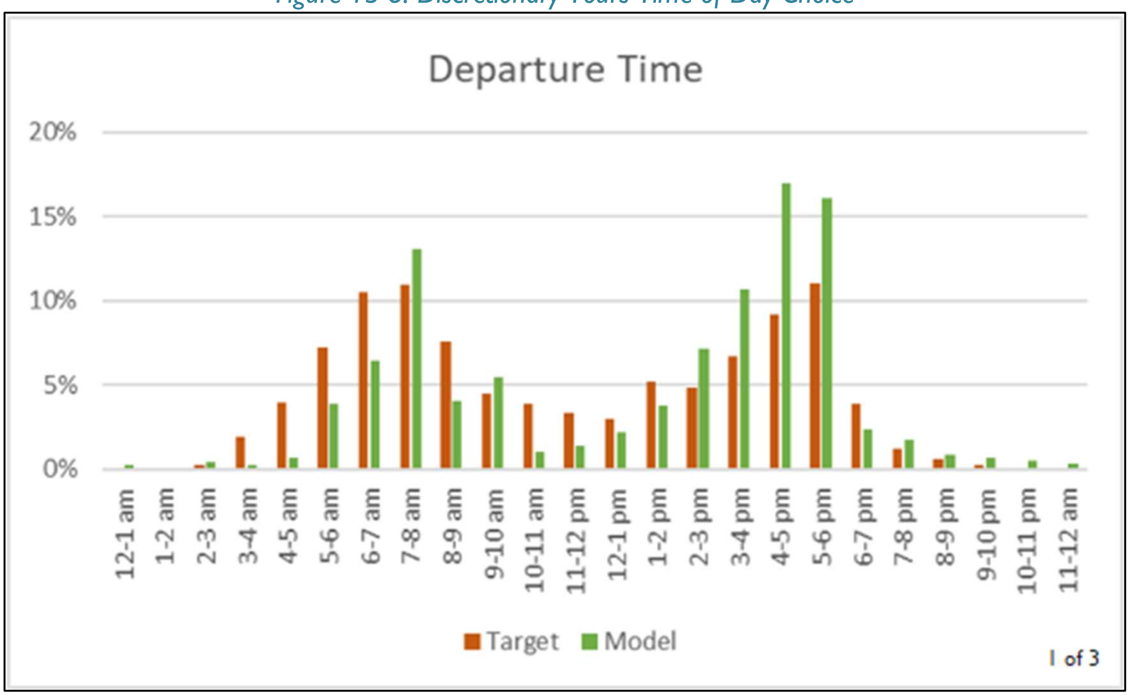
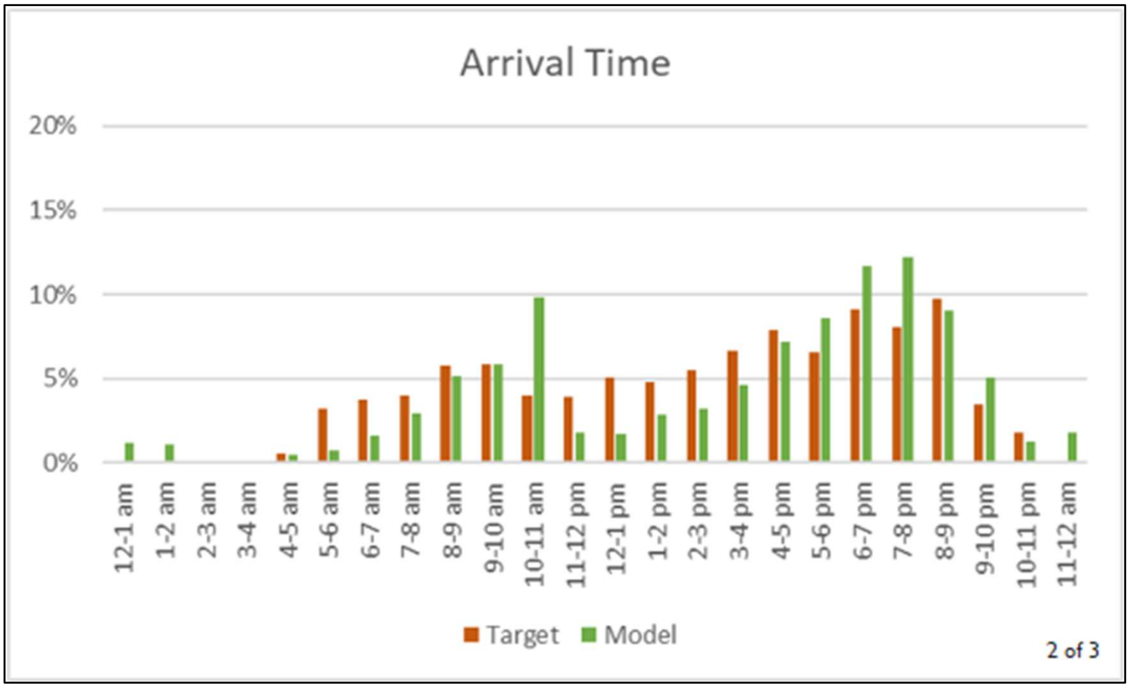
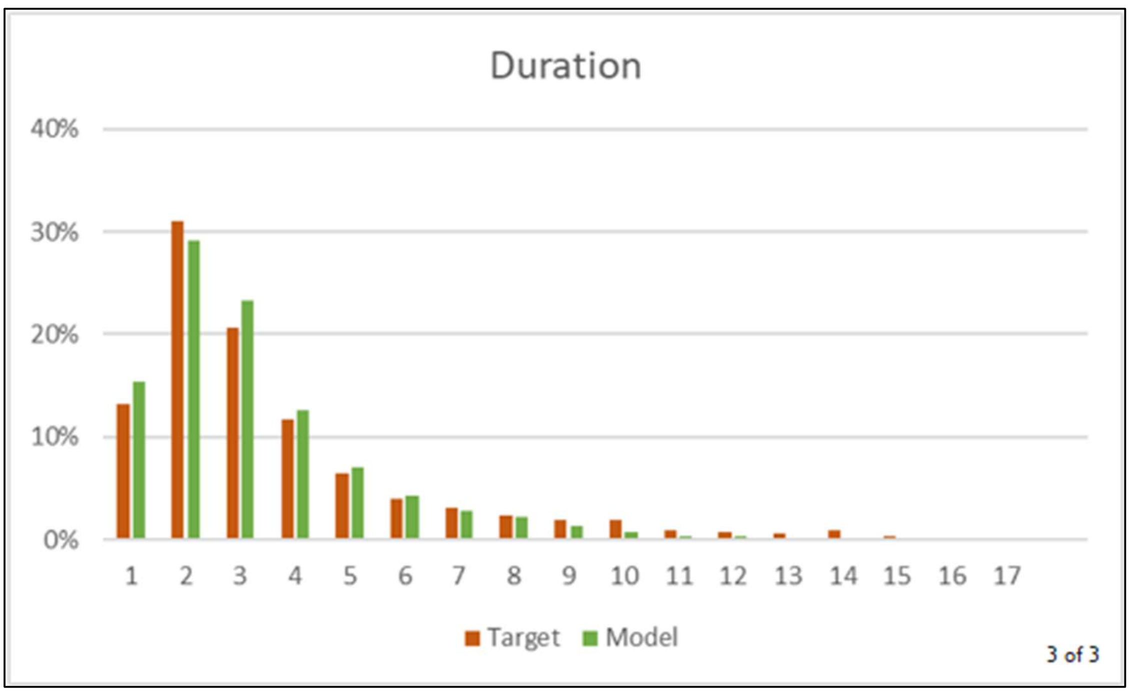


Figure 13-8: Discretionary Tours Time of Day Choice




Arrival Time
20%
15%
10%
5%
0%
12-1 am
1-2 am
2-3 am
3-4 am
4-5 am
5-6 am
6-7 am
7-8 am
8-9 am
9-10 am
10-11 am
11-12 pm
12-1 pm
1-2 pm
2-3 pm
3-4 pm
4-5 pm
5-6 pm
6-7 pm
7-8 pm
8-9 pm
9-10 pm
10-11 pm
11-12 am
Target
Model
2 of 3


Duration
40%
30%
20%
10%
0%
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
Target
Model
3 of 3

Chapter 14 Mode Choice

Introduction

In the SCAG ABM, the tour-level and trip-level mode choices are integrated in a network combinatorial representation that considers all feasible trip mode combinations on the tour. The model exhibits the following desirable properties:

- Ensures full consistency between the tour-level and trip-level mode choices considering the locations of all stops on the tour,
- Accounts for multiple combinatorial constraints on available trip modes by explicitly tracking car status at each trip end,
- Integrates multi-modal combinations, and specifically, PNR lot location choices into the trip mode choice structure in a consistent way for the entire tour,
- Avoids explicit enumeration of all possible trip mode combinations by applying an efficient network shortest path algorithm in model application, and a parsimonious choice set structure for each trip in model estimation,
- Accounts for differential similarities between trip mode combinations by simulating correlated error terms for tour modes from trip-mode error terms.

Observed Tour Mode Combinations

The model considers a total of 14 trip modes (m), shown in Table 14-1. The mode of a tour depends on the modes observed in all trips that comprise the tour, and is defined using priority rules. Typically more than 70% of all trips in a tour exhibit the same mode. This is especially so for simple one-destination tours (i.e., two trips in the tour). There remains however a large number of cases, especially complex multi-destination tours, where the tour mode combination includes more than one mode.

In the combinatorial mode choice model, consistent tour mode combinations emerge by tracking car status through the trip chain. At any trip origin or destination, the car status (s) is classified into 4 possible states:

"Car from home" which means that until this point the car was used on all preceding trips and has never been parked outside the home, hence the car is available for the subsequent trip.

"Car parked" which means that car was used originally (at least for the first trip from home) but it was subsequently parked outside home on one of the preceding trips, hence the car is not available for the subsequent trip.

"Car from parking" which means that car was parked earlier on this tour but then it was taken upon return trip to the parking lot and is available for the subsequent trip.

"No car on tour" which means that a car was not used for the very first trip on the tour and hence it is not available for any subsequent trip.

Tracking car status defines many logical constraints on the trip mode choice, as shown in Table 14-1. For example, if the car status at the trip origin is car parked, then the Driver trip modes are not available for the trip. Since car status at trip destination defines the car status at the origin of the next trip, this creates a framework for describing all feasible trip mode combination.

Table 14-1: Feasible Combinations of Trip Origin Car Status, Trip Mode, & Trip Destination Car Status

Car status at trip origin				**Trip mode**	**Car status at trip destination**			
Car from home (1)	**Car from parking (3)**	**Car parked (2)**	**No car on tour (4)**		**(1)**	**(3)**	**(2)**	**4**
✓	✓			1=SOV/driver	✓	✓	✓	
✓	✓			2=HOV2/driver	✓	✓	✓	
✓	✓			3=HOV3+/driver	✓	✓	✓	
			✓	4=HOV/passenger				✓
		✓	✓	5=Conventional transit/walk		✓	✓	✓
			✓	6=Conventional transit/KNR				✓
		✓		7=Conventional transit/PNR		✓		
		✓	✓	8=Premium transit/walk		✓	✓	✓
			✓	9=Premium transit/KNR				✓
		✓		10=Premium transit/PNR		✓		
		✓	✓	11=Walk		✓	✓	✓
		✓	✓	12=Bike		✓	✓	✓
			✓	13=Taxi/TNC				✓
			✓	14=School bus				✓

Formulation of Feasible Tour Mode Combinations

A tour mode combination is considered feasible if it obeys the system of logical constraints imposed across multiple dimensions. Basic feasibility rules are applied in a framework of sequential joint choice of mode and destination car status for each trip, conditional upon the car status at the trip origin. The application of feasibility rules for the entire sequence of trips in a tour ensures that no trip sequence includes impossible trip mode combinations.

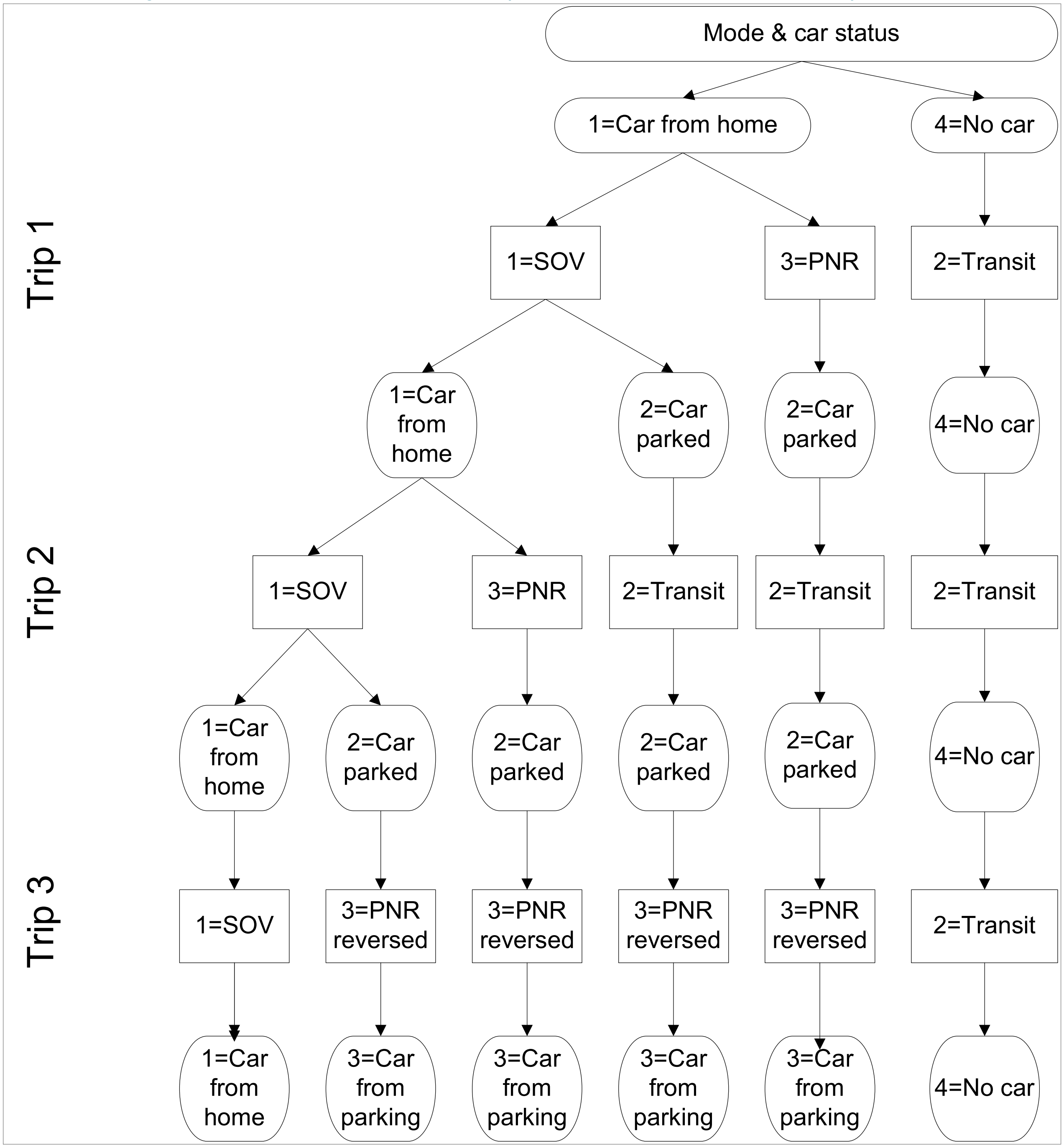
There are additional rules that further truncate the possible trip mode combinations, imposed using the same technique. These feasibility rules are applied separately for outbound and inbound half-tours, they constrain the number of car status switches from "car parked" to "car from parking" and vice-versa, and they ensure that the car taken from home always arrives back home. The usual set of trip-level mode constraints are also applied, such as transit availability based on level-of-service. Person-level constraints further truncate the set of possible mode combinations. Person-level constrains include for example car availability, driver license, participation in joint travel, etc.

The feasibility constraints can be viewed as a decision-making tree, where the modes available for each subsequent trip are branched out of the chosen modes and car statuses for the previous trips. For illustration purposes, consider the example of a 3-trip home-based tour with three possible modes (1=SOV, 2=Walk to transit, 3=PNR to transit), shown in Figure 14-1. The example assumes that the first two trips (Trip 1 and Trip 2) occur in the outbound direction while the third trip occurs in the inbound direction (Trip 3). For the outbound trips, there is the option of PNR switching to car status 2 (essentially, leaving the car at the PNR lot and continuing by transit), while for the inbound trip the corresponding option is riding transit and picking up the car from the PNR lot, which is identified as reverse PNR with a switch to car status 1.

At the beginning of the tour (origin of Trip 1) only two car status are possible (1=car from home and 4=no car on tour). The possible modes for Trip 1 are SOV and PNR to transit (conditional on car status 1) and Walk to transit (conditional on car status 4). At the end of Trip 1, all possible car status can be readily identified, based on the possible Trip 1 modes. Car status at the destination of Trip 1 defines the possible trip modes for Trip 2. The end of Trip 2 is the primary destination, so as indicated above, the next trip is in the inbound direction and therefore only reverse PNR is available. At the end of the tour, only three car status options (1, 3, and 4) are available.

This example illustrates the importance of a properly constraining trip mode and car status combinations. While a simplified Cartesian consideration of all possible trip mode and car status combinations results in 3^3=27 combinations, the actual number of feasible combinations given logical car tracking is only 6.

Figure 14-1: Feasible Combinations of Trip Modes and Car Statuses on a 3-Trip Tour



Trip Mode Utility Function

The combinatorial trip mode utility exhibits two important differences relative to the utility of a standard (logit) mode choice model.

First, the combinatorial trip mode utility includes entire-tour effects and transaction costs associated with mode switches. Utility $V_t(m)$ is dependent on the choices implied by previous trips in the feasible mode and car status combination. The most statistically significant mode transaction effects include:

Transit mode switching penalties that reflect fare discounts and/or transit pass consideration and make transit mode fare for the given trip a function of the previously chosen transit modes.

Car occupancy switching penalties that reflect systematic car occupancy changes by direction where passenger drop-offs happen mostly in the direction from home, while passenger pick-ups happen mostly in the direction towards home.

PNR symmetry, i.e., taking a car from the same parking lot it was originally parked; this utility component is not a statistically estimated penalty but a constraint on how LOS variables are calculated for the reversed PNR trip. Distance, travel time, and cost for inbound reversed PNR are conditional upon the chosen parking location in the outbound PNR trip. Since choice of both the outbound and reversed PNR trips are part of the feasible entire-tour alternative, the choice of PNR lot is also somewhat optimized.

Second, the utility function for each trip and mode is structured in such a way that it is always negative $(V_t(m) < 0)$. This is essential for an efficient application algorithm that borrows from the network shortest path techniques. For this reason, the mode utility structure is specified to have only negative constants and negative coefficients on positive variables (such as travel time and cost).

As in the case of a logit model, trip mode utility has both deterministic and random components. The deterministic component is a function of LOS, mode-specific constants, and person, household or trip attributes. The random component is assumed to be Gumbel distributed.

Several tour mode combinations have common components, and therefore cannot be considered as independent alternatives. For example, in Table 14-1, three of the six feasible tour mode combinations include reverse PNR for Trip 3. These common components are known as overlapping routes in the network literature. Overlapping routes will have common random terms and will be more correlated with each other than with non-overlapping routes. This correlation is addressed with an additive-by-link error term, rather than through a complex entire-route random term.

Model Calibration and Application

Pre-Mode Choice Checks

The number of person and vehicle trips in each time periods were checked before validation and calibration of mode choice in Table 14-2.

Table 14-2: Person and Vehicle Trip Diurnal Distribution

Time Period	Person Trips			Vehicle Trips		
	Total Predicted	Predicted Share	Observed Share	Total Predicted	Predicted Share	Observed Share
AM	15,038,892	22%	21%	9,045,059	21%	21%
MD	18,851,096	28%	35%	13,215,480	31%	38%
PM	20,634,576	30%	29%	12,267,245	29%	27%
EV	6,392,099	9%	7%	3,527,009	8%	7%
NT	7,274,394	11%	7%	4,494,880	10%	8%
Total	68,191,057	100%	100%	42,549,673	100%	100%

Built Environment Effects

Several built environment variables were added to the mode choice model, with coefficients calibrated using the CHTS. These variables are important because they give the model sensitivity to the land use strategies that will be examined as part of the 2024 RTP/SCS. The calibration results for the built environment variables are shown in Table 14-3 to Table 14-4 respectively for residential population density, and bike lane density.

Table 14-3: Mode Share by Residential Population Density

Mode	Low (1)	2	3	4	5	High (6)
Driver, 1-person	41.7%	39.8%	40.1%	39.0%	35.7%	28.8%
Driver, 2-persons	13.5%	14.7%	12.8%	12.0%	10.9%	8.3%
Driver, 3+ persons	9.0%	9.2%	9.2%	8.6%	7.1%	5.3%
Passenger, HOV	26.9%	29.9%	26.8%	26.2%	25.1%	22.5%
Transit, walk access	0.6%	0.6%	1.4%	2.3%	6.1%	11.4%
Transit, KNR Access	0.2%	0.1%	0.2%	0.2%	0.2%	0.2%
Transit, PNR Access	0.1%	0.0%	0.2%	0.1%	0.2%	0.4%
TNC	0.4%	0.2%	0.3%	0.5%	0.4%	0.3%
Walk	4.5%	4.2%	7.1%	8.7%	11.7%	19.7%
Bike	0.5%	0.7%	1.3%	1.7%	1.9%	2.2%
School bus	2.7%	0.6%	0.6%	0.9%	0.8%	0.6%

Table 14-4:: Mode Share by Bike Lane Density

Mode	Low (1)	2	3	4	5	High (6)
Driver, 1-person	44.1%	44.1%	43.6%	43.2%	41.0%	35.3%
Driver, 2-persons	12.1%	11.8%	11.6%	11.5%	11.4%	11.4%
Driver, 3+ persons	8.8%	8.9%	8.8%	8.8%	8.8%	8.5%

Mode	Low (1)	2	3	4	5	High (6)
Passenger, HOV	26.9%	25.9%	25.2%	24.8%	24.8%	24.2%
Transit, walk access	0.3%	0.4%	0.5%	0.8%	1.6%	4.2%
Transit, KNR Access	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%
Transit, PNR Access	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%
TNC	1.5%	1.4%	1.4%	1.2%	1.2%	0.9%
Walk	4.5%	5.9%	7.3%	8.0%	9.2%	12.9%
Bike	0.7%	0.8%	1.0%	1.1%	1.2%	0.9%
School bus	1.1%	0.8%	0.7%	0.6%	0.6%	0.8%

A comparison of the observed and estimated mode shares is shown Table 14-5, for the major tour purpose classifications.

Table 14-5: Trip Mode Shares

Trip mode		Driver, 1-person	Driver, 2-persons	Driver, 3+ persons	Passenger, HOV	Transit, walk access	Transit, KNR Access	Transit, PNR Access	Walk	Bike	TNC	School bus
Work Tours	**Obs.**	72.00%	8.50%	4.10%	7.40%	2.30%	0.20%	0.50%	3.40%	0.80%	0.50%	0.20%
	Est.	74.90%	7.80%	5.70%	4.60%	2.20%	0.10%	0.10%	3.40%	1.30%	0.00%	0.00%
School Tours	**Obs.**	1.30%	0.60%	0.30%	69.80%	2.20%	0.20%	0.00%	17.80%	1.20%	0.10%	6.70%
	Est.	1.90%	0.60%	0.10%	70.90%	0.30%	0.00%	0.00%	18.80%	1.40%	0.00%	5.90%
College Tours	**Obs.**	46.50%	7.20%	2.50%	19.50%	12.20%	1.20%	0.20%	6.60%	1.80%	0.70%	1.60%
	Est.	49.40%	8.10%	4.20%	16.70%	3.70%	0.60%	0.00%	13.90%	3.30%	0.00%	0.00%
Joint Non-Mand. Tours	**Obs.**	0.70%	26.00%	17.60%	54.60%	0.10%	0.00%	0.00%	0.70%	0.00%	0.20%	0.00%
	Est.	0.00%	20.90%	15.10%	54.50%	0.80%	0.00%	0.00%	2.70%	0.00%	6.00%	0.00%
Individual Non-Mand. Tours	**Obs.**	44.00%	9.70%	4.90%	19.90%	4.00%	0.00%	0.00%	14.20%	2.70%	0.50%	0.10%
	Est.	52.00%	9.30%	5.00%	16.60%	1.80%	0.00%	0.00%	13.50%	1.70%	0.10%	0.00%
School Pickup/ Dropoff Tours	**Obs.**	31.90%	30.90%	36.30%	0.90%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Est.	35.20%	30.70%	29.00%	3.40%	0.90%	0.00%	0.00%	0.50%	0.30%	0.00%	0.00%
All Tours	**Obs.**	38.80%	12.50%	8.50%	26.70%	2.50%	0.20%	0.10%	8.00%	1.30%	0.40%	1.00%
	Est.	40.20%	12.20%	8.90%	25.80%	1.40%	0.00%	0.00%	8.40%	1.20%	1.10%	0.70%

Table 14-6 showcase work trip mode chare by car sufficiency and income group. Car sufficient households are the households than own equal or more vehicles compared to the drivers while car insufficient households have less vehicles compared to the drivers.

Table 14-6: Work Trip Mode Share by Car Sufficiency and Income

Trip mode	Zero Cars		Car Insufficient		Car Sufficient & Income<$35k		Car Over-Sufficient & Income: $35k-$75k		Car Sufficient and Income > $75K	
	Obs.	Est.	Obs.	Est.	Obs.	Est.	Obs.	Est.	Obs.	Est.
Driver, 1-person	8.7%	0.0%	43.6%	67.3%	69.1%	68.0%	73.8%	78.4%	74.9%	81.3%
Driver, 2-persons	2.0%	0.0%	11.2%	9.9%	9.3%	10.3%	8.3%	7.5%	8.5%	7.0%
Driver, 3+ persons	3.0%	0.0%	0.9%	7.0%	3.5%	6.8%	5.2%	5.8%	4.0%	5.3%
Passenger, HOV	17.4%	50.7%	19.6%	5.4%	9.7%	5.4%	7.0%	3.3%	6.1%	2.8%
Transit, walk access	47.7%	22.2%	10.4%	2.8%	3.8%	2.5%	1.5%	1.2%	0.8%	0.8%
Transit, KNR Access	0.0%	0.9%	0.7%	0.1%	0.2%	0.1%	0.3%	0.1%	0.7%	0.1%
Transit, PNR Access	1.0%	0.0%	0.8%	0.1%	0.2%	0.1%	0.2%	0.1%	0.1%	0.1%
Walk	14.4%	16.1%	8.1%	5.9%	1.7%	5.2%	2.9%	2.6%	3.5%	1.7%
Bike	5.1%	10.1%	2.9%	1.3%	0.8%	1.6%	0.5%	1.0%	0.8%	0.9%
TNC	0.5%	0.1%	1.9%	0.0%	0.1%	0.0%	0.3%	0.0%	0.6%	0.0%
School bus	0.0%	0.0%	0.0%	0.0%	1.7%	0.0%	0.0%	0.0%	0.0%	0.0%

Chapter 15 Heavy Duty Truck Model

Introduction

This Chapter addresses the various elements of the Heavy Duty Truck (HDT) Model, including internal and external HDT trips, Port HDT trips and Intermodal HDT trips. Included is a description of the model inputs, an overview of the various model components, and a summary of the 2019 HDT Model results[1].

HDT Model Structure

Figure 15-1 provides a flow chart of the overall structure of the HDT model. The model forecasts trips for three HDT weight classes: light-heavy (8,500 to 14,000 lbs. gross vehicle weight (GVW); medium-heavy (14,001 to 33,000 lbs. GVW); and heavy-heavy (>33,000 lbs. GVW). The key components of the new HDT Model are the following:

> ***External Trip Generation and Distribution Model.*** This component estimates the trip table for all interregional truck trips that link Southern California with the rest of the nation. The updated external HDT model is based on variations of disaggregate supply chain models to better represent differences in the movements of each commodity and the linkage to industries within the SCAG region. The updated model is covering trucks origins and destinations outside the

1 Cambridge Systematics, Inc., *SCAG Task 4 Data Verification and Analysis – Final Report*, October 2010.

model region. The distribution of external flows are finally calibrated using sample of GPS probe data from year 2019.

Internal Trip Generation and Distribution Models. This component of the HDT Model estimates trip tables for intraregional trips. Trip generation is based on trip rates (number of trips per employee or household) for different land uses/industry sectors at the trip ends. The trip rates derived from establishment surveys, Transearch data and GPS data.

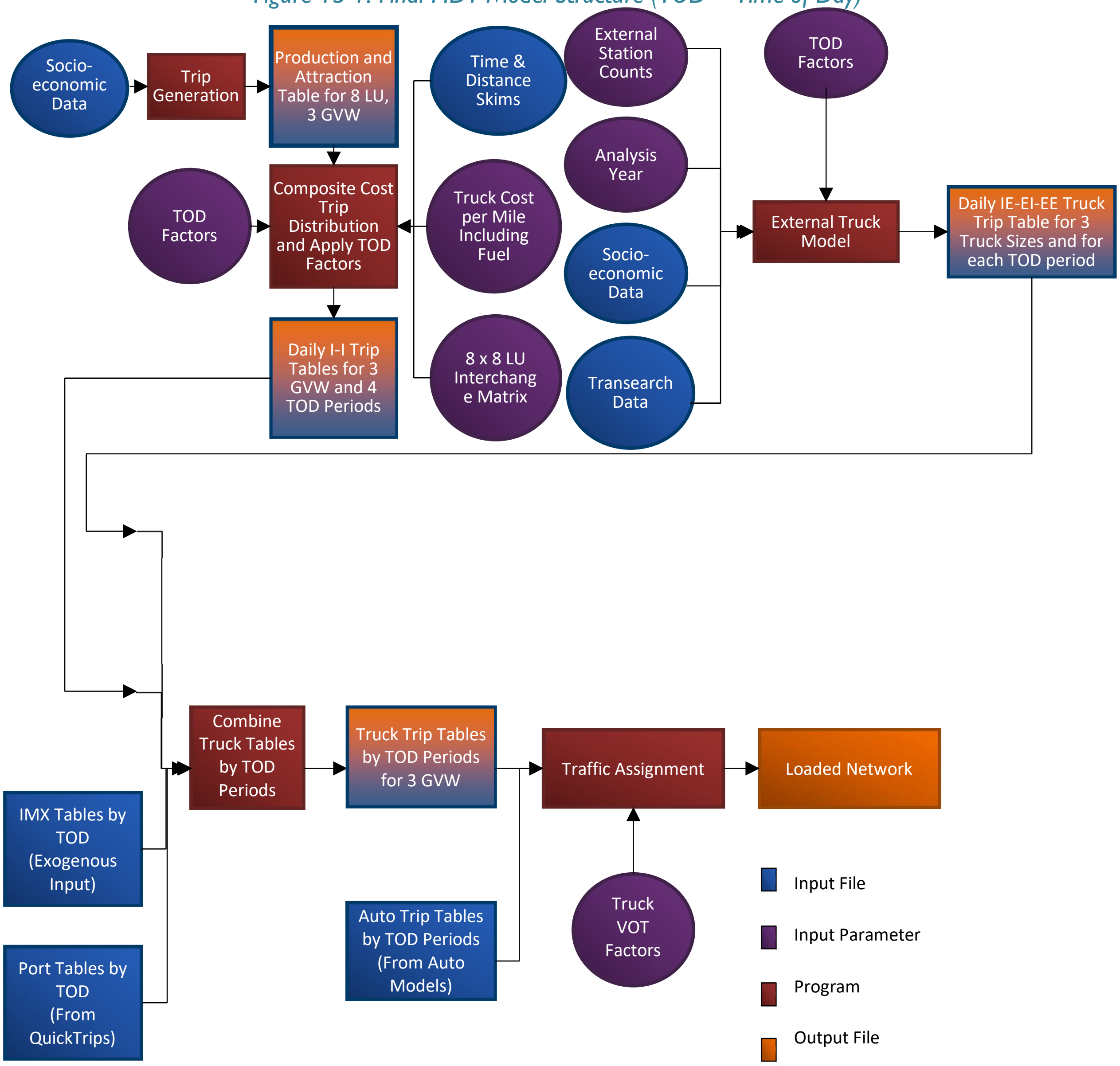
The trip distribution process was originally developed in 2008 by developing a matrix of factors that indicate the trip interchange relationships among different land use types (i.e., what fraction of trips originating at a land use such as manufacturing sites go to warehouses vs. other manufacturing sites, etc.). The GPS survey data was used to develop a series of gravity models for each truck class. This offers some of the benefits of tour-based models by directing trips from zone to zone based on logical relationships amongst land use types without the extensive data requirements (typically difficult to collect from trip diary surveys) that are required to support development of a full tour-based model. The original factors are further calibrated using recent 2019 GPS data.

Special Generator Trip Generation and Distribution Models. These models include the port model and the intermodal rail model. All of the input parameters to the port trip generation model were updated to reflect current port capacity improvements and throughput forecasts. This model update also implements a procedure to incorporate two types of secondary port truck trips. Transload secondary trips are cargo trips from intermediate handling locations (i.e., transloading sites where cargo is moved from international to domestic containers) to final destinations. Additionally, there are secondary repositioning movements of trucks associated with port truck trips. These movements include trips made by trucks that originated at a port but do not immediately return to a port. Similarly, secondary repositioning movements also include trips that travel to a location from a non-port zone prior to traveling to a port. Secondary transload trips are distributed by the port model using a combination of a gravity model and an intermodal railyard model. Secondary repositioning trips are allocated to other zones in the region using the gravity model distribution.

Trip Assignment. The model incorporates a multiclass assignment combining the truck trip tables with the passenger trip tables. Prior to assignment, the truck trip tables are converted to PCEs. The PCE factors were adapted from the Transportation Research Board (TRB) Highway Capacity Manual2 (HCM), and are a function of the percent truck volume and length and steepness of grades. Five time periods are used to assign truck trips, consistent with the auto trip assignment. Updated time-of-day factors were developed using data from permanent classification count stations, weigh-in-motion (WIM), and vehicle classification counts.

2 Highway Capacity Manual. Volume 2: Uninterrupted Flow. Transportation Research Board: Washington D.C., 2010.

Figure 15-1: Final HDT Model Structure (TOD = Time-of-Day)



INTERNAL HDT MODEL

Internal HDT Trip Generation Model

The internal truck trip generation model is land use-based, where trip rates are multiplied by employment by industry sector to obtain internal truck trip productions and attractions. All the internal truck travel in the region is associated with ten broad but distinct land uses, namely, households, agriculture, mining/construction, retail, manufacturing, transportation, wholesale, general warehousing, high cube warehousing, and other (service). The trip rates (i.e., truck trips per employee) were updated based on 2019 Transearch data and third-party truck GPS data. Trip rates for general warehousing and high cube warehousing were updated using a combination of establishment surveys and independent trip generation studies.

Land Use and Socioeconomic Data

The socioeconomic data used by the Internal HDT Model is consistent with those data used by the passenger model, except that the employment data are stratified into more employment categories. The 22 two-digit NAICS categories of employment were mapped to 9 categories to account for truck trip generation similarities. This employment category mapping is shown in Table 15-1. These stratified employment types, plus households, support ten land use purposes for the HDT trip generation models: Households, Agriculture, Mining/Construction, Retail, Governments, Manufacturing, Transportation, General Warehousing, High Cube Warehousing, Wholesale, and Other (service). The warehousing land use categories were separated from the transportation and utility category using data from secondary establishment surveys and warehousing studies.

Table 15-1: Aggregated Two-Digit NAICS Categories

Survey Number	Two-Digit	Two-Digit Description	ABM number	Aggregate Categories for Trip Generation Mode
1	11	Agriculture, Forestry, Fishing, and Hunting	1	Agriculture, Forestry, Fishing, and Hunting
2	21	Mining	2	Mining/Construction
3	22	Utilities	9	Other
4	23	Construction	2	Mining/Construction
5	31	Manufacturing	4	Manufacturing
6	42	Wholesale Trade	6	Wholesale Trade
7	44	Retail Trade	3	Retail Trade
8	45	Retail Trade	3	Retail Trade

Survey Number	Two-Digit	Two-Digit Description	ABM number	Aggregate Categories for Trip Generation Mode
9	48	Transportation and Warehousing	5	Transportation and Warehousing
10	49	Transportation and Warehousing	5	Transportation and Warehousing
11	51	Information Services	9	Other
12	52	Finance and Insurance	9	Other
13	53	Real Estates, and Rental and Leasing	9	Other
14	54	Professional, Scientific, and Technical Services	9	Other
15	55	Management of Companies and Enterprises	9	Other
16	56	Administrative and Support, and Waste Management and Remediation Services	9	Other
17	61	Educational Services	9	Other
18	62	Health Care, and Social Assistance	9	Other
19	71	Arts, Entertainment, and Recreation	9	Other
20	72	Accommodation, and Food Services	9	Other
21	81	Other Services (Except Public Administration)	9	Other

Internal HDT Trip Rates

Trip rates derived from TRANSEARCH data, and GPS data for each truck type. The TRANSEARCH data are provided as annual county level flows in tons and are converted to daily weekday flows using an annualization factor of 306 (6 days per week for 51 weeks) for all commodities. The county flows were disaggregated to RSAs using economic-input-output relationships. 43 commodities in TRANSEARCH data were aggregated to 3 commodity groups and then flows are converted from tons to trucks using the payload factors shown in Table 15-2. These payload factors were developed using data from the 2018 California Vehicle Inventory and Use Survey (VIUS).

Table 15-2: Internal HDT Commodity Payload Factors

SCTG	Commodity Name	Commodity Group	Payload (ton)
1	Animals and Fish (live)		21.72
2	Cereal Grains		28.43

SCTG	Commodity Name	Commodity Group	Payload (ton)
3	Agricultural Products	Agricultural & Bulk natural resource (AGBNR)	22.19
10	Monumental or Building Stone		26.69
11	Natural Sands		29.78
12	Gravel and Crushed Stone		32.96
13	Other Non-Metallic Minerals NEC		31.56
14	Metallic Ores and Concentrates		31
15	Coal		34.95
16	Crude Petroleum		24.01
19	Other Coal and Petroleum Products NEC		20.01
25	Logs and Other Wood in the Rough		25.77
5	Meat, Poultry, Fish, Seafood	Finished goods (FG)	15.72
6	Milled Grain Products and Preparations		9.37
7	Other Prepared Foodstuffs, Fats and Oils		17.81
8	Alcoholic Beverages and Denatured Alcohol		18.69
9	Tobacco Products		11.29
21	Pharmaceutical Products		14.41
29	Printed Products		10.26
30	Textiles, Leather, and Articles of		12.38
31	Non-Metallic Mineral Products		31.39
34	Machinery		16.76
35	Electronic and Other Electrical Equipment		13.14
36	Motorized and Other Vehicles (includes parts)		17.43
37	Transportation Equipment NEC		23.54
38	Precision Instruments and Apparatus		9.49
39	Furniture, Mattresses and Mattress Supports, etc.		14.17
40	Miscellaneous Manufactured Products		14.84
43	Mixed Freight		26.53
99	Commodity unknown		20.57
4	Animal Feed, Eggs, Honey, and Other	Intermediate processed goods (IPG)	22.92
17	Gasoline, Aviation Turbine Fuel, and Ethanol		21.11
18	Fuel Oils (includes Diesel, Bunker C, and Biodiesel)		27.88

SCTG	Commodity Name	Commodity Group	Payload (ton)
20	Basic Chemicals		21.79
22	Fertilizers		23.79
23	Other Chemical Products and Preparations		20.05
24	Plastics and Rubber		14.26
26	Wood Products		19.5
27	Pulp, Newsprint, Paper, and Paperboard		21.81
28	Paper or Paperboard Articles		11.04
32	Base Metal in Primary or Semi-Finished Forms		15.1
33	Articles of Base Metal		15.07
41	Waste and Scrap		23.44

Note: SCTG – Standard Classification of Transported Goods

Linear regression equations were developed to estimate trips generated by TAZs. Transearch flows are based on tonnages of goods traded between regions, therefore it does not cover all truck movements. Truck movements related to last mile delivery, empty trucks, municipality services, landscaping, maintenance, etc. are not part of Transearch data set.

To have complete representation of truck movements in the model, a sample of truck GPS OD flows between TAZs were expanded using more than 7000+ count locations across SCAG regions. The classified truck counts were developed using HPMS and Caltrans traffic count data. The Transcad Origin-Destination Matrix Estimations (ODME) procedure was used to expand the sample flows to match traffic counts. The GPS sample data was classified by autos, medium trucks (14,001 to 26,000 lbs. GVWR); and heavy trucks (>26,000 lbs. GVWR). Using California VIUS data it is estimated that 18.4% of trucks with GVWR greater than 26,000 lbs. are in HHDT class (with GVWR greater than 33,000 lbs).

The truck count data were presented based on FHWA axel classification. To map the truck counts data to HDT model truck classes, a cross walk was developed as shown in Table 15-3.

Table 15-3: FHWA 13-Class to HDT Trucks Crosswalk

FHWA /SCAG	LHDT	MHDT	HHDT	Sum
3	81.4%	18.3%	0.3%	100%
5	34.2%	64.0%	1.8%	100%
6	3.2%	25.3%	71.5%	100%
7	0.0%	3.0%	97.0%	100%
8	27.6%	4.7%	67.7%	100%
9	0.1%	2.5%	97.4%	100%

10	9.1%	2.2%	88.7%	100%
11	0.0%	5.1%	94.9%	100%
12	0.0%	0.0%	100.0%	100%
13	0.0%	0.0%	100.0%	100%

This expanded matrix was used as a control total for all truck trips. Truck trips from Transearch was estimated to be about 8% of total trips. Regression equations are developed for non-Transearch truck trips by vehicle class. The initial trip rates were later calibrated based on model traffic assignment results compared with screenlines. All rates are defined as employee per land use category or number of households and shown in Table 15-4.

Table 15-4: Internal HDT Trip Rates per employees / Households

Category	Light HDT Trip Rate	Medium HDT Trip Rate	Heavy HDT Trip Rate
Households	0.0767	0.0126	0.0009
Agriculture	0.0020	0.0019	0.0018
Mining/Construction	0.0095	0.0092	0.0085
Retail	0.0594	0.0446	0.0446
Manufacturing	0.0273	0.0291	0.0412
Transportation	0.0353	0.0406	0.0716
Wholesale	0.0940	0.0994	0.1351
General Warehousing(Employment)	0.2670	0.1780	0.4450
High Cube Warehousing (Employment)	0.2828	0.1414	0.2828
Other	0.0186	0.0062	0.0062

Table 15-5 shows the 2019 HDT trip generation estimates. As expected, households in the region generate a high number of trip ends, especially for Light HDT. This is mostly due to the fact that land uses such as transportation and warehousing, utilities, service and retail deliver goods and provide services to residential neighborhoods. The largest HDT trip generator is the transportation and utility land use that includes trucks involved in power generation, water supply and sewage treatment, all kinds of transportation (trucking industry, taxi, and chartered services), and postal and courier services. The second highest generators of HDT trips are retail and manufacturing land uses, which account for a major share of employment in the region and serve the vast area and population of the six-county SCAG region.

Table 15-5: 2019 Internal HDT Trip Generation Estimates

Land Use	Light HDT Trip Ends	Medium HDT Trip Ends	Heavy HDT Trip Ends	Total Trip Ends	Percent of Total Trip Ends
Households	475,005	78,032	5,574	558,610	43%
Mining/Construction	4,981	4,823	4,456	14,261	1%
Retail	50,136	37,644	37,644	125,423	10%
Agriculture	124	118	112	353	0%
Manufacturing	19,751	21,053	29,807	70,610	5%

Land Use	Light HDT Trip Ends	Medium HDT Trip Ends	Heavy HDT Trip Ends	Total Trip Ends	Percent of Total Trip Ends
Transportation	16,866	19,399	34,210	70,475	5%
Wholesale	41,626	44,018	59,827	145,471	11%
Other	106,616	35,539	35,539	177,694	14%
General Warehousing	27,625	18,417	46,042	92,085	7%
High Cube Warehousing	18,709	9,355	18,709	46,774	4%
Total	761,439	268,397	271,920	1,301,756	100%

Internal HDT Trip Distribution Model

The trip distribution process was modified by developing a matrix of factors that indicate the trip interchange relationships among different land use types (i.e., what fraction of trips originating at a land use such as manufacturing sites go to warehouses vs. other manufacturing sites, etc.). The internal HDT trip distribution model uses a gravity formulation, stratified by land use type at both the production and the attraction end of the trip. This results in a total of 100 gravity models for each truck type: Light-Heavy Duty Truck (LHDT), Medium-Heavy Duty Truck (MHDT) and Heavy-Heavy Duty Truck (HHDT). After trip distribution, the 100 different trip matrices are combined into a single matrix for each truck type, so that only three matrices are passed on to time-of-day factoring and trip assignment.

Truck trips are distributed using composite cost impedances that account for time and distance-based monetary costs in addition to travel time. Based on a review of the literature, the appropriate distance-based costs for the SCAG model are identified in a report commissioned by the Minnesota Department of Transportation (DOT)3. These costs account for fuel, tires, maintenance and repair, and depreciation.

The link composite cost is calculated as shown in the equation below. The corresponding unit costs are shown in Table 15-6.

*Composite Cost = Cost per hour * Congested time + [Fuel Price / Fuel efficiency + Cost per mile (excluding fuel)] * Distance*

Table 15-6: Composite Truck Unit Costs

Truck Type	Cost per Hour	Fuel Efficiency (MPG)	Cost per Mile (excluding fuel)	Fuel Price per Gallon (a)
LHDT	$28.62	14.40	$0.29	$3.18
MHDT	$32.55	8.80	$0.55	$3.31 (b)
HHDT	$32.55	5.80	$0.62	$3.31 (b)

3 Levinson, David Matthew, Corbett, Michael J. and Hashami, Maryam, *Operating Costs for Trucks*, (2005) http://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID1736159_code807532.pdf?abstractid=1736159&mirid=1.

(a) Assumes all MHDT and HHDT trucks are diesel a fleet mix of 62% gasoline and 38% diesel powered trucks for LHDT.
(b) Fuel prices based on average 2019 California gasoline and diesel prices.

The GPS survey of truck trips provided the data to calibrate the model friction factors. These data were used to build observed truck trip flow matrices, stratified by truck type (MHDT and HHDT). The TransCAD gravity model calibration utility was used to calibrate the friction factors that best matched the observed truck flow matrices, given the composite cost impedances and land-use based trip productions and attractions. The 2019 sample GPS data did not include LHDT, therefore older data was used for model calibration. Figures 15-1 to 15-3 show the trip length calibration performed for the 2019 HDT model update, respectively for each truck class. Calibrated model parameters have been retained in the 2019 base year model.

Figure 15-2: LHDT Internal Truck Trip Length Calibration

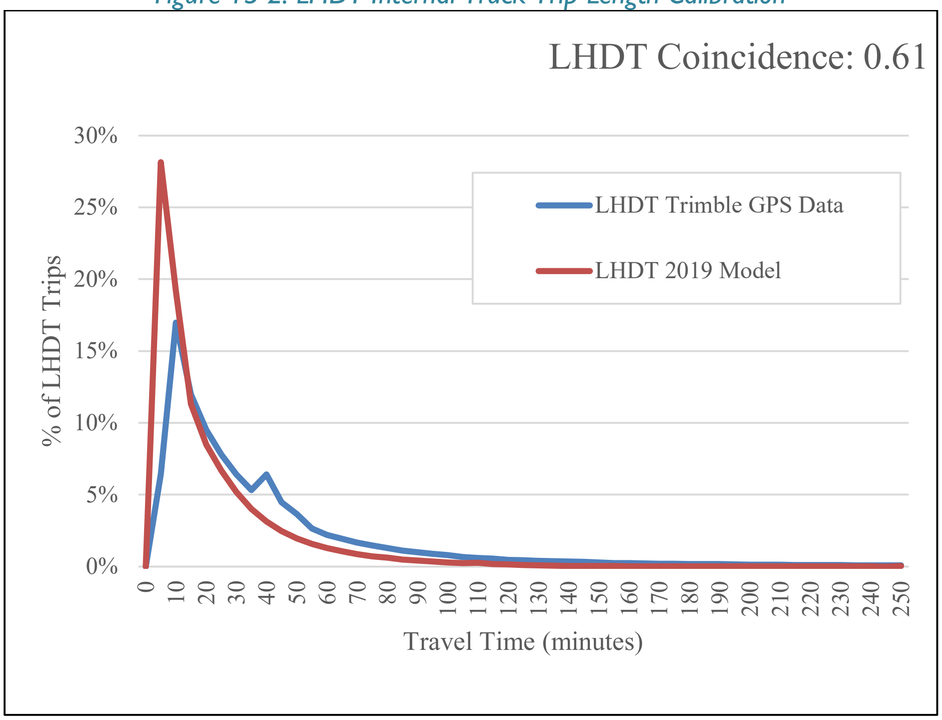


Figure 15-3: MHDT Internal Truck Trip Length Calibration

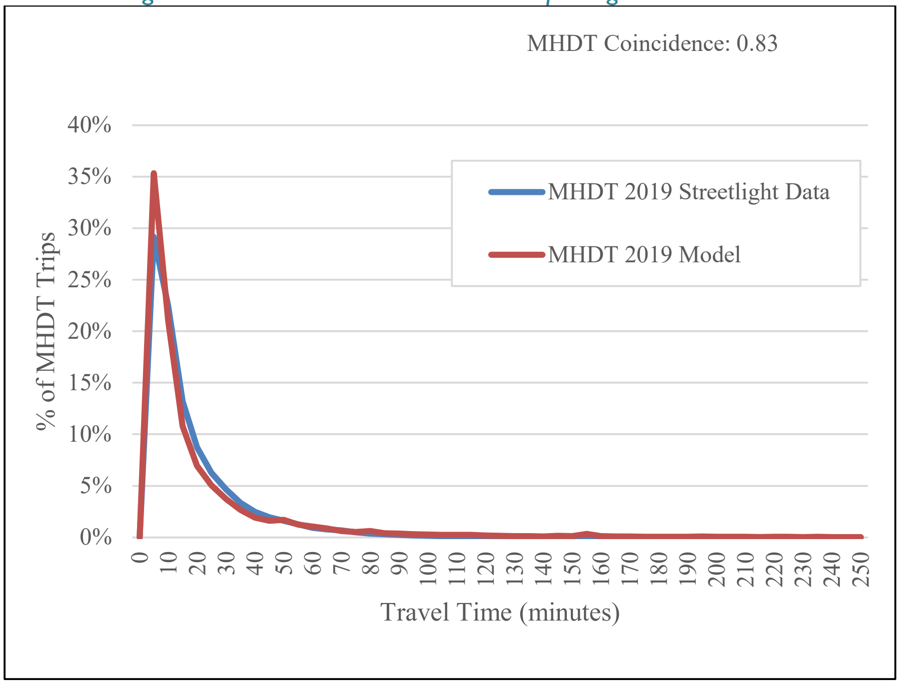
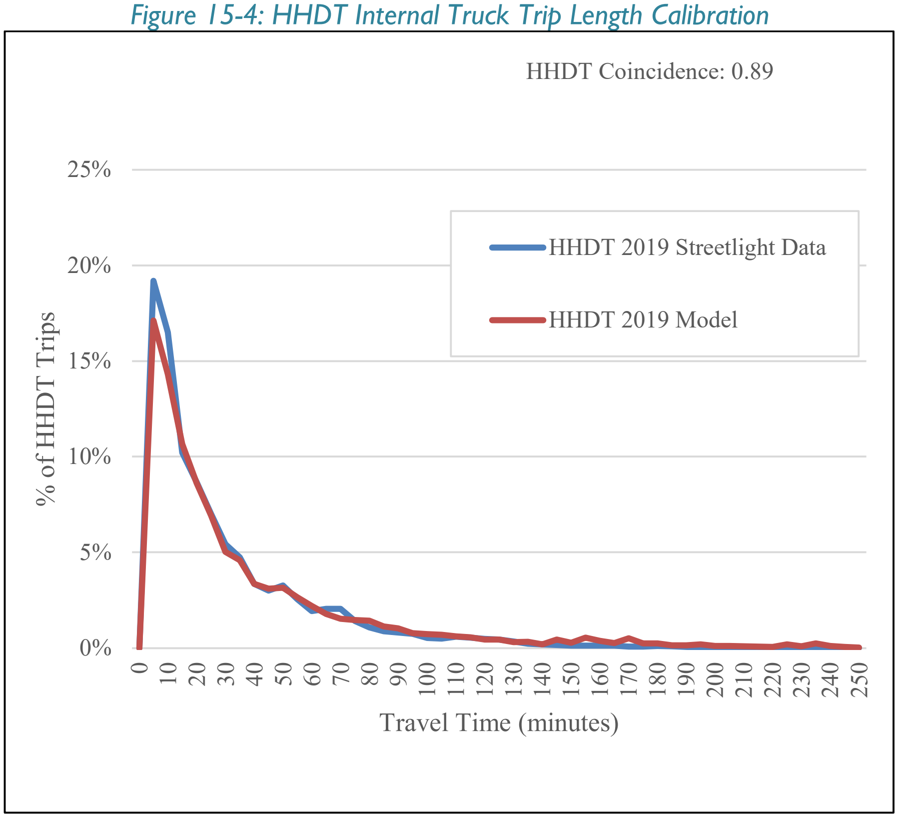


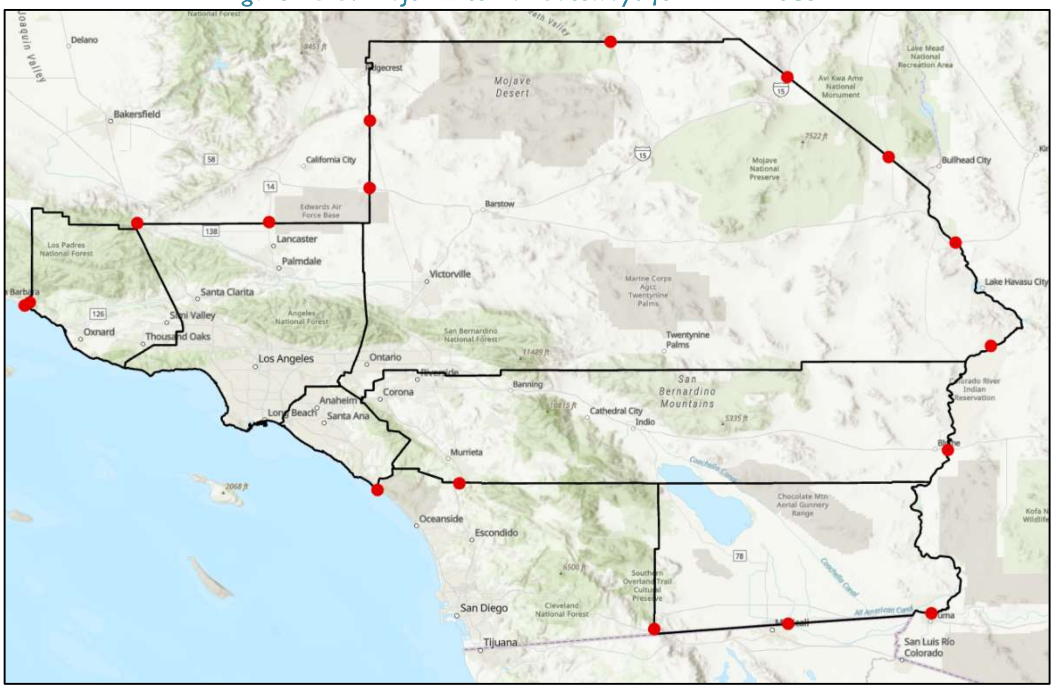
Figure 15-4: HHDT Internal Truck Trip Length Calibration



External HDT Model

The external HDT Model consists of internal-external and external-internal truck trips, and external-external (EE) truck trips. The model has 40 external gateways of those 17 of them carry over 90% of total external traffic. The daily traffic volume by vehicle class at these 17 gateways of SCAG region were estimated using GPS sample data.

Figure 15-5: Major External Gateways for HDT Model



The IE/EI HDT trips are generated and distributed using a combination of Transearch commodity flow data at the county level and GPS data for distribution to RSAs and later to TAZs.

The external HDT Model is based on the 2019 TRANSEARCH commodity flow table. The TRANSEARCH data are provided as annual flows in tons and are converted to daily weekday flows using an annualization factor of 306 (6 days per week for 51 weeks) for all commodities. The flows are converted from tons to trucks using the payload factors shown in Table 152. These payload factors were developed using data from the 2018 Vehicle Inventory and Use Survey (VIUS).

However, the TRANSEARCH flows for IE/EI flows were much smaller than the sum of medium and heavy truck volumes at the major gateways. Therefore, the matrix has to be calibrated to represent the conditions on the ground.

The distribution of flows within RSAs at each county was developed based on a sample of GPS data. for this purpose, the GPS probe data was processed with various assumptions:

A truck trip starts or ends when the vehicle is not moving for at least 5 min.

A truck trip starts or ends when the vehicle is not moving for at least 90 min.

A truck trip starts or ends when the vehicle is not moving for at least 120 min.

The 5 min processed data was significantly different from the 90 min and 120 min data sets. The 90 min and 120 min datasets were showing fairly close patterns. The 90 min data set was used as starting point. For TAZs with a major Intermodal facility such as UP rail yard at Colton or Ontario the distribution were further calibrated based on screen line counts and overall VMT targets by each region.

External – External HDT Trips

The 2019 TRANSEARCH data identify EE truck freight flows passing through the SCAG region. To assign the cordon station to each EE trip end, a method similar to the one used for the external end of the IE/EI trips was used.

Table 15-7: 2019 Daily Truck Volume at major External Gateways

Node ID	Description	Medium HDT	Heavy HDT
4110	CA-101 @ Ventura| Santa Barbara County borderline	3,241	2,237
4111	Near 101- Ventura	202	47
4130	CA-95@ Nevada border line	275	413
4128	I-15 @ Nevada border line	2,086	6,243
4134	CA-62 @ Arizona borderline	417	336
4132	I-40 @ Arizona borderline	1,283	6,892
4136	I-8 @ Arizona borderline	804	2,898
4135	I-10 @ Arizona borderline	895	9,236
4125	CA-127 @ San Bernardino | Inyo County borderline	85	73
4117	CA-14 @ Los Angeles | Kern borderline	1,901	1,509
4114	I-5 @ Los Angeles | Kern borderline	4,196	10,802
4121	CA-58 @ San Bernardino | Kern County borderline	1,297	4,359
4122	CA-395 @ San Bernardino | Kern County borderline	362	873
4140	I-8 @ Imperial County | San Diego borderline	902	1,395
4145	I-15 @ Riverside | San Diego County border line	6,676	4,740
4149	I-5 @ Orange | San Diego County border line	6,254	3,421
4138	CA-7 @ Mexico borderline	483	432
	Sum	**31,359**	**55,906**

Port HDT Model

Ports TAZ Development

The SCAG Tier 1 Zone System consists of 4,192 TAZs, including 42 TAZs that represent the Ports areas. The Port HDT Model was updated to use a more refined set of port TAZs, developed by the Ports of Los Angeles and Long Beach. This zone system, called Port Transportation Analysis Model (Port TAM), includes a total of 90 Port area TAZs, for a total of 4,253 Tier 1 TAZs. Table 15-8 below provides a summary breakdown of the 4,253 TAZ system.

Table 15-8: Port TAM 4,253 TAZ System

from Zone ID	To Zone ID	Zone Type	Total
1	4109	Internal zones	4,109
4110	4149	External zones	40
4150	4161	Airport zones	12
4162	4251	Port zones	90
4251	4253	Extra zones	2
Total Zones			**4,253**

Port Truck Trip Generation

The port trip generation model was developed on a detailed port area zone system and specialized trip generation rates for autos and trucks by type (Bobtail, Chassis, and Containers). Port truck trip generation has two components: 1) container terminal truck trips, and 2) non-container terminal truck trips.

Container Terminal Truck Trip Generation

The container terminal truck trip generation model for the ports is referred to as the QuickTrip Model. QuickTrip was originally developed for the Ports of Los Angeles and Long Beach. The Model includes detailed input variables such as mode split (rail versus truck moves), time-of-day factoring, weekend moves, empty return factors, and other characteristics that affect the number of trucks entering and exiting through the terminal gates. The relevant input data for each container terminal include the following:

Peak monthly Twenty-Foot Equivalent Units (TEU) throughput.

TEU-to-lift conversion factor: factor determining the average number of TEUs associated with each lift at the terminal.

TEU land-side throughput distributions: percent of TEU throughput associated with on-dock intermodal imports, on-dock intermodal exports, off-dock intermodal imports, off-dock intermodal exports, local imports, local exports, empties, and trans-shipments across the wharf.

Number of operating days during the week.

Percent of throughput moved during each terminal operating shift (for the day, second and hoot shifts).

QuickTrip produces the following truck trip outputs for each terminal:

Monthly gate transactions

Peak week truck trip volume

Daily truck trips, and truck trips by each hour of the day by type of truck trip (bobtail, chassis, container, empty), and direction (arrival at and departure from the terminal)

QuickTrip can be used to generate base as well as future year truck trips by truck type and direction for each terminal, using the model inputs described earlier for each specific year. The inputs that are particularly expected to change for different years include the peak monthly TEU throughput, and the TEU land-side throughput distributions (based on expected increase in on-dock intermodal capacity at the port terminals in the future). Additionally, the model has the capability to analyze the impacts of other port truck trip reduction strategies such as virtual container yards and off-peak truck diversions, using specific inputs associated with these strategies.

The Model was enhanced to allow the user to assess whether the estimated capacity of each rail yard has been exceeded. If so, traffic is iteratively re-allocated to other yards that are not over capacity. The enhanced model also allows the user to choose different efficiency factors, such as "percent double cycle trucks," for different off-dock yards. In the original version, the user had to use the same variables for the entire off-dock market.

Non-Container Terminal Truck Trip Generation

Non-container terminal truck trip generation estimates were also developed for the Ports as part of the Port truck trip generation process. This includes trips to and from all of the other types of marine terminals (automobile terminals, dry bulk terminals, liquid bulk terminals and break-bulk terminals). In addition, there are many non-terminal land uses located throughout the ports (e.g., administrative offices, recreation, commercial, government buildings) that potentially generate truck traffic.

Existing non-container terminal truck trips were developed by conducting a series of driveway and midblock truck counts throughout the Ports. A number of specific terminals were counted at their driveways, while other terminals and miscellaneous land use activities were reflected via the use of downstream roadway truck counts. In some cases, a roadway truck count was used to represent the trip generation of a group of non-container terminals and other land uses.

Port Trip Table Distribution

The zone-to-zone distribution of port truck trips is based on a fixed OD matrix. A detailed and comprehensive truck driver survey was undertaken by the ports at the marine container terminals. The survey was used to develop detailed origin-destination trip tables for use in the Port area travel demand model. The stated trip OD from every valid survey was correlated with the travel demand model TAZ system. The survey results were then used to develop port truck OD frequency distributions by truck type for use in the model. Distribution patterns were developed separately for arrival trips and departure trips for each terminal. A total of 15 Port Truck Trip Tables were developed (5 time periods by 3 vehicle classes): AM, MD, PM, EV and NT time periods, and Bobtails, Chassis and Container truck trips. The time periods are consistent with those used by the passenger model, but combine the night and evening periods into a single night time period. Empty container and loaded container truck types are combined into one truck type called container truck type.

For terminals with few or no observations (Pier C, YTI and APL) an average distribution of all surveyed records was used. Before creating survey frequency distribution vectors, survey sample trips were adjusted to exclude trips that have both OD within the same terminal.

Base Year Port Trip Tables Summary

Summaries of 2019 Port truck trips are shown in Table 15-9 and Table 15-10.

Table 15-9: 2019 Port HDT Trips by Truck Type

Time Period	Bobtails	Chassis	Containers	Total
AM	1,710	560	3,011	5,281
MD	8,750	2,345	15,391	26,487
PM	4,166	1,019	7,058	12,243
EV	2,003	515	3,551	6,068
NT	4,093	1,052	7,255	12,401
Daily	20,723	5,491	36,266	62,480

Table 15-10: 2019 Port HDT Trips by Time Period and County

County	Time Period					
	AM	**MD**	**PM**	**EV**	**NT**	**Total**
Imperial	0	0	0	0	0	0
Los Angeles	4,980	25,216	11,679	5,763	11,777	59,414
Orange	25	106	47	26	53	257
Riverside	132	558	247	133	273	1,343
San Bernardino	135	569	253	137	280	1,373
Ventura	0	0	0	0	0	0
External Stations	9	38	17	9	19	92
Total	5,281	26,487	12,243	6,068	12,401	62,480
% of Daily Trips	8.45%	42.39%	19.59%	9.71%	19.85%	

INTERMODAL HDT TRIPS

Intermodal Trips and Secondary Transload HDT Trips

Intermodal (IMX) trucks trips are heavy HDT movements generated at the six regional intermodal facilities in the SCAG region. These intermodal facilities are shown in Figure 15-5. In addition to trips to and from the Ports and intermodal railyards, the PortTAM model accounts for secondary trips associated with transloading of container cargo. Transloading occurs when cargo in 20- and 40-foot international containers is moved to larger (usually 53-foot) domestic containers. The loaded domestic containers are drayed to intermodal railyards, trucked to other warehouse or wholesale locations, or trucked outside of the SCAG region.

A summary of these truck movements is shown in Table 15-11 These truck trips were all assumed to be HHDTs. The daily truck trips were developed assuming an annualization factor of 306.

Figure 15-6: Intermodal Facilities in the SCAG Region

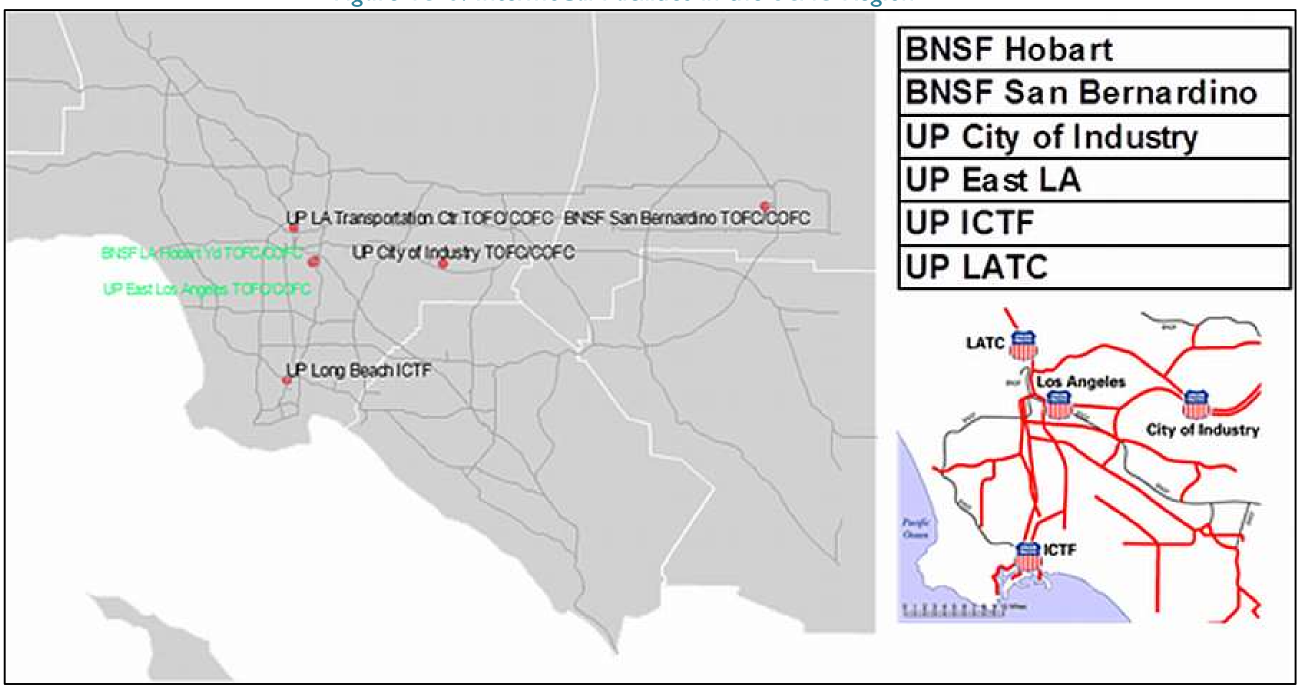


Table 15-11: 2019 Intermodal trips and secondary transload trips by County

	Imp	LA	Ora	Riv	SBD	Ven	Total
Intermodal (IMX)	9	5567	373	295	1920	63	8,228
Secondary	2	7270	189	325	1205	25	9,015
Total	11	12838	561	620	3125	88	17,242

HDT Time-of-Day Factoring & Assignment

The HDT Model uses fixed time-of-day factors derived from observed truck counts. The HDT time of time periods are consistent with the passenger model periods, namely:

AM Peak: 6:00 AM – 9:00 AM
Mid-day: 9:00 AM - 3:00 PM
PM Peak: 3:00 PM - 7:00 PM
Evening: 7:00 PM – 9:00 PM
Night: 9:00 PM – 6:00 AM

The HDT diurnal factors were derived from the 2007 Vehicle Travel Information System (VTRIS)4 database. VTRIS is maintained by the FHWA Office of Highway Policy Information to track traffic trends, vehicle distributions and weight of vehicles to meet data needs specified in highway legislation. The VTRIS database contains truck classification counts spanning nearly half a year at many locations on SCAG interstate and state highways. The HDT time of day factors are shown in Table 15-12.

Table 15-12: HDT Time-of-Day Factors

Time Period	Diurnal Factors		
	LHDT	MHDT	HHDT
AM Peak (6 AM - 9AM)	18.8%	18.0%	13.9%
Midday (9 AM-3PM)	42.9%	46.5%	35.3%
PM Peak (3 PM- 7PM)	20.3%	15.5%	16.7%
Evening (7 PM - 9 PM)	4.8%	3.5%	7.2%
Night (9 PM - 6AM)	13.2%	16.5%	26.9%

HDT trips are assigned simultaneously with the auto trips as part of a user equilibrium multiclass assignment. The assignment methodology is described in detail in Chapter 16– Trip Assignment. Truck volumes are converted to PCEs following the procedures recommended in the 2010 Highway Capacity Manual. The PCE factors are a function of grade, length of the climb segment, and percent of truck volume, and vary by truck type (LHDT, MHDT and HHDT). These factors are shown in Table 15-13.

4 http://www.fhwa.dot.gov/ohim/ohimvtis.cfm

Table 15-13: HDT Passenger Car Equivalent Factors

Percent Trucks	Length of Grade in miles	Light -Heavy				Medium-Heavy				Heavy-Heavy			
		% Grade				% Grade				% Grade			
		< 2	2 - 4	4 - 6	> 6	< 2	2 - 4	4 - 6	> 6	< 2	2 - 4	4 - 6	> 6
0-5%	< 1	1.3	1.5	3.0	4.0	1.5	2.0	3.5	5.0	2.5	2.5	4.5	6.0
	1 - 2	1.3	2.5	4.0	5.0	1.5	3.5	5.0	6.5	2.5	5.0	7.5	12.5
	> 2	1.3	2.5	4.0	5.0	1.5	3.5	5.0	6.5	2.5	5.0	7.5	12.5
5-10%	< 1	1.3	1.5	2.5	3.0	1.5	2.0	3.0	4.0	2.5	2.5	4.5	5.5
	1 - 2	1.3	2.0	3.5	4.0	1.5	3.0	4.0	5.5	2.5	4.0	8.0	11.5
	> 2	1.3	2.0	3.5	4.0	1.5	3.0	4.0	5.5	2.5	4.0	8.0	11.5
>10%	< 1	1.3	1.5	2.0	2.5	1.5	2.0	2.5	3.0	2.5	2.5	4.0	4.0
	1 - 2	1.3	2.0	3.0	3.5	1.5	2.5	3.5	4.0	2.5	3.5	6.0	9.0
	> 2	1.3	2.0	3.0	3.5	1.5	2.5	3.5	4.0	2.5	3.5	6.0	9.0

Chapter 16 TRIP ASSIGNMENT

INTRODUCTION

This Chapter describes the various trip assignment methodologies and 2019 validation results. Assignments used in the 2019 model include a static, multiclass user equilibrium highway assignment to the highway network, and a multi-path (Pathfinder) transit assignment to the transit network.

Highway assignment validation is one of the crucial steps in the modeling process. The ability of the model to produce base year volume estimates within acceptable ranges of tolerance compared to actual ground counts is essential to validate the entire travel demand model. The screenline analysis for the 2019 validation year is presented in this Chapter. Also, key to highway assignment validation is the comparison of model estimated VMT to estimates from the Highway Performance Monitoring System. An acceptable tolerance level is mandatory for regional air quality planning and conformity purposes. Specifics regarding the comparative analyses are summarized in this Chapter and assignment statistics for the SCAG region are also presented.

The multi-class highway assignment simultaneously loads the vehicle forecasted by the mode choice model, the internal-external and external-external vehicle trips, and the three classes of heavy-duty trucks (light, medium and heavy). The OD trip tables loaded to the highway network include the following vehicle classes:

- Drive Alone
- Shared Ride 2 Non HOV
- Shared Ride 3+ Non HOV
- Shared Ride 2 HOV
- Shared Ride 3+ HOV
- Light Trucks
- Medium Trucks
- Heavy Trucks

The internal-external and external-external trips are included in the Drive Alone and Shared-Ride trip tables. The next section briefly describes the methodology used to generate these trips, while the rest of the chapter discusses the highway assignment process, validation results and transit assignment process.

External Trips

External trips are trips with one or both ends outside the modeling area. External trips for light-and-medium duty vehicles (LM) are estimated independently from heavy duty vehicles (HDT). The following provides a brief description of the methodology used to estimate the LM external trips. For the HDT external trips, refer to Chapter 15 (Heavy Duty Truck Model).

SCAG designates 40 cordon stations along the perimeter of the modeling area to identify external or interregional trips. To estimate the external trips of light-and-medium duty vehicles for the base year 2019, SCAG staff used two steps.

Step 1: SCAG staff collected existing traffic counts passing through each cordon. Two data sources were available. For freeway cordons, we used Caltrans' Annual Average Daily Traffic (AADT) after subtracting Caltrans' Annual Average Daily Truck Traffic (AADTT). For arterial cordons, since Caltrans' AADT is not available, SCAG decided to use AADT provided by the StreetLight InSight platform. To extract the LM duty vehicles from the StreetLight AADT, we utilized the previous traffic count survey conducted by SCAG in 2017, which includes 13 FHWA vehicle classification data. Both Caltrans AADT and StreetLight AADT were further processed to have the Average Daily Traffic (ADT) for a typical weekday by applying a weekday factor for each cordon. The day distribution feature of PeMS and StreetLight was useful to estimate the weekday factors.

Step 2: SCAG staff allocated the base year 2019 cordon traffic counts to 4,109 Traffic Analysis Zones (TAZs) based on observed O-D distribution patterns. Previously, a regional cordon survey conducted by SCAG during 2002 and 2003 was used to estimate the observed O-D distribution of external trips. For 2024 RTP, we decided to update the observed external O-D distribution, using transportation Big Data such as StreetLight. It is important to note that the StreetLight O-D data were customized by including trips in the same long-distance travel if there is less than 90 minutes and 1.0 kilometer between consecutive trip stops. We think that this customization could detect the final stop of a long-distance interregional passenger travel, rather than interim stops for lunch, shopping, or break. SCAG staff carefully reviewed and revised the customized StreetLight O-D distribution by comparing with the previous cordon survey results at the level of 56 Regional Statistical Areas (RSAs). The external O-D matrix at the RSA level was first disaggregated to 369 Community Statistical Areas (CSAs) to maximize observed patterns from StreetLight data that were collected at the CSA level. And then the external O-D matrix at the CSA level was disaggregated to 4,109 TAZs based on population and employment. Finally, the TAZ-level O-D matrix was further disaggregated by 5 time periods (AM Peak, Midday, PM Peak, Evening, and Night) and 3 auto modes (Drive Alone, Share Ride 2, and Share Ride 3+).

Highway Assignment Procedures

Highway assignment is the process of loading vehicles onto the appropriate highway facilities to produce traffic volumes, congested speeds, vehicle-miles traveled, and vehicle-hours traveled (VHT) estimates, for each of the five time periods. Link or segment assignments by time period are added to produce average daily traffic volumes (ADT) for the model network. The 2019 model assignments consist of a series of multi-class simultaneous equilibrium assignments for the eight classes of vehicles listed above, and for each of the five time periods. During the assignment process, trucks are converted to passenger-car equivalents for each link based on the percentage of trucks, grade, link length and level of congestion. Transit vehicles are pre-loaded to the highway links.

To achieve travel time convergence between the highway assignment and the demand model, a three loop feedback procedure is used in the 2019 model. The following describes the travel time feedback process:

Step 1: The core demand model is run using the speeds coded on the input highway networks. These coded speeds represent observed speeds, where available. The resulting trip tables for each vehicle class and time-period are assigned to the highway networks, which yields the first pass loaded volumes and congested speeds.

Step 2: These congested speeds are fed back into the demand model to produce a second set of congested speeds for the AM peak, PM peak, and midday periods. An averaging process is used to smooth the volume variation between the first and second pass assignments. These averaged speeds are again fed back to the demand model, and the process is repeated two more times for a total of three feedback loops.

Step 3: During the final, 3rd loop assignment, all highway assignments are performed: AM peak, midday, PM peak, evening and nighttime.

The averaging process used to smooth volume variations across feedback loops is the method of successive averages, with a 1/n step, where n is the number of iterations. Convergence for each assignment process (as opposed to model-wide convergence) is achieved when the bi-conjugate user equilibrium assignment achieves a relative gap of 0.001or 200 iterations, whichever occurs first.

Generalized Cost Function

The 2019 model uses a generalized cost function during highway assignment to measure and compare the travel time and cost associated with alternative highway paths. The equation of this cost function is as follows:

$$GenCost = travel\ time + HOT\ penalty + {}^{(auto\ operating\ cost\ +\ tolls)}\big/_{cost\ conversion\ factor}$$

Each of the terms of this equation in turn is calculated as follows:

Travel time is computed using volume-delay functions, described in detail in the next section

The tolls are a model input, specified by the user as appropriate

The high occupancy toll (HOT) lane penalty represents a perceived cost of accessing and exiting the HOT lanes. This penalty applies only when the toll flag identifies a HOT lane. It defaults to a value of 0.5 minutes per mile for drive alone vehicles, as shown in Table 16-1.

The auto operating cost measures the contribution of distance to the generalized cost; for 2019 the auto operating cost is 20.364 cents per mile (in constant $2011); its derivation is shown in Appendix B.

The cost conversion factor, which may be interpreted as a value of time, varies by vehicle class and time period, as shown in the equation and Table 16-1 below.

$$Cost\ conversion\ factor = Distance\ cost\ conversion\ factor * cost\ multiplier * VOT\ multiplier$$

Table 16-1: Generalized Cost Function Parameters

Vehicle Class		**Drive Alone**	**Shared Ride 2**	**Shared Ride 3+**	**Light-Duty Trucks**	**Medium Duty Trucks**	**Heavy Duty Trucks**
HOT Penalty (min/mile)		0	0	0.2	0	0	0
Distance Cost Conversion Factor ($/hr)		33.9	40.5	40.5	52.4	65.8	70.7
Time Period		AM Peak	Midday	PM Peak	Evening	Night	
Cost Multiplier	**Auto**	0.9	0.55	0.75	0.55	0.55	
	Truck	1.0	1	1	1	1	
VOT Multiplier	**AM Toll/HOT**	1.5/2.5	1.5/2.5	1.5/2.5	1	1	1
	Midday Toll/HOT	1.25/2	1.25/2	1.25/2	1	1	1
	Peak Toll/HOT	1.5/2.5	1.5/2.5	1.5/2.5	1	1	1
	Evening Toll/HOT	1.25/2	1.25/2	1.25/2	1	1	1
	Night Toll/HOT	1/1.5	1/1.5	1/1.5	1	1	1

Volume-Delay Function

The volume delay function (VDF) utilized for the traffic assignment portion of the Regional Model is the Bureau of Public Roads (BPR) function. The volume-delay function is used in assignment to simulate the relationship between traffic volume, congestion delay, and congested speeds. The equation of the function is as follows:

$$t_i \cdot \left[1 + \alpha_i \left(\frac{x_i}{C_i}\right)^{\beta_i}\right]$$

where:

t_i	=	Free flow travel time on link i
C_i	=	Capacity of link i
x_i	=	Flow on link i
α	=	Constant
β	=	Constant

If $\frac{x_i}{C_i}$ <= 1 then β is set to the specific value of 4.0. If $\frac{x_i}{C_i}$ > 1, then α and β are set to values that vary by link facility type, posted speed, and area type as shown in Table 16-2.

Table 16-2: Volume-Delay Function Parameters

Facility Type	Posted Speed	Area Type	Alpha	Beta
Freeways and HOV	All	All	1.00	8.0
Expressways	<=45mph	1-5	0.80	5.0
Expressways	<=45mph	6-7	0.80	6.0
Expressways	>45mph	All	0.80	8.0
All Others	All	1-5	0.80	5.0
All Others	All	6-7	0.80	6.0

Freeway on-ramps (facility types 82 and 84) have a separate volume-delay function. The function is as follows:

$$\frac{L_i}{FFS_i} + \frac{\left[\frac{PLPHx_i}{120} * 5.0 * \left(1 + \frac{x_i}{C_i}\right)^8\right]}{60}$$

where:

L_i = Length on link i in miles

FFS_i = Free Flow Speed on link i in miles/hour

C_i = Capacity of link i

x_i = Flow on link i

$PLPHx_i$ = Per-Lane-Per-Hour Flow on link i

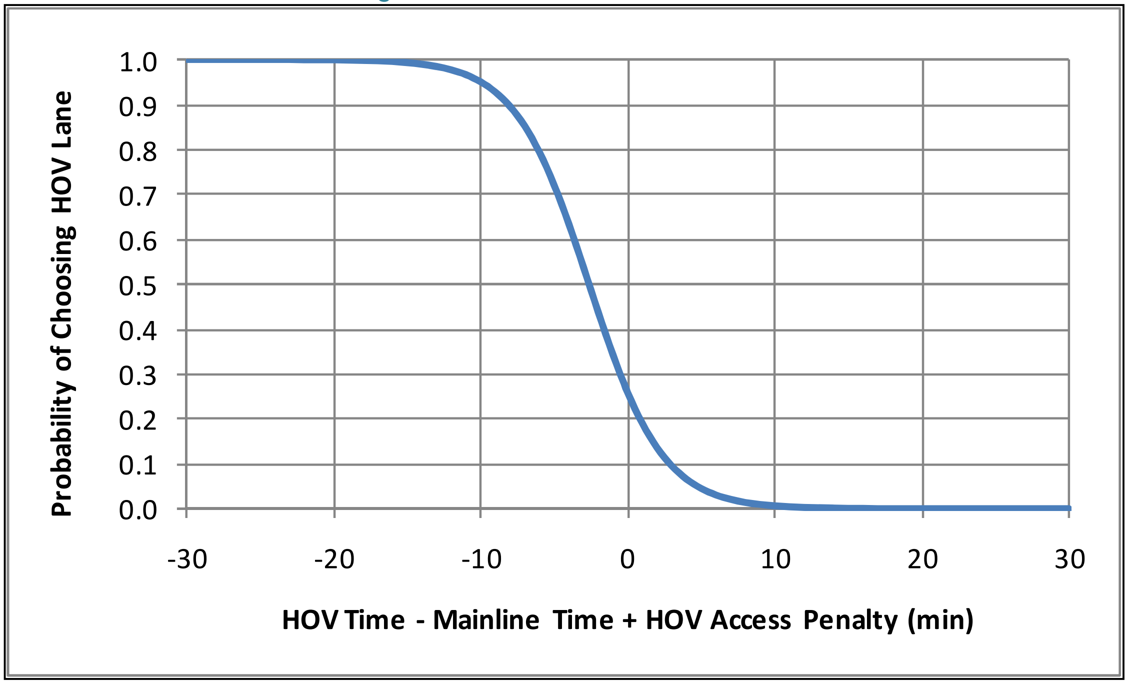
HOV Diversion

A binomial diversion model is applied prior to highway assignment to split carpool trips between vehicles that use the HOV lanes and vehicles that remain on the general purpose flow lanes. The probability of choosing the HOV facility is given by the function:

$$P(HOV) = \frac{b}{b + e^{at}}$$

Where t represents the travel time savings from using the HOV facility, $t = HOV\ time - GP\ time + access\ penalty$, and a and b are calibrating factors. The HOV access penalty measures the inconvenience of entering and exiting the lanes, given that many of them are buffer or barrier-separated with limited opportunities for access and egress. The access penalty is 0.5 minutes across all time periods. The calibrating factor a determines the steepness of the logistic curve, while b determines the likelihood of using the HOV lanes at zero travel time savings. To encourage carpool trips to stay on the HOV lanes, a factor of 1.1 is used on the mainline travel times. All the parameters of the HOV diversion function can be specified by time period, however, currently the same parameters are used for all time periods.

Figure 16-1: HOV Diversion Function



HPMS Factoring

After the entire model has converged, the estimated link volumes are factored prior to performing the emission calculations. Although the model achieves a good match to HPMS estimates without any factoring, as shown in the tables below, HPMS factoring is used to overcome the small remaining discrepancies and ensure consistency among the emission calculations and HPMS. The adjustment factors are calculated by comparing model VMT estimates to HPMS estimates by air basin, county and vehicle type (light vehicles and heavy duty trucks).

Highway Assignment Validation and Summary

This section describes how the 2019 Regional Model's highway trip assignment module has been validated to observed conditions. It includes results for Heavy Duty Truck and mixed-flow components of the trip assignment model. Figure 16-2 and Figure 16-3 provide a visual representation of the SCAG regional screenlines.

Figure 16-2: Screenlines (Regional)

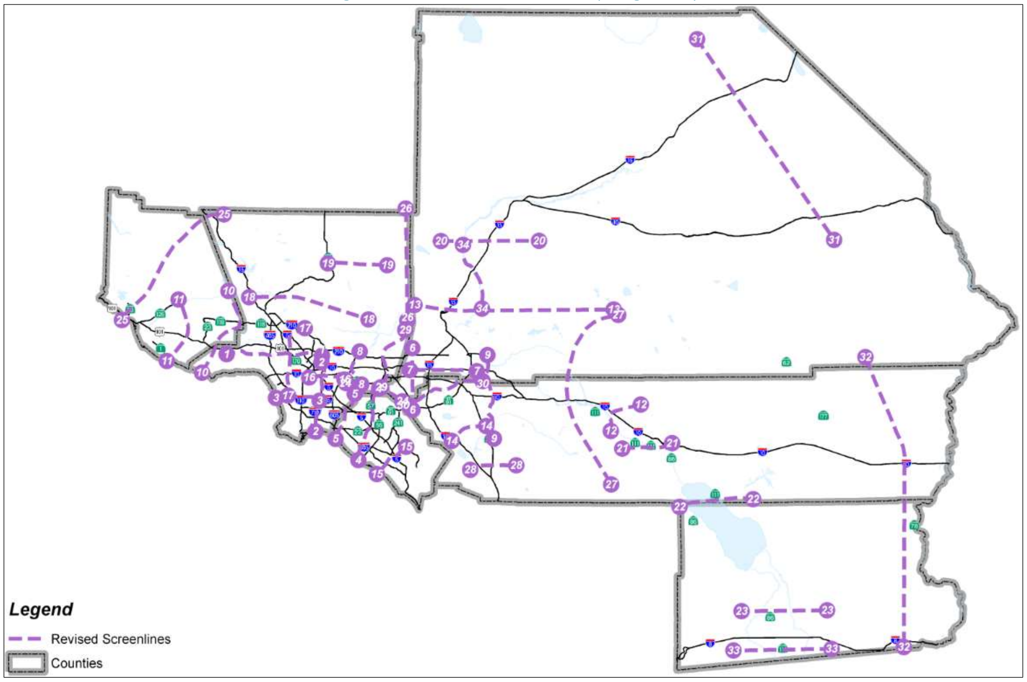
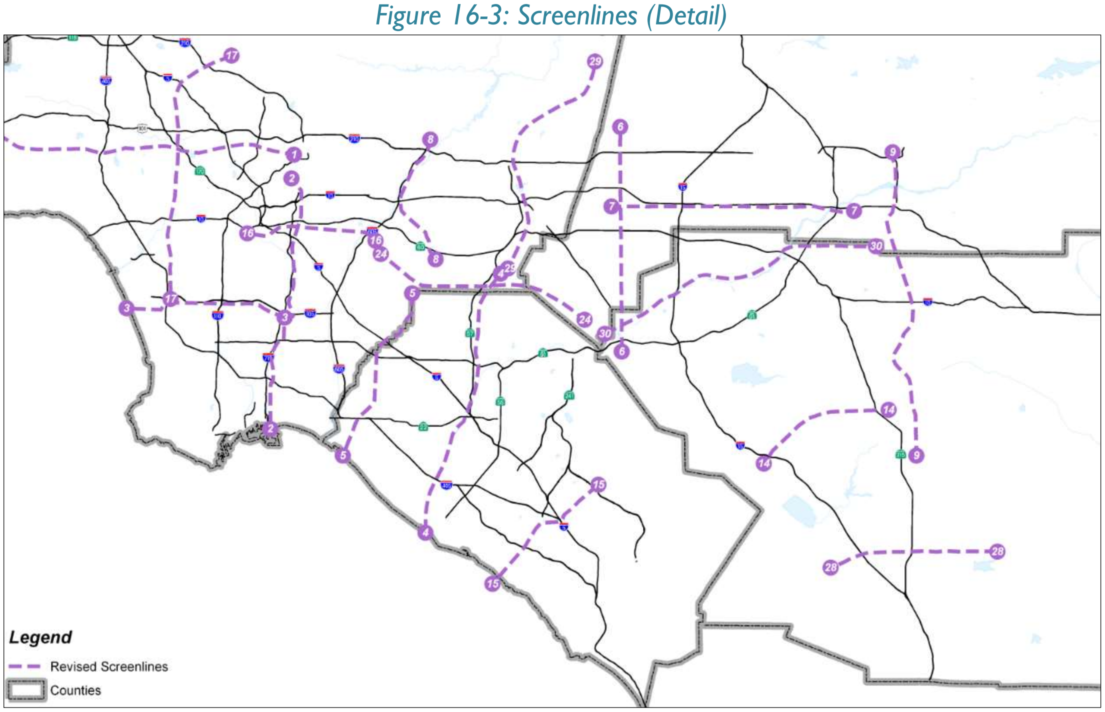


Figure 16-3: Screenlines (Detail)



Validation of the Mixed-Flow Trip Assignment Model

Table 16-3 through Table 16-8 present an overview of the highway assignment statistics for each model time period and daily total. After the HPMS volume adjustment, the model forecasts 428,770,000 VMT on an average weekday in 2019 within the model area for light and medium duty vehicles. In addition, the model forecasts 32,579,000 VMT for heavy-duty vehicles in the expanded model area. The total for all vehicle types combined is 461,349,000 VMT.

A comparison of 2019 model speeds to National Performance Management Research Data (NPMSDS) speed data is shown in Figure 16-5 to Figure 16-12.

Table 16-3: Year 2019 Loaded Highway Network Summary

From Assignment						
Light & Medium Duty Vehicles	**AM Peak**	**PM Peak**	**Midday**	**Evening**	**Night**	**Total**
Average Speed (mph)	31.8	31.4	38.6	40.0	47.4	35.7
Vehicle Miles Traveled (,000)	81,377	116,646	118,664	33,578	56,876	407,140
Vehicle Hours Traveled (,000)	2,563	3,720	3,075	840	1,199	11,397
Vehicle Hours Delay (,000)	679	1,011	352	75	19	2,137
Heavy Duty Vehicles	**AM Peak**	**PM Peak**	**Midday**	**Evening**	**Night**	**Total**
Average Speed (mph)	38.6	38.2	46.7	50.7	55.9	44.9
Vehicle Miles Traveled (,000)	5,229	5,896	12,916	1,811	6,041	31,895
Vehicle Hours Traveled (,000)	135	154	276	36	108	710
Vehicle Hours Delay (,000)	36	44	40	3	2	125
All Vehicles Combined	**AM Peak**	**PM Peak**	**Midday**	**Evening**	**Night**	**Total**
Average Speed (mph)	32.1	31.6	39.3	40.4	48.1	36.3
Vehicle Miles Traveled (,000)	86,606	122,542	131,580	35,390	62,917	439,035
Vehicle Hours Traveled (,000)	2,698	3,874	3,351	876	1,307	12,107
Vehicle Hours Delay (,000)	716	1,055	392	79	21	2,262
After HPMS Adjustment						
Light & Medium Duty Vehicles	**AM Peak**	**PM Peak**	**Midday**	**Evening**	**Night**	**Total**
Average Speed (mph)	32.0	31.5	38.9	40.3	47.7	36.0
Vehicle Miles Traveled (,000)	82,697	118,589	120,753	34,120	57,804	413,962
Vehicle Hours Traveled (,000)	2,583	3,762	3,103	847	1,212	11,507
Vehicle Hours Delay (,000)	668	1,008	333	70	13	2,093
Heavy Duty Vehicles	**AM Peak**	**PM Peak**	**Midday**	**Evening**	**Night**	**Total**
Average Speed (mph)	38.4	38.0	46.6	50.2	55.0	44.7
Vehicle Miles Traveled (,000)	4,945	5,572	12,247	1,724	5,783	30,271
Vehicle Hours Traveled (,000)	129	147	263	34	105	678
Vehicle Hours Delay (,000)	35	42	38	3	3	122
All Vehicles Combined	**AM Peak**	**PM Peak**	**Midday**	**Evening**	**Night**	**Total**
Average Speed (mph)	32.3	31.8	39.5	40.7	48.3	36.5
Vehicle Miles Traveled (,000)	87,642	124,161	133,000	35,844	63,587	444,233
Vehicle Hours Traveled (,000)	2,712	3,909	3,365	882	1,317	12,185
Vehicle Hours Delay (,000)	703	1,050	370	74	17	2,214

Table 16-4: Year 2019 VMT Comparison by County and by Air Basin (in Thousands)

County		VC SCCAB		SCAB		MDAB		SSAB		Total		County
		Auto	Truck	Auto	Truck	Auto	Truck	Auto	Truck	Auto	Truck	Total
Imperial	Model	-	-	-	-	-	-	4,313	499	4,313	499.35	4,812
	HPMS							5,984	989	5,984	989	6,973
Los Angeles	Model	-	-	195,832	14,345	7,051	469	-	-	202,883	14,813	217,696
	HPMS			199,121	12,756	7,933	434			207,054	13,191	220,245
Orange	Model	-	-	71,893	3,923	-	-	-	-	71,893	3,923	75,816
	HPMS			72,261	4,224					72,261	4,224	76,485
Riverside	Model	-	-	46,231	2,987	1,318	614	9,185	930	56,734	4,532	61,265
	HPMS			42,230	2,958	1,643	701	10,197	1,302	54,070	4,962	59,032
San Bernardino	Model	-	-	35,475	2,469	19,289	4,620	-	-	54,763	7,088	61,852
	HPMS			37,639	2,822	19,456	2,856			57,096	5,678	62,774
Ventura	Model	16,555	1,039	-	-	-	-	-	-	16,555	1,039	17,593
	HPMS	17,522	1,099							17,522	1,099	18,622
Total	**Model**	**16,555**	**1,039**	**349,430**	**23,724**	**27,658**	**5,702**	**13,498**	**1,429**	**407,140**	**31,895**	**439,035**
	HPMS	**17,522**	**1,099**	**351,251**	**22,761**	**29,033**	**3,992**	**16,181**	**2,291**	**413,987**	**30,143**	**444,130**
	Ratio	**0.945**	**0.945**	**0.995**	**1.042**	**0.953**	**1.428**	**0.834**	**0.624**	**0.983**	**1.058**	**0.989**

Figure 16-4: Year 2019 Screenline Location Volumes

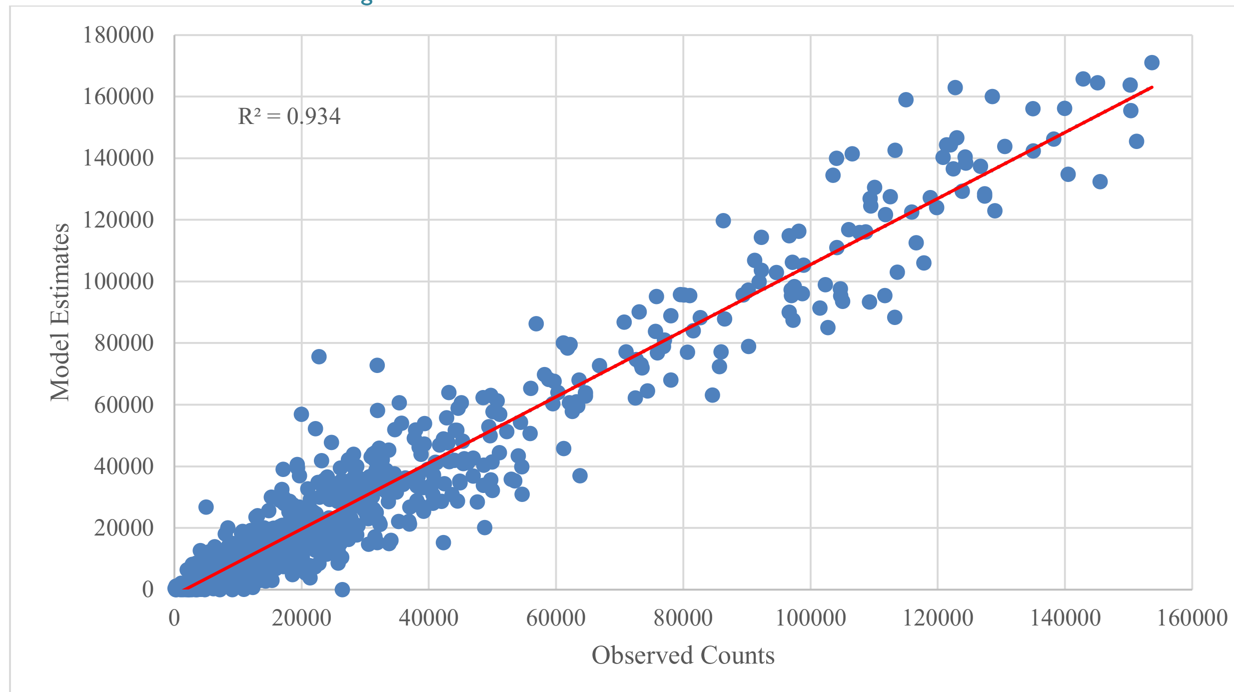


Table 16-5: Year 2019 Screenline Comparison of Model Weekday ADT and Ground Counts

				Light & Medium Duty Vehicles				Heavy Duty Vehicles				Total		
z	Location	Direction	Obs	Model	Count	Ratio	RMSE	Model	Count	Ratio	RMSE	Model	Count	Ratio
1	Los Angeles	EW	33	1,479,935	1,440,497	1.027	18	106,897	71,455	1.496	140	1,589,746	1,511,951	1.051
2	Los Angeles	NS	67	2,547,808	2,511,049	1.015	20	199,020	209,536	0.950	101	2,755,107	2,720,586	1.013
3	Los Angeles	EW	40	1,326,214	1,353,056	0.980	27	97,285	92,979	1.046	87	1,427,172	1,446,033	0.987
4	Orange	NS	48	2,017,550	1,983,037	1.017	28	116,622	126,800	0.920	81	2,137,740	2,109,837	1.013
5	Los Angeles/ Orange	NS	32	1,457,378	1,348,140	1.081	28	109,342	88,452	1.236	121	1,567,797	1,436,598	1.091
6	San Bernardino/ Riverside	NS	43	1,156,632	1,253,224	0.923	33	117,248	98,420	1.191	111	1,274,698	1,351,643	0.943
7	San Bernardino	EW	28	836,632	844,113	0.991	30	56,099	118,149	0.475	81	893,602	962,263	0.929
8	Los Angeles	NS	28	977,240	1,024,329	0.954	22	96,629	119,854	0.806	100	1,075,954	1,144,184	0.940
9	San Bernardino/ Riverside	NS	30	511,365	572,908	0.893	41	28,501	62,296	0.458	88	540,900	635,202	0.852
10	Ventura/ Los Angeles	NS	11	379,362	372,921	1.017	22	33,582	22,900	1.466	114	413,126	395,823	1.044
11	Ventura	NS	9	243,022	200,742	1.211	30	20,590	12,952	1.590	194	263,723	213,694	1.234
12	Riverside	NS	8	166,125	168,981	0.983	30	12,243	36,820	0.333	96	178,840	205,800	0.869

z	Location	Direction	Obs	Light & Medium Duty Vehicles				Heavy Duty Vehicles				Total		
				Model	Count	Ratio	RMSE	Model	Count	Ratio	RMSE	Model	Count	Ratio
13	San Bernardino	EW	8	167,838	168,305	0.997	15	19,245	32,499	0.592	59	187,122	200,805	0.932
14	Riverside	EW	10	309,084	260,304	1.187	27	25,689	41,928	0.613	51	335,145	302,232	1.109
15	Orange	NS	16	653,035	546,867	1.194	61	18,211	17,604	1.035	65	671,670	564,471	1.190
16	Los Angeles	EW	33	1,322,412	1,206,706	1.096	25	111,355	123,836	0.899	57	1,437,224	1,330,540	1.080
17	Los Angeles	NS	68	2,360,708	2,375,511	0.994	31	157,522	123,232	1.278	118	2,525,994	2,498,740	1.011
18	Los Angeles	EW	17	395,520	472,207	0.838	41	38,016	49,994	0.760	70	434,203	523,051	0.830
19	Los Angeles	EW	21	188,053	196,744	0.956	50	10,875	19,549	0.556	103	199,432	216,293	0.922
20	San Bernardino	EW	5	65,702	54,724	1.201	32	13,164	21,418	0.615	48	78,907	76,142	1.036
21	Riverside	EW	12	160,499	164,945	0.973	29	13,896	26,098	0.532	59	174,667	191,041	0.914
22	Riverside/ Imperial	EW	3	19,507	12,072	1.616	68	1,251	5,655	0.221	87	20,758	17,728	1.171
23	Imperial	EW	14	32,757	37,535	0.873	47	2,148	16,341	0.131	105	34,963	53,877	0.649
24	Los Angeles/ San Bernardino	EW	10	450,968	377,740	1.194	27	30,362	27,918	1.088	59	481,426	405,658	1.187
25	Ventura/ Los Angeles	NS	8	166,956	138,230	1.208	32	27,121	29,866	0.908	30	194,184	168,097	1.155
26	Los Angeles	NS	4	28,907	17,329	1.668	80	3,249	3,985	0.815	66	32,157	21,315	1.509
27	San Bernardino/ Riverside	NS	3	94,129	82,399	1.142	15	12,161	26,140	0.465	66	106,298	108,539	0.979
28	Riverside	EW	12	307,113	282,990	1.085	44	20,303	28,056	0.724	63	327,566	311,045	1.053
29	Los Angeles	NS	26	860,016	913,871	0.941	25	91,806	71,081	1.292	110	952,797	984,951	0.967
30	Riverside	EW	24	792,139	763,539	1.037	26	61,422	90,446	0.679	57	854,058	853,987	1.000
31	San Bernardino	NS	5	44,640	37,187	1.200	26	19,919	14,300	1.393	49	64,559	51,487	1.254
32	San Bernardino/ Riverside/ Imperial	NS	6	39,843	29,625	1.345	51	14,366	16,361	0.878	18	54,222	45,986	1.179
33	Imperial	EW	15	63,119	58,394	1.081	53	5,907	10,060	0.587	83	69,131	68,455	1.010
34	San Bernardino	NS	7	181,661	161,663	1.124	21	15,248	38,214	0.399	67	197,121	199,877	0.986
35	Los Angeles	NS	15	276,700	283,312	0.977	22	11,096	29,874	0.37	87	288,691	313,186	0.922
Total			717	**22,080,567**	**21,715,194**	**1.02**	**30.08**	**1,718,389.801**	**1,925,066**	**0.89**	**94.52**	**23,840,700**	**23,641,117**	**1.01**

Notes:
RMSE – percentage root mean square error
OBS – number of observed roadway facilities in the group

Table 16-6: Year 2019 Screenline Comparison of Model Weekday ADT and Ground Counts by Volume Group

	Volume Group By Facility	OBS	Daily Vehicle Volumes				Daily Vehicle Volumes				Daily Vehicle Volumes		
			Light And Medium Duty Vehicles				Heavy-Duty Vehicles				Total		
			Model	Count	Ratio	RMSE	Model	Count	Ratio	RMSE	Model	Count	Ratio
1	0 - 4,999	67	272,551.46	220,554.28	1.24	141.22	11,250.30	36,377.00	0.31	108.53	284,082.09	256,936.00	1.11
2	5,000 - 24,999	345	4,735,034.17	4,817,944.23	0.98	51.21	195,199.06	378,151.34	0.52	87.41	4,946,422.90	5,196,949.00	0.95
3	25,000 - 49,999	170	5,302,525.59	5,234,095.48	1.01	34.40	264,686.38	504,047.05	0.53	81.69	5,588,436.48	5,738,142.00	0.97
4	50,000 - 99,999	77	5,312,136.05	5,129,697.95	1.04	16.80	539,170.32	494,372.04	1.09	69.27	5,854,761.20	5,624,068.00	1.04
5	100,000 - 199,999	58	6,478,604.08	6,312,901.72	1.03	13.16	708,110.58	512,118.95	1.38	62.35	7,187,307.99	6,825,022.00	1.05
	Total	**717**	**22,080,567**	**21,715,194**	**1.02**	**30.08**	**1,718,389.801**	**1,925,066**	**0.89**	**94.52**	**23,840,700**	**23,641,117**	**1.01**

Notes:
RMSE – percentage root mean square error
OBS – number of observed roadway facilities in the group

Table 16-7: Year 2019 Screenline Comparison of Model Weekday ADT and Ground Counts by Facility Type

	Area Type	OBS	Light And Medium Duty Vehicles				Heavy-Duty Vehicles				Total		
			Model	Count	Ratio	RMSE	Model	Count	Ratio	RMSE	Model	Count	Ratio
10	Freeway	162	11,804,247	11,488,051	1.03	16.07	1,359,083	1,094,009	1.24	64.98	13,166,668	12,582,057	1.05
20	HOV	64	794,071	1,076,353	0.74	43.83	0	0	0	0	795,534	1,077,204	0.74
30	Expressway/Parkway	14	191,158	171,564	1.11	19.27	14,733	34,609	0.43	68.48	206,054	206,173	1.00
40	Principal Arterial	200	6,033,550	5,560,936	1.08	39.11	232,377	504,316	0.46	97.28	6,290,604	6,065,253	1.04
50	Minor Arterial	187	2,791,405	2,815,269	0.99	46.74	99,450	227,536	0.44	85.20	2,902,119	3,042,809	0.95
60	Major Collector	87	454,901	594,428	0.77	70.88	12,285	63,998	0.19	107.73	468,025	658,430	0.71
70	Minor Collector	2	11,235	8,592	1.31	55.13	461	599	0.77	87.83	11,696	9,191	1.27
	Total	717	**22,080,567**	**21,715,194**	**1.02**	**30.08**	**1,718,389.801**	**1,925,066**	**0.89**	**94.52**	**23,840,700**	**23,641,117**	**1.01**

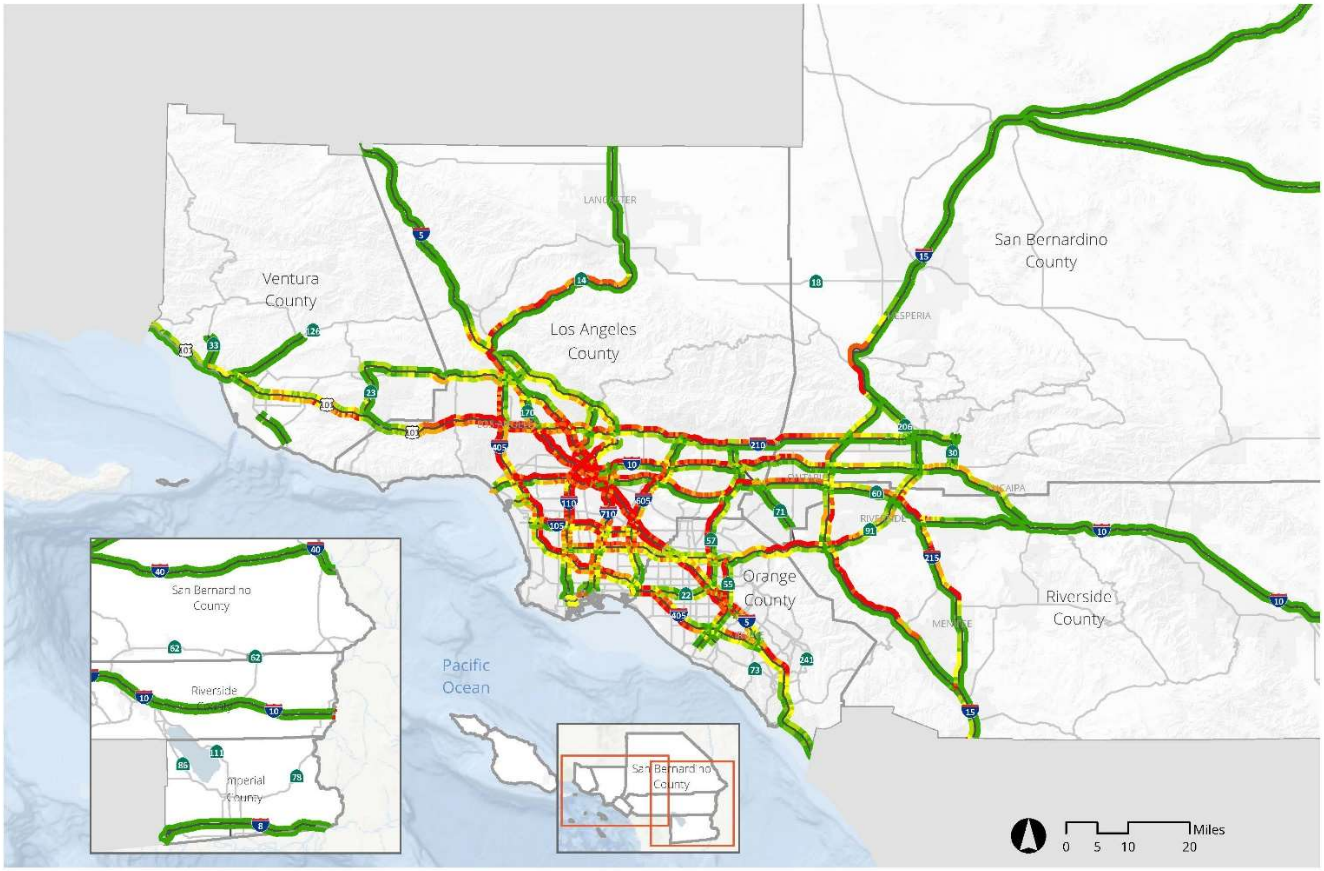
Notes:
RMSE – percentage root mean square error
OBS – number of observed roadway facilities in the group

Table 16-8: Year 2019 Screen line Comparison of Model Weekday ADT and Ground Counts by Area Type

	Area Type	OBS	Light And Medium Duty Vehicles				Heavy-Duty Vehicles				TOTAL		
			Model	Count	Ratio	RMSE	Model	Count	Ratio	RMSE	Model	Count	Ratio
1	Core	-	-	-	-	-	-	-	-	-	-	-	-
2	Central Business District	4	110,827	117,205	0.95	43	3,596	4,638	0.78	32	114,912	121,843	0.94
3	Urban Business District	131	5,219,532	5,324,453	0.98	26	380,670	358,198	1.06	110	5,613,836	5,682,643	0.99
4	Urban	241	8,003,724	7,995,266	1.00	27	598,175	641,250	0.93	83	8,620,965	8,636,525	1.00
5	Suburban	237	7,241,099	6,971,933	1.04	31	561,083	637,532	0.88	104	7,810,049	7,610,314	1.03
6	Rural	94	1,365,587	1,171,140	1.17	59	162,281	261,315	0.62	72	1,528,514	1,432,460	1.07
7	Mountain	10	139,798	135,198	1.03	23	12,584	22,133	0.57	83	152,423	157,332	0.97
Total		717	**22,080,567**	**21,715,194**	**1.02**	**30.08**	**1,718,389.801**	**1,925,066**	**0.89**	**94.52**	**23,840,700**	**23,641,117**	**1.01**

Notes:
RMSE – percentage root mean square error
OBS – number of observed roadway facilities in the group

Figure 16-5: Year 2019 Model Estimated AM Peak Period Speeds (Freeway)

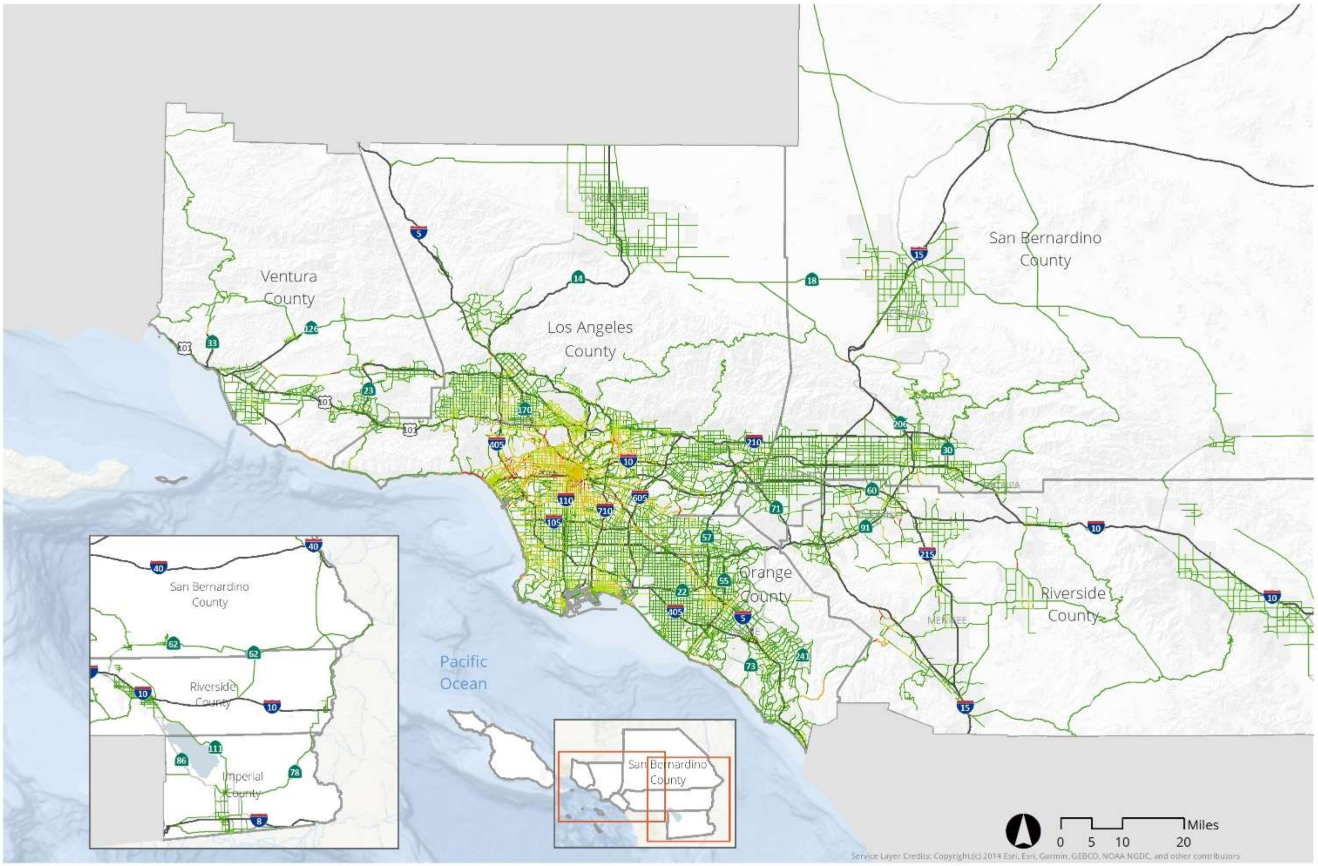


Speed in Miles per Hour

< 35 | 35 - 39 | 40 - 44 | 45 - 49 | 50 - 54 | 55 - 59 | 60 +

Source: SCAG, 2024 RTP

Figure 16-6: Year 2019 Model Estimated AM Peak Period Speeds (Arterial)



Speed in Miles per Hour

lower than 15 | 15.0 - 24.9 | 25.0 - 29.9 | 30 or higher

Source: SCAG, 2019 Base Year (AM)

Figure 16-7: Year 2019 NPMRDS AM Peak Speeds (Freeway)

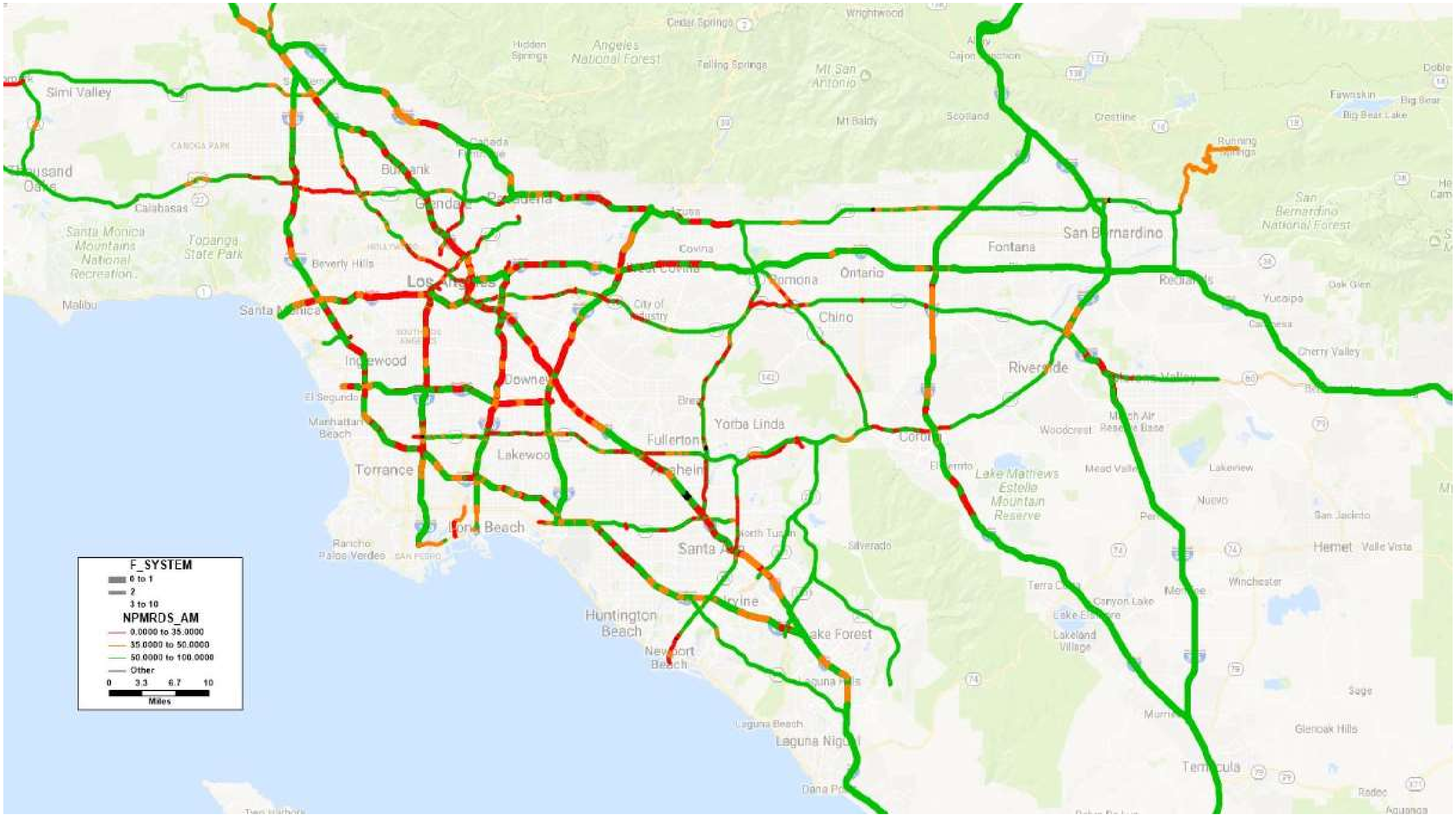


Figure 16-8: Year 2019 NPMRDS AM Peak Speeds (Arterial)

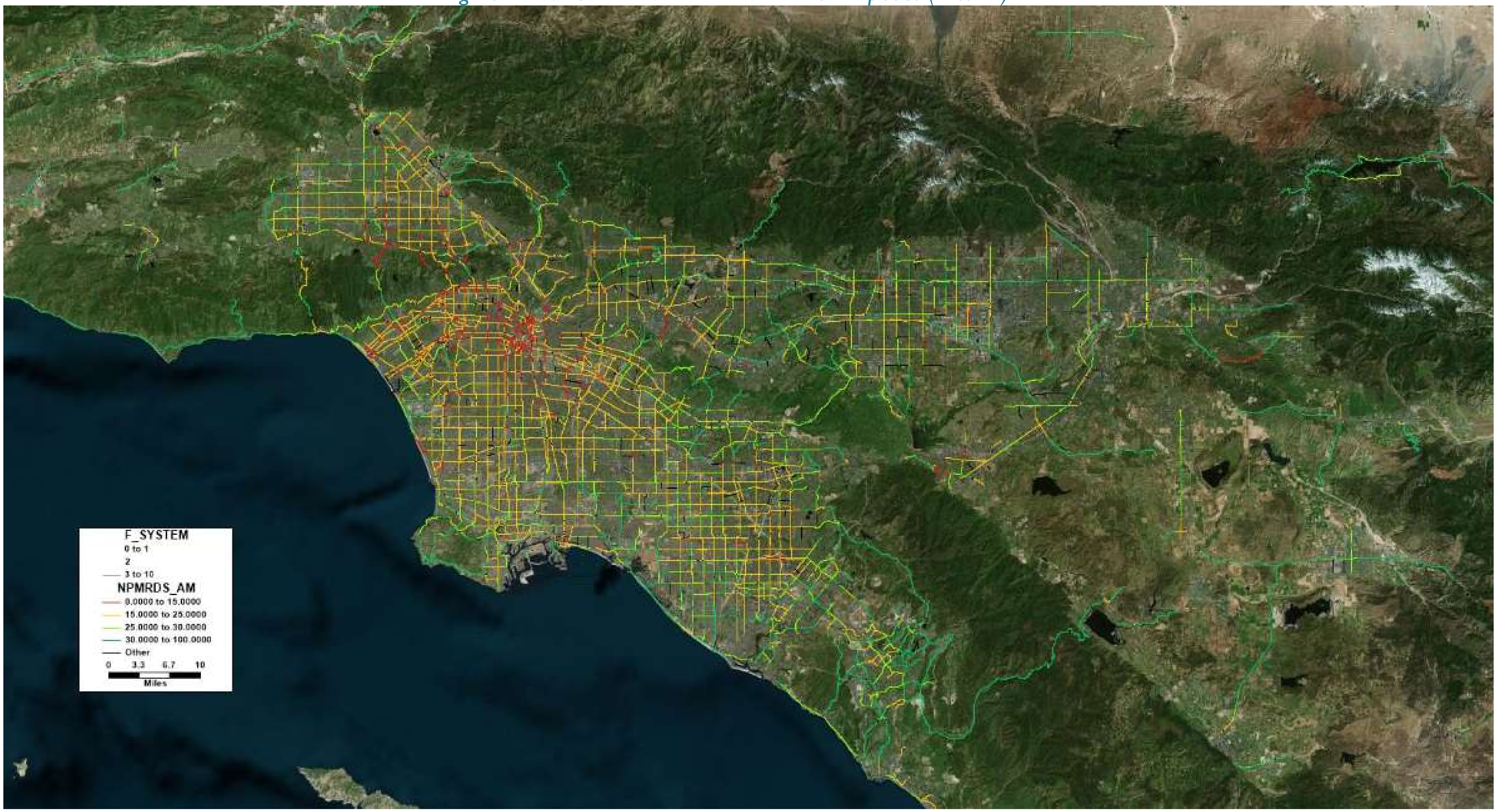
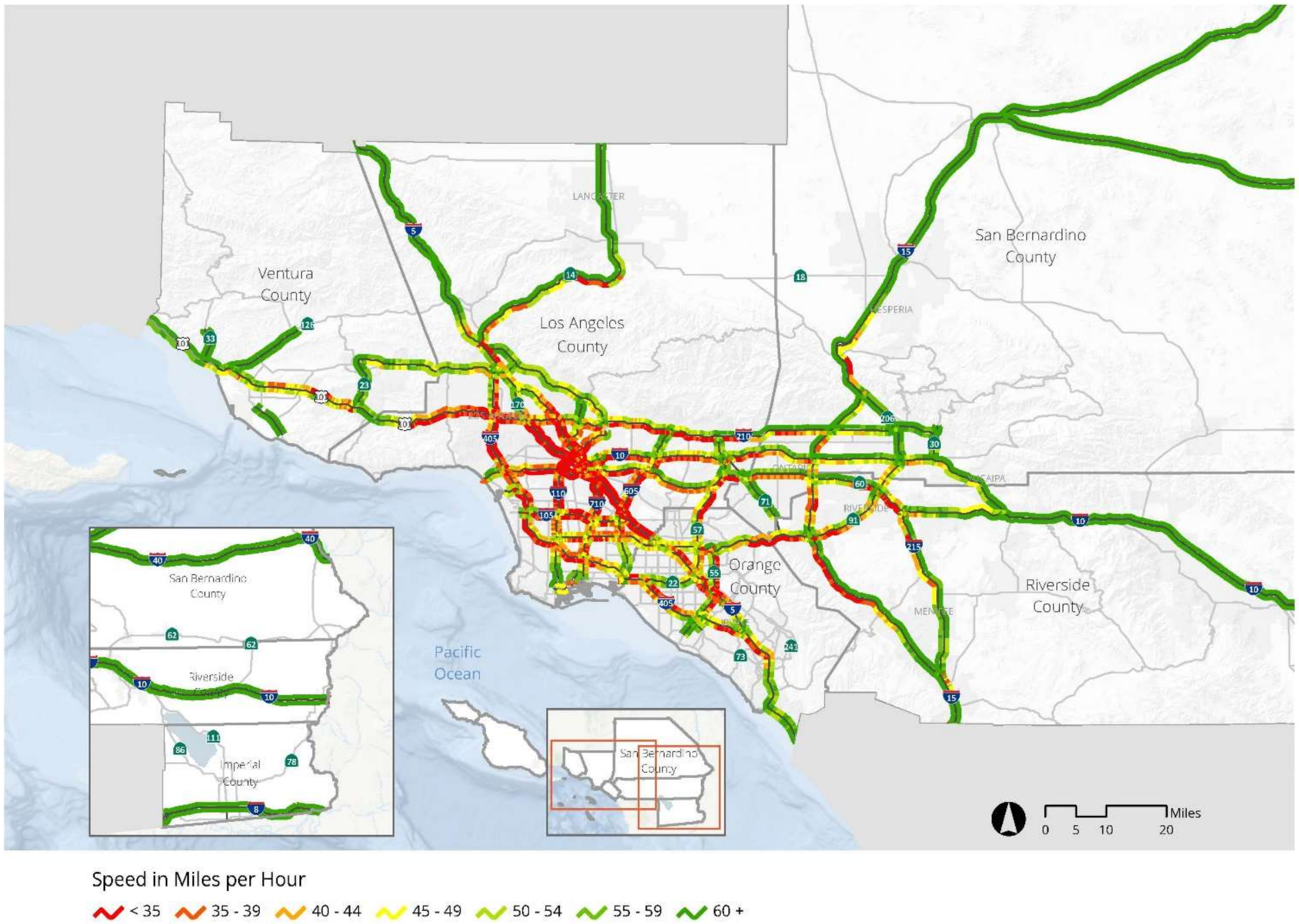
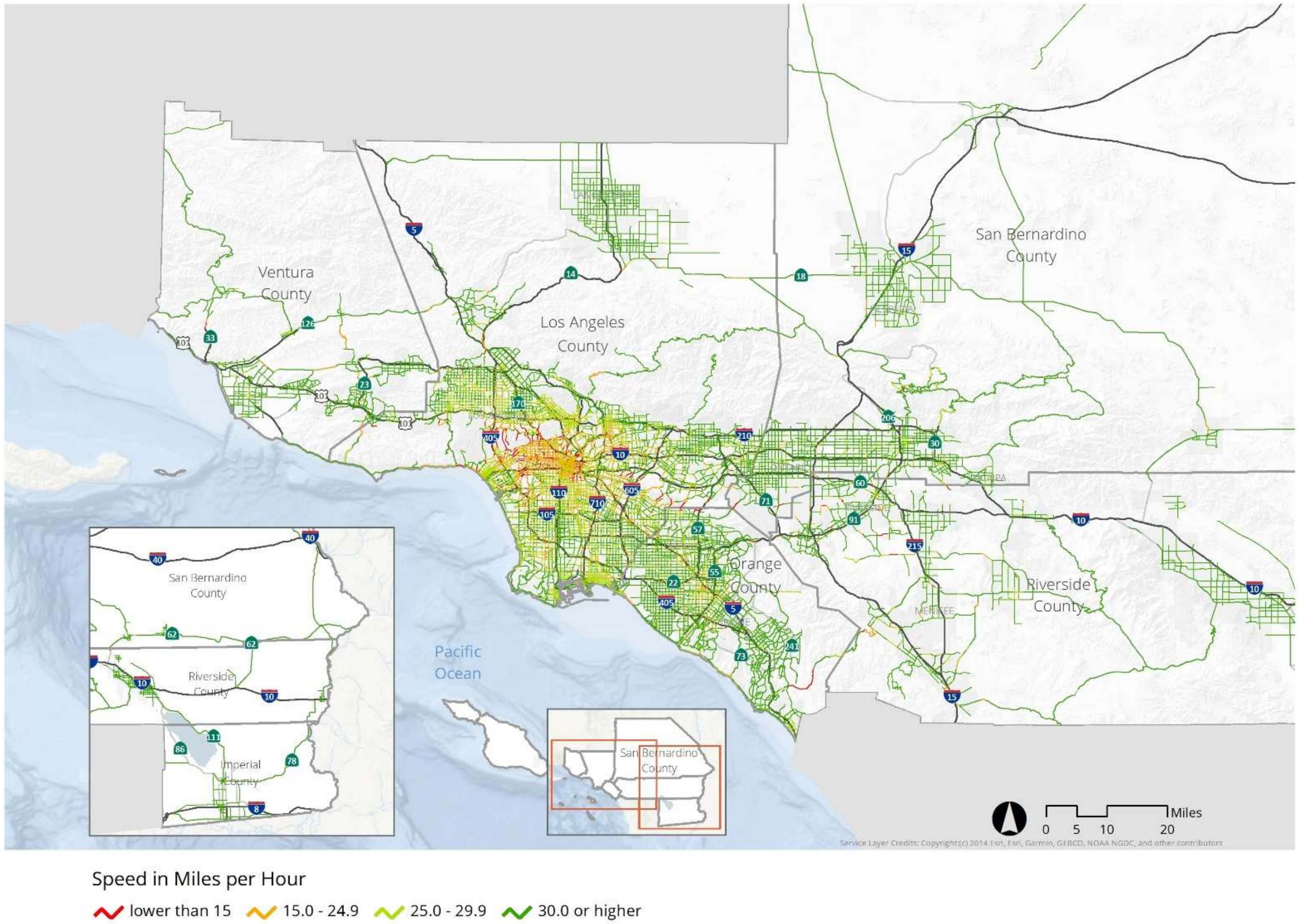


Figure 16-9: Year 2019 Model Estimated PM Peak Period Speeds (Freeway)



Source: SCAG, 2024 RTP

Figure 16-10: Year 2019 Model Estimated PM Peak Period Speeds (Arterial)



Source: SCAG, 2019 Base Year (PM)

Figure 16-11: Year 2019 NPMRDS PM Peak Speeds (Freeway)

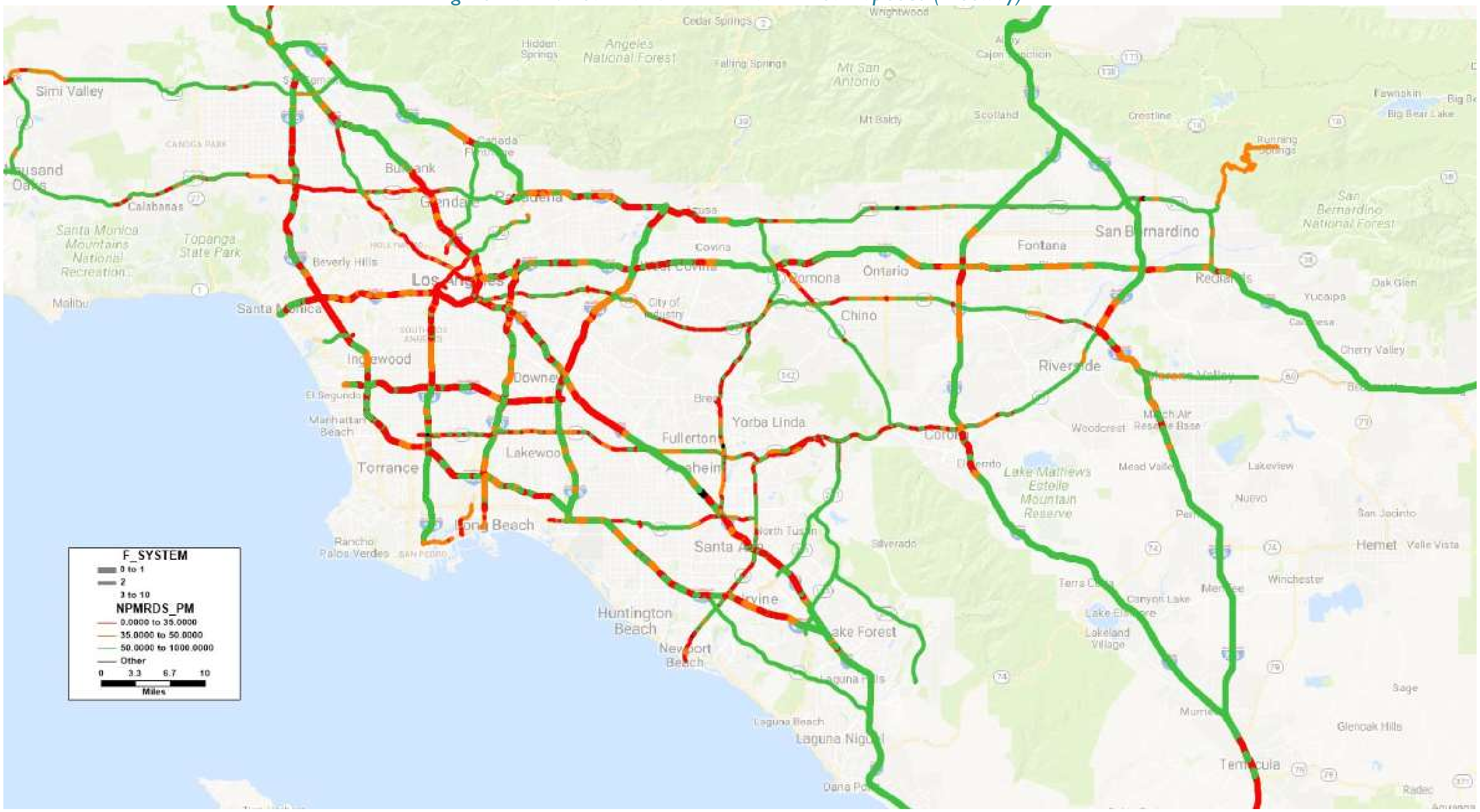
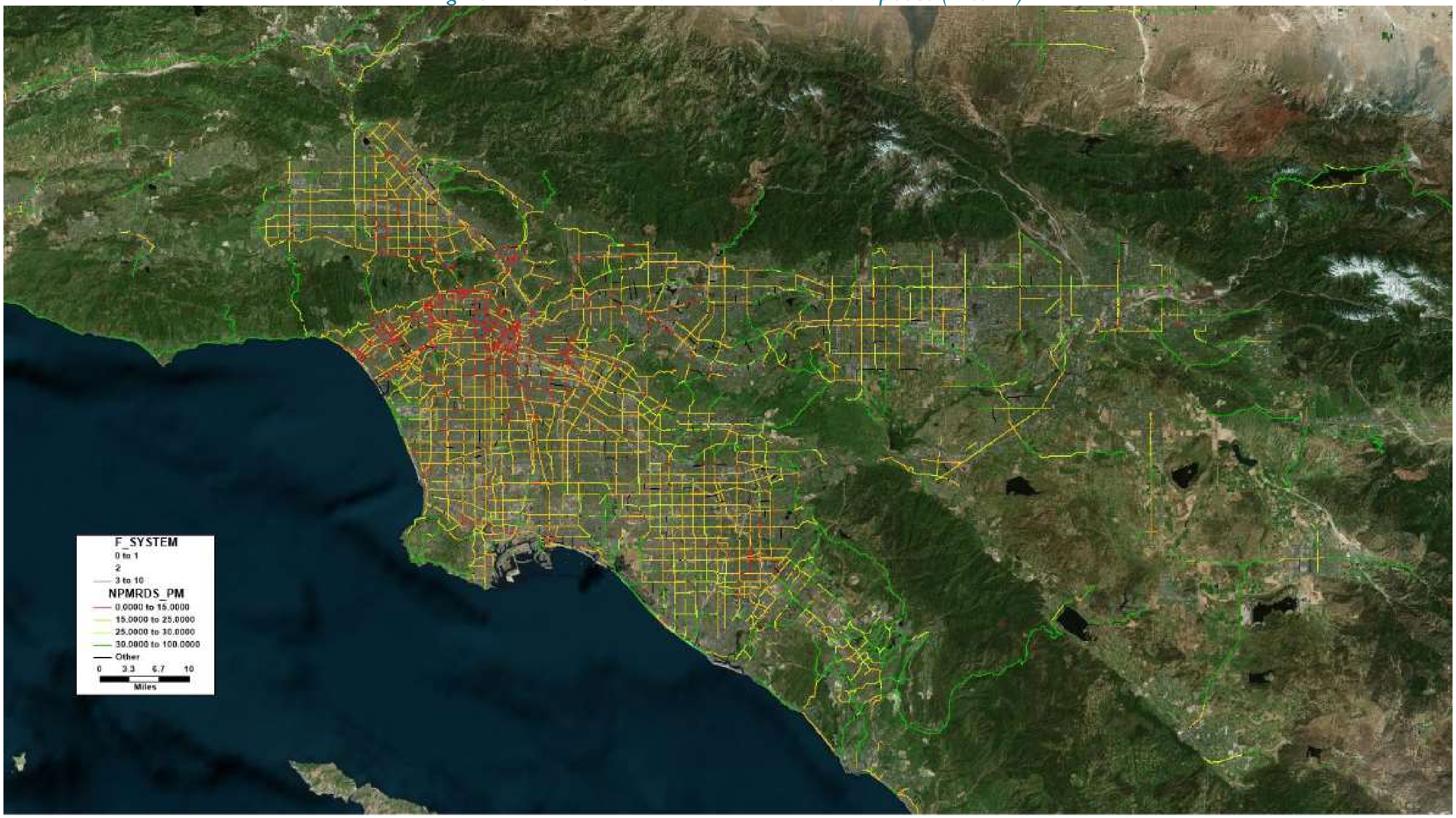


Figure 16-12: Year 2019 NPMRDS PM Peak Speeds (Arterial)



TRANSIT ASSIGNMENT PROCEDURES

Transit assignment is the process of loading the transit trips onto the appropriate transit routes, to produce boardings on each route, by station, etc. Transit trips are assigned in origin-destination format, and for five time periods, AM, MD, PM, EVE, NT.

Transit trips estimated by the trip formation model on the final feedback loop are aggregated across trip purposes to create unlinked transit trips for each two mode groups, conventional and premium, resulting in five transit trip tables.

The resulting loaded transit network files are aggregated to create total daily loaded trips.

Transit Assignment Validation and Summary

The 2019 transit assignment loaded 1,888,246 unlinked passenger trips (boardings) on the transit network. Table 16-9 compares the model estimated daily transit boardings to the 2019 actual transit boardings at the line level for rail transit and the agency level for bus transit.

Table 16-9: Year 2019 Daily Transit Boardings - Model Estimates vs. Actual Counts

Transit Group	Model	Actual	Ratio	%RSME	R-Squared
Rail Boarding	**376,592**	**372,495**	**1.01**		
Metrolink - VC/PS	4,359	3,639	1.20	19.02	0.978
Metrolink - OC/PS	10,463	8,699	1.20		
Metrolink - AV	10,792	5,729	1.88		
Metrolink - SB	7,503	9,736	0.77		
Metrolink - RV	3,533	4,251	0.83		
Metrolink - IEOC	4,724	4,501	1.05		
Metrolink - 91L	5,163	2,934	1.76		
LA Metro - Red/Purple	142,596	133,413	1.07		
LA Metro - Blue	71,763	64,648	1.11		
LA Metro - Expo	43,707	58,002	0.75		
LA Metro - Green	30,492	29,287	1.04		
LA Metro - Gold	41,496	47,656	0.87		
Bus Boarding	**1,511,654**	**1,479,367**	**1.02**		
LA Metro	946,001	909,600	1.04	11.11	0.998
OCTA	106,140	121,600	0.87		
Long Beach	54,893	64,500	0.85		
LADOT	56,161	60,295	0.93		
Santa Monica	59,097	52,500	1.13		
Foothill	62,096	40,100	1.55		
Omnitrans	39,835	35,600	1.12		
Riverside Transit Agency	27,267	26,200	1.04		
Montebello	21,893	20,600	1.06		
Culver City	20,025	15,500	1.29		
All Other Agencies	118,246	132,873	0.89		
Total Boarding	**1,888,246**	**1,851,862**	**1.02**		

Appendix A1: Highway Network Coding Conventions: Facility Type

1 – Freeways	10 – Freeway
2 – HOV	20 – HOV 2 21 – HOV 3+ 22 – HOV – HOV Connector
3 - Expressway/Parkway	30 – Undivided 31 – Divided, Interrupted 32 – Divided, Uninterrupted
4 - Principal Arterial	40 – Undivided 41 – Divided 42 – Continuous Left Turn
5 - Minor Arterial	50 – Undivided 51 – Divided 52 – Continuous Left Turn
6 – Major Collector	60 – Undivided 61 – Divided 62 – Continuous Left Turn
7 - Minor Collector	70 – Undivided 71 – Divided 72 – Continuous Left Turn 73 – Posted Speed 25 74 – Posted Speed 15
8 – Ramps	80 – Freeway to Freeway Connector 81 – Freeway to arterial 82 – Arterial to freeway 83 – Ramp Distributor 84 – Ramp from Arterial to HOV 85 – Ramp from HOV to Arterial 86 – Collector distributor 87 – Shared HOV Ramps to MF 89 – Truck only
9 – Trucks	90 – Truck only
100 – Centroid Connector - Tier 1 200 – Centroid Connector - Tier 2	

Flag Fields

Main Lane – Through Freeway Lanes
Aux_Lane – Auxiliary Lane of Capacity Significance
Accel_Decel Lane - Other Freeway Lane

Truck Climbing Lanes Flag	0 – None 1 – 1 Truck Climbing Lane 2 – 2 Truck Climbing Lane 3 – 3 + Truck Climbing Lane
Toll Flag	11 – Toll road with fixed tolls 12 – Toll road with per-mile tolls 21 – Express/HOT lane with fixed tolls 22 – Express/HOT lane with per-mile tolls
Signals Flag	0 – None 1 – Signal and progression optimized streets 2 – Divided and signal optimized 3 – Continuous left-turn Lanes
HOV Operation Flag	0 – Standard HOV 1 – HOV AM Peak Only 2 – HOV PM Peak Only 3 – HOV AM & PM Peak Only
Truck Prohibition Flag	0 - Truck Not Prohibited 1 - Trucks Prohibited

APPENDIX A2: AUTO OPERATING COSTS

The 2019 base year auto operating cost comprises the following components: fuel price, fuel efficiency, and non-fuel costs (including maintenance, repair, and tires, or abbreviated as MRT costs). AOC is computed using those data specific to vehicles categorized by fuel types as identified in the current EMFAC model (EMFAC 2021). These fuel types encompass gasoline, diesel, PHEV (powered by gas and by electricity), and electricity. Given that a travel demand model simulates an average vehicle and its costs, a composite AOC value is computed.

Data Source:

- Fuel Price (FP): Gasoline and diesel fuel price is based on annual average data from U.S. Energy Information Administration (EIA); electricity price for EV/PHEV is estimated by California Energy Commission (CEC).

- Fuel Efficient (FE): Fuel economy for vehicles of different fuel types (gasoline, diesel, PHEV, and electricity) is calculated based on VMT and fuel consumption data from EMFAC 2021.

- Non-fuel Costs (NFC) are based on data from the annually released "Your Driving Costs" brochure by the American Automobile Association (AAA). Operating costs, specifically maintenance and tire expenses, are used for the analysis.

- Vehicle Fleet Mix - Vehicle fleet mix refers to the percentage of VMT for vehicles categorized by fuel type. It serves as a weighting factor in computing the composite average value for an average vehicle. SCAG derives the VMT fleet mix from EMFAC 2021.

- All price and cost data was converted to 2011-dollar value.

Auto operating cost (AOC) for vehicles by each fuel type (f) for each year (y) is calculated as:

$$AOC(f,y) = [\ FP\ (f,y)\ /\ FE\ (f,y)\ ] + NFC\ (f,y)$$

After Year 2019 AOC for each fuel type is calculated, using fleex mix as weight, a composite average AOC change is determined. The table below summarizes the Year 2019 auto operation cost for vehicles by each fuel type as well as its fleet mix in 2019, as percentage of total VMT (based on EMFAC 2021).

2019 Auto Operating Cost (2011-dollar value)

Item	AOC	% VMT in 2019
Gasoline	20.529	97.48%
Diesel	19.147	0.44%
PHEV (Gasoline)	17.230	0.61%
PHEV (Electricity)	10.899	0.52%
EV (Electricity)	11.282	0.95%
Average Auto Operating Cost	**20.364**	

Average auto operating cost for year 2019 is 20.364 cents per mile.

To ensure the model accurately reflects the evolving dynamics of travel behavior influenced by changes in auto operating costs and its elements, SCAG, in collaboration with modelers from other California MPOs, has enhanced the methodology used for projecting AOC in future years. Please refer to Appendix B1 for details.

Appendix A3: Work from home

Work from home

Work from home is considered "Home" as one of the travel modes for work trips, reflecting the percentage of workers who work from home on an average weekday. The work arrangement sub-model of SCAG ABM incorporates assumptions for the percent of workers who work from home, including telecommuting, home office, or other strategies.

Inputs can be either WfH workers as percent of total workers, or by eight different household income segments: <$25K, $25k-$50k, $50k-$75k, $75k-$100k, $100k-$125k, $125k-$150k, $150k-$200k and >$200k.

2019 Work from Home input

Household Inc	Model Input
<$25K	8.91092
$25k-$50k	6.38491
$50k-$75k	6.34348
$75k-$100k	6.15290
$100k-$125k	6.66592
$125k-$150k	8.45538
$150k-$200k	9.37614
>$200k	10.68698

APPENDIX A4: TELEMEDICINE

Due to the advancement in wireless/communication technology, there is on-going increase in engaging activities at home through on-line access to services, including telemedicine. SCAG enhanced ABM by adding an at-home non-mandatory activity choice module. Predicting trip substitution due to factors such as online shopping and telemedicine is beyond the scope of a travel demand model. Instead, external quantification of the substitution effect was required, and this sub-model directly incorporates these factors.

Based on the analysis of 2015-2018 California Health Interview Survey (CHIS), SCAG developed model baseline input for telemedicine module. The needed model input for telemedicine is to input the percentage of telemedicine activities to total personal maintenance activities, by age cohorts.

2019 telemedicine input (base case)

Model Test Input: % of telemedicine activities to total personal maintenance activities:

Year\Age	<18	18-29	30-44	45-64	65-74	75+
2019	1.21%	0.67%	1.25%	1.28%	1.08%	1.59%

APPENDIX A5: SCAG MODEL PEER REVIEW RESULTS

BACKGROUND

Peer review plays a crucial role in SCAG's model validation process, aiming to evaluate the validated model and seek recommendations for future enhancements. On May 10, 2023, SCAG hosted an in-person peer review meeting at its office.

The peer review of SCAG's transportation model assembled a distinguished panel of experts in the field of transportation modeling and analysis, representing a diverse range of entities, including Federal and State agencies, leading modeling experts from MPOs and LA Metro, academia, and professional consultants.

Following a comprehensive day of discussions, panel members provided feedback on SCAG's model and offered recommendations for both short-term and long-term improvements. This collaborative effort aims to enhance the quality and effectiveness of SCAG's transportation modeling practices, contributing to the ongoing enhancement of transportation planning in the Southern California region, benefiting both current and future initiatives.

Peer Review Panel Members	
Name	**Organization**
Guy Rousseau (Chair)	Atlanta Regional Commission
Anthony Catalina	Los Angeles County Metropolitan Transportation Authority (LA Metro)
Brian Gardner	USDOT, Federal Highway Administration
Konstadinos Goulias	University of California Santa Barbara
Nesamani Kalandiyur	California Air Resources Board
Wu Sun	San Diego Association of Government (SANDAG)
Mike Wallace	Fehr & Peers

RECOMMENDATIONS AND FINDINGS

Overall Findings of the Peer Review Panel

The current SCAG travel demand model is an advanced activity-based model based on CT-RAMP2 structure that meets and, in many cases, exceeds the state of the practice. The model is suitable for use in preparing 2024 RTP, conformity analysis, and SCS.

Model Strengths

The Panel feels that the level of effort for the SCAG model is impressive and ambitious. SCAG should continue to manage and coordinate the overall model enhancement program and individual consultant work efforts. Positive highlights of the SCAG ABM include:

SCAG's ABM model design considers the requirement of State and Federal mandates.

The calibration and validation processes for the model were both rigorous and adaptable, incorporating a range of data sources. These included the Department of Motor Vehicle data, third-party location datasets (such as Replica and Streetlight), and publicly accessible data sets like LEHD, NHTS, and CTPP.

There has been a marked improvement in validation results since the last peer review, with additional validation dimensions being integrated.

The sensitivity analysis provided valuable insights, encompassing a variety of model metrics (e.g., VMT, mode share, transit boarding, number of trips) and influenced by different input parameters (like land use patterns, auto operational costs, transit fares, roadway capacities, and work-from-home scenarios). The sensitivity tests provide useful guidance to policy and infrastructure investment planning, especially in the context of meeting the SB375 GHG reduction target.

The revised model possesses enhanced capabilities to more precisely account for telemedicine and online shopping preferences through the at-home activity model.

Both work and school location models have seen significant enhancements.

Updates in the mode choice model estimation, paired with the integration of TNC as a novel mode, offer significant value.

Model execution time has been optimized, and the user interface now allows users to pick up the run from any given point.

The newly integrated sub-model for trip departure time choice has been refined to eliminate nonsensical travel patterns.

In the updated model, activities displaying negative trip durations have been eradicated.

Recommendations for Model Validation & 2024 RTP Process (Short-Term)

The major conclusions and recommendations of the Peer Review Panel for short-term consideration by SCAG are listed in this section. The recommendations described herein are intended for short-term implementation in the model prior to using the model for developing the 2024 RTP. In some cases, the recommendations do not require additional efforts on the part of the model development team. SCAG had incorporated some of the recommended items for 2024 RTP Model. SCAG will assess the remaining items for future model enhancement based on planning priorities and available of resources.

It is recommended to enhance the documentation pertaining to travel market segmentation and ABM models. Further, documentation on how ABM can be seamlessly integrated with the land use model would be beneficial.

An expanded transit validation, particularly for specific services and designated sub-areas, is advisable.

It would be valuable to incorporate daily VMT by facility type in the validation summary.

Comparing model trip tables with CTPP data, especially for finer geographies and specific market segments, is recommended.

We suggest sensitivity analysis focusing on factors like population and employment dynamics, the balance between jobs and housing, emerging technologies, as well as comprehensive pricing policies including parking.

Enhanced estimation methods for vehicle occupancy are recommended.

Validating speed data should also be a priority.

Recommendations for Model Enhancement Program (Long-Term)

The major conclusions and recommendations of the Peer Review Panel for longer-term consideration by the SCAG and consultant modeling team are listed in this section. The recommendations described herein are intended for exploration or implementation in the model after the 2024 model validation is final. In some cases, the recommendations do not require additional efforts on the part of the model development team. SCAG will assess the recommended items for future model enhancement based on planning priorities and available of resources.

Integrate parking costs into the mode choice model. Time of day travel and parking demand are greatly enhanced with activity-based models and incorporating parking demand will enhance many modeling aspects including destination choice.

Given the upcoming Summer 2028 Olympics, modeling for special events is recommended.

Long distance and interregional travel needs to get added attention. Incorporating a visitor model could enhance the SCAG model.

Consider the development of an air passenger model, focusing specifically on an airport ground access mode choice model.

Special travel markets, such as a commercial vehicle model is also recommended.

Provide a clearer distinction between "Work-from-home" and telecommuting frequency segmented by industry/occupation. Offer a more explicit definition for “Essential Workers” within the model. Ensure that employment patterns and economic shifts, including the rise of flexible workspaces, are adequately reflected in the model.

Combine arrival time distributions with departure time distributions to achieve more accurate and logical trip durations.

Define a post-pandemic base year for modeling purposes considering the new-norm.

Update all travel surveys, including household and on-board transit surveys, considering their age and the evolving post-pandemic norms.

Ensure efficient feedback mechanisms between the land use model and ABM.

Prioritize the development of a regional DTA model to account for transit capacity and crowding on pivotal corridors.

Explicitly model first-mile and last-mile deliveries within the freight model.

Implement a vehicle type model that encompasses EVs, Avs, and integrates charging stations within the ABM.

Consider the introduction of micro-zones to enhance the modeling of walk and bike trips.

Integrate micro-mobility as a distinct mode within the model.

Ensure that transit network coding aligns with GTFS standards.

Maintain coordination with Caltrans' statewide travel demand model and interface with adjacent MPO models, such as SANDAG.

APPENDIX B1: IMPROVING MODEL INPUTS FOR AUTO OPERATING COSTS

1. Introduction

Auto Operating Cost (AOC) plays a pivotal role as a fundamental parameter within travel demand models. This parameter represents the expenses associated with the usage of vehicles, expressed in cents per mile or dollars per mile. AOC is used as key variable across several major model components of the travel demand model, such as vehicle ownership, destination choice, mode choice, route choice, and other relevant components.
In a travel demand model, AOC is treated as a single (combined) value used as a model input, rather than considering its individual components separately (for example, fuel price, fuel efficiency, maintenance costs, fuel types), which limits the model's ability to generate more appropriate outcomes in response to changes in AOC's components. This highlights the importance of refining the modeling procedure/adjustment to consider and incorporate a more nuanced understanding of AOC, ensuring that the model accurately reflects the dynamic nature of travel behavior influenced by shifts in AOC and its various elements.
The objective of this document is to describe the assumptions, methodology, and procedure to improve modeling procedure to reflect reasonable model outcome in relation to the future change of AOC components.

2. Auto Operating Cost Components

The auto operating cost comprises the following components: fuel price, fuel efficiency, and non-fuel costs (including maintenance, repair, and tires, or abbreviated as MRT costs). AOC is computed using those data specific to vehicles categorized by fuel types as identified in the current EMFAC model (EMFAC 2021). These fuel types encompass gasoline, diesel, PHEV (powered by gas and by electricity), and electricity. Given that a travel demand model simulates an average vehicle and its costs, a composite AOC value is computed by average of AOC, weighted by % VMT for each fuel type. This AOC calculation approach is described in the Third SCS Guideline (November 2019).

3. VMT Response and Model Elasticity

Based on the interaction between demand and supply, it is expected that when travel cost increases, vehicle usage (demand) and associated VMT will decrease. This relationship is crucial to understand the VMT responses, which is quantified and expressed through the concept of "elasticity." Within a travel demand model, the elasticity of VMT with respect to auto operating cost can be assessed and estimated via sensitivity tests. It is crucial for the model's estimated elasticity to be aligned with reasonable travel behavior and auto usage with respect to overall travel costs and its components that have been researched, and within reasonable range as identified through literature review and research. A model that produces reasonable VMT elasticity is considered capable of reflecting reasonable travel behavior responses to changes in model input and/or policy instruments.

As previously discussed, two primary components influencing auto operating cost are fuel price and fuel efficiency. Sections 3.1 and 3.2 review of literature and research focusing on the reasonable range of VMT response, as measured by elasticity, to fuel price and fuel efficiency. Sections 3.3 and 3.4 describe the analysis and improvement to modeling procedure to reflect reasonable model outcome in relation to the future change of AOC components.

3.1 VMT Response to Fuel Price

Table 3.1 summarizes the VMT elasticity with respect to fuel price, as derived from literature reviews. The average elasticity calculated from these studies is -0.083, with an overall range between -0.075 and -0.11. In a model sensitivity test, a travel demand model is considered reasonable in reflecting VMT response to fuel price if the VMT elasticity value falls within this range. It is noted that these studies were completed before the recent surge in electric vehicles (EVs). Given the absence of more recent research on EVs' VMT response effects to auto operating cost or fuel price – electricity charges, we assume the same VMT elasticity to fuel price among vehicles by fuel types – gasoline, diesel, or electricity changes, including EVs.

Table 3.1 VMT Elasticity to Fuel Price

Fuel Price	Study Location	VMT Elsticity	SR/LR
Hymel, Small and Van Dender (2010)	U.S.A - Nationwide	-0.026	SR
		-0.131	LR
Burt and Hoover (2006)	Canada	-0.08	cars
Boilard (2010)	Canada	-0.092	SR
		-0.256	LR
Goodwin et al. (2004)	International	-0.1	SR
		-0.3	LR
Gillingham et al. (2015)		-0.1	
Wenzel and Fujita (2018)	U.S.A - Texas	-0.075	
Langer et al. (2017)		-0.11	
Average (SR)		-0.083	

3.2 VMT Response to Fuel Efficiency – Not significant, almost no impact

Table 3.2 summarizes the VMT elasticity with respect to fuel efficiency, based on findings from literature reviews. The range of elasticity identified in these studies spans from 0 to 0.01. These analyses indicate that with a 10% increase in fuel efficiency, the impact on vehicle use is either negligible or results in approximately a 0.1 percent increase in VMT. In a model sensitivity test, a travel demand model is considered reasonable in reflecting VMT rebound effects due to changes in fuel efficiency if the VMT elasticity value falls within this range (0 ~ 0.01).

Table 3.2 VMT Elasticity to Fuel Efficiency

Fuel Efficiency	VMT elasticity
CARB (2018)	0 ~ 0.01
US EPA	Near zero
West et al. (2017)	0
Greene (2012)	0
Gillingham (2011)	0.01

3.3 VMT Elasticity in Travel Demand Model

In a travel demand model, the auto operating cost (expressed in cents per mile) is utilized as a key parameter to calculate the cost for a vehicle. It is noteworthy that the model does not directly use fuel price or fuel efficiency as separate inputs. The computed AOC, which integrates both fuel price and fuel efficiency, is used as a model input. Changes in fuel price or fuel efficiency lead to corresponding adjustments in the auto operating cost.
Because fuel price and fuel efficiency are served as numerator and denominator of the AOC formula, the two AOC components have a similar magnitude of impact on AOC and, consequently, the VMT rebound. However, according to the above literature review, in the realm of reasonable travel behavior assumptions, the VMT rebound effect appears to be more pronounced in response to changes in fuel price compared to fuel efficiency.

Below Table 3.3 displays model sensitivity test results with changes in fuel price. When the fuel price rises by 25%, the auto operating cost increases by 16.01%, and the VMT's response shows a 1.97% reduction. The resulting -0.079 VMT elasticity to fuel price falls within the reasonable range, indicating that the model accurately reflects reasonable travel behavior. Other test scenarios show the similar results.

In another test (Table 3.4), for example, when the fuel efficiency increases by 25%, the auto operating cost decreases by 12.81%, and the VMT's response shows a 1.63% increase. However, the resulting 0.065 VMT elasticity to fuel efficiency is significantly outside the reasonable range, which is 0-0.01 according to the literature review. This suggests that the model cannot accurately reflect reasonable travel behavior in the response of the change on vehicle's fuel efficiency.

Table 3.3 VMT Elasticity Tests to Fuel Price

		Model Input			Elasticity to
Fuel Price	AOC (base)	AOC (Sce.)	% AOC	% VMT	Fuel Price
+25%	20.37	23.63	16.01%	-1.97%	-0.079
-25%	20.37	17.11	-16.01%	2.10%	-0.084
+50%	20.37	26.89	32.02%	-3.78%	-0.076
-50%	20.37	13.85	-32.02%	4.09%	-0.082
Average					-0.080

Detailed model sensitivity test output is available in the SCAG Model Test Report

Table 3.4 VMT Elasticity Tests to Fuel Efficiency

		Model Input			Elasticity
Fuel Efficiency	AOC (base)	AOC (Sce.)	% AOC	% VMT	Fuel Price
+25%	20.37	17.76	-12.81%	1.63%	0.065
+50%	20.37	16.02	-21.35%	2.72%	0.054
Average					0.060

Detailed model sensitivity test output is available in the SCAG Model Test Report

3.4. Model Improvement (Adjustment) Procedure to Address VMT Elasticity to Fuel Efficiency

To address the inconsistency in VMT response related to fuel efficiency improvement between the model results and observed travel behavior, SCAG propose a model improvement procedure. This involves employing a fuel efficiency adjustment procedure during the calculation of model inputs to create more accurate representations of reasonable response behavior with the model, considering both fuel price and fuel efficiency.

The adjustment is straightforward. Below Table 3.5 displays model sensitivity test results with changes in fuel efficiency. Taking the earlier example of a 25% increase in fuel efficiency, if we adjust the fuel efficiency increase to 3% when calculating the model input for AOC, the percentage change in VMT will be reduced, resulting in a VMT elasticity of 0.008. This value, achieved through the adjusted fuel efficiency, is within the reasonable range. The formula of the adjustment procedure can be found in Appendix I.

In the previous (third) SCS, SCAG employed a similar adjustment procedure to address this modeling issue. The proposed adjustment procedure, developed by the Big 4 MPOs, signifies an enhancement over previous method, producing more accurate and reasonable results. As the fuel efficiency remains unchanged for all forecast years for electric vehicles (87 miles/GGE from CARB's draft AOC Calculator), the adjustment of fuel efficiency will be applied exclusively to gasoline- and diesel-powered vehicles.

Table 3.5 VMT Elasticity Tests to Fuel Efficiency (through Model Improvement/Adjustment Procedure)

		Model Input			Elasticity to
Fuel Efficiency	AOC (base)	AOC (Sce.)	% AOC	% VMT	Fuel Price
+25%	20.37	19.96	-2.00%	0.21%	0.008
-25%	20.37	20.78	2.00%	-0.19%	0.008
+50%	20.37	19.56	-4.00%	0.48%	0.010
-50%	20.37	21.19	4.00%	-0.49%	0.010
Average					0.009

Detailed model sensitivity test output is available in the SCAG Model Test Report

4. Composite AOC Calculation and Electric Vehicles

As mentioned earlier, a travel demand model relies on a composite AOC as one of its key inputs. Changes in AOC in the future, whether driven by changes in fuel costs or the implementation of policies such as VMT fees, have significant implications for both future travel demand and air quality. This is because these changes directly influence the travel costs associated with using a car. Therefore, it is crucial to thoroughly review the methodology used to develop this model input, especially its projected growth in the future years.

4.1 Review of Current Methodology

Table 4.1 below presents the current (2019) and projected (2035, 2050) auto operating costs for vehicles based on different fuel types, along with their growth and usage as a percentage of total VMT. Several observations regarding the methodology for calculating AOC and its growth emerge from this data:

Firstly, future electric vehicles (EVs) are anticipated to experience significant growth in the SCAG region, with the percentage of total VMT attributed to EVs projected to rise from the current 0.9% to 6.8% in 2035 and further to 7.7% in 2050. This growth is expected to be further accelerated by the adoption of the Advanced Clean Car II (ACCII) regulation, reaching approximately 50% in 2035 and 80% in 2050.

Secondly, the AOC value for EVs is notably lower than that for Internal Combustion Vehicles (ICVs). On average, the AOC for EVs is approximately 40% lower than that for gasoline-fueled vehicles. Given the discussion above, the growth and value of the composite AOC will be influenced by the increasing proportion of EV usage. As the proportion of EV usage grows, the composite AOCs will decrease, reflecting the 40% lower AOC for EVs.

Considering the substantial increase in EV adoption over the years, the majority of increased EV usage (in VMTs) comes from individuals transitioning from ICVs to EVs, and some from new drivers choosing EVs as their first vehicles. Recent studies from UC Davis (2021) and MIT (2023), along with SCAG's review of the new 2022 NHTS data (Appendix II) show no significant differences in vehicle usage or annual VMT between EVs and ICVs. This indicates that for those transitioning from ICVs to EVs, their travel patterns and annual VMT remain similar to ICVs, despite the lower AOC for EVs. The implication is that the lower AOC for new EV usages, whether through a transition from ICVs or for new drivers, should not impact VMT. However, in terms of AOC calculation, the current methodology from SCS Guideline, which applies the lower AOC value to all EV usage, may lead to an underestimation of AOC.

Table 4.1 AOC by Fuel Types for SCAG Region

	Gasoline / Diesel			Electricity	
Fuel	Gas	Diesel	PhEV	PhEV	EV
% of Total VMT					
2019	97.5%	0.4%	0.6%	0.5%	0.9%
2035	89.8%	0.3%	1.3%	1.8%	6.8%
2050	88.7%	0.3%	1.4%	2.0%	7.7%
Auto Operating Cost - Model Input (AOC)					
2019	20.529	19.147	17.230	12.181	11.282
2035	25.324	23.958	22.170	16.474	14.655
2050	26.879	25.609	23.721	18.885	16.678
% AOC Change from 2019					
2019					
2035	23%	25%	29%	35%	30%
2050	31%	34%	38%	55%	48%

4.2 Improvement Approach and Procedure

To incorporate a reasonable VMT response in the model, the proposed improvement involves calculating the average AOC change. This average AOC change is determined through a weighted average of AOC change for each fuel type, where the weights are based on the percentage of VMT associated with each fuel type. Since there is no VMT change for new EV usage, AOC is assumed to remain unchanged (or have 0% growth) for new EV usage.

This improvement in the modeling procedure is particularly crucial, especially in terms of the third observation - auto operating costs have shown a significant increase across different fuel types. From 2019, AOCs for gasoline vehicles are projected to increase by 23% in 2035 and 31% in 2050, while for electric vehicles, the increases are 30% and 48%, respectively. Upon examining the data in Table 4.1, the overall AOCs should experience an increase of at least 23% in 2035 and 31% in 2050. However, based on the current approach from the SCS Guideline, the composite AOC is projected to increase by 20% in 2035 and 28% in 2050—figures significantly lower than our observations described above (23% and 31%). This notable disparity could lead to unreasonable model outputs in planning analysis, especially when considering future scenarios with the anticipated larger growth in EV usage.

To address this issue, SCAG proposes an improvement procedure. Firstly, calculating a composite AOC growth, which is an average of AOC growth by fuel types weighted by their respective vehicle usage. Subsequently, the base year AOC and the calculated growth rate are used to compute AOC for all years. This approach ensures that the significant increase in AOC growth across different fuel types is reflected in the model input.

1. Calculate Composite AOC Growth (Percentage Growth of AOC)

$$\% AOC_{y_1-y_2} = \sum_i (\% AOC_{i,y_1-y_2} \times \% VMT_{i,y_2}) \quad (1)$$

Where:

$\% AOC_{y_1-y_2}$ *= the percentage growth of auto operating cost from year y1 to year y2*

$\% AOC_{i,y_1-y_2}$ *= the percentage growth of auto operating cost for a specific fuel type i from year y1 to year y2*

$\% VMT_{i,y_1}$ *= the percentage of VMT by vehicles using fuel type i to total VMT for year y2*

Year y1 is one year prior to year y2

2. Calculate SCAG Base Year (2019) AOC

The base year, 2019, AOC is calculated as

$$AOC_{2019} = \sum_i (AOC_{i,2019} \times \% VMT_{i,2019}) = 20.37 \text{ cents/mile} \quad (2)$$

Where:

AOC_{2019} *= the calculated auto operating cost for base year 2019*

$AOC_{i,\,2019}$ *= the calculated auto operating cost for specific fuel type i, for year 2019*

$\% VMT_{i,2019}$ *= the percentage of VMT to total VMT by vehicles using fuel type i for year 2019*

Detailed information regarding data, assumptions, and method for 2019 AOC calculation are described in the SCS Technical Methodology.

3. Calculate AOC for Each Year

After percentage growth of AOC between two consecutive years as well as base year AOC is calculated, the equation to calculate AOC for each year is shown below:

AOC for 2020:

$$AOC_{2020} = AOC_{2019} \times (1 + \% AOC_{2019\text{-}2020}) \quad (3)$$

AOC for each subsequent year, y2:

$$AOC_{y_2} = AOC_{y_1} \times (1 + \% AOC_{y_1-y_2}) \quad (4)$$

Where:

AOC_{y_2} *= the calculated auto operating cost for year y2*

AOC_{y_1} *= the calculated auto operating cost for year y1, which is one year prior to year 2*

$\% \, AOC_{y1-y2}$ *= the percentage growth of auto operating cost from year y1 to year y2*

The following sections discuss the two main inputs used in calculating composite AOC growth (as shown in Equation 1): the percentage changes in AOC growth by fuel type and the percentage of VMT by fuel type."

4.3 Auto Operating Cost by Fuel Types

Table 4.2 presents auto operating costs by vehicle types and their year-to-year changes, using the SCAG data as an example from 2019 to 2030. To calculate AOC by fuel types, SCAG uses reliable data categorized by fuel types, including fuel price (EIA, CEC projection), fuel efficiency, and the percentage of VMT (calculated from EMFAC 2021), along with MRT - Maintenance, Repair, and Tires costs (CARB's draft AOC calculator, 2023). SCAG's SCS Technical Methodology provides a comprehensive description of the detailed information necessary for AOC calculations by fuel types. It is noteworthy that SCAG applies the fuel efficiency adjustment outlined in Section 3 exclusively to gasoline- and diesel-fueled vehicles, exempting EVs or PHEVs from this adjustment.

$$\% \, AOC_{i,y1-y2} = (AOC_{i,y2} - AOC_{i,y1}) \,/\, AOC_{i,y1} \tag{5}$$

Where:

$\% \, AOC_{i,y1-y2}$ *= the percentage growth of auto operating cost for a specific fuel type i from year y1 to year y2*

AOC_{y1} , AOC_{y2} *= the calculated auto operating cost for year y1, y2. Year y1 is one year prior to year y2*

The significant fluctuations in AOC for vehicles using gasoline and diesel between 2019 and 2023 can be attributed to the patterns of fuel prices, as shown by EIA data, may be influenced by the pandemic and Ukraine war.

Table 4.2 Auto Operating Cost by Fuel Types for SCAG Region (2019-2030)

Auto Operating Cost by Fuel Types ($AOC_{i,y}$)					
	Gas/ Diesel			Electricity	
Year	Gas	Diesel	PhEV (gas)	PhEV (ev)	EV
2019	20.529	19.147	17.230	12.181	11.282
2020	18.404	17.362	15.678	12.590	12.009
2021	21.441	19.428	18.392	13.239	12.396
2022	24.568	23.548	20.652	13.186	12.019
2023	22.332	21.247	19.161	14.338	12.847
2024	22.928	22.002	19.701	14.675	13.158
2025	23.048	21.936	19.853	14.717	13.160
2026	23.188	22.139	20.018	14.918	13.336
2027	23.315	22.281	20.166	15.167	13.568
2028	23.473	22.424	20.341	15.306	13.684
2029	23.666	22.610	20.547	15.546	13.894
2030	23.959	22.884	20.835	15.729	14.051
% AOC Change from Previous Year ($\% \, AOC_{i,y1-y2}$)					
Year (y2)					
2020	-10.35%	-9.32%	-9.01%	3.36%	6.45%
2021	16.50%	11.90%	17.31%	5.16%	3.22%
2022	14.58%	21.20%	12.29%	-0.40%	-3.05%
2023	-9.10%	-9.77%	-7.22%	8.74%	6.89%
2024	2.67%	3.55%	2.82%	2.35%	2.42%
2025	0.52%	-0.30%	0.77%	0.28%	0.01%
2026	0.61%	0.92%	0.83%	1.37%	1.34%
2027	0.55%	0.64%	0.74%	1.67%	1.74%
2028	0.67%	0.64%	0.87%	0.92%	0.86%
2029	0.82%	0.83%	1.01%	1.57%	1.53%
2030	1.24%	1.21%	1.40%	1.18%	1.13%

4.4 Vehicle Usage (% of VMT) by Fuel Types

Table 4.3 presents the vehicle usage, expressed as a percentage of the total VMT by fuel types, between 2019 and 2030. The "VMT Change from Previous Year" data in the table illustrates the change in vehicle usage from the previous year. The table indicates a consistent decline in vehicle usage for gasoline and diesel vehicles, with an increase observed for Plug-in Hybrid Electric Vehicles (PHEV) and Electric Vehicles (EV).

As mentioned earlier, whether the new EV usage involves a transition from ICVs or pertains to new drivers, their travel behavior or VMT is not influenced by changes in the auto operating cost of EVs. Consequently, when calculating the average change in AOC, the vehicle usage of these vehicles will not be included.

By reviewing data from 2019 to 2020 in Table 4.3, the data reveals a significant shift in VMT shares for gasoline and electric vehicles from 2019 to 2020. The VMT share for gasoline vehicles decreases from 97.48% to 96.93%, indicating that 96.93% of the total VMT is attributable to continuous usage of gasoline vehicles from 2019 to 2020. The remaining 0.55% (97.48% - 96.93%) represents a shift to other modes, EVs or PHEVs. Conversely, for EVs, the VMT share increases from 0.95% in 2019 to 1.37% in 2020. This signifies that 0.95% of the total VMT corresponds to ongoing EV usage from 2019 to 2020, while the additional 0.43% (1.37% - 0.95%) represents new EV usage from either a mode shift from ICVs or new drivers. Similar patterns can be observed in other years.

Table 4.3 Vehicle Usage by Fuel Types for SCAG Region (2019-2030)

% VMT by Fuel Types					
	Gas/Diesel		Electricity		
Year	Gas	Diesel	PhEV (gas)	PhEV (ev)	EV
2019	97.48%	0.44%	0.61%	0.52%	0.95%
2020	96.93%	0.43%	0.68%	0.59%	1.37%
2021	96.36%	0.42%	0.77%	0.68%	1.77%
2022	95.64%	0.42%	0.86%	0.80%	2.28%
2023	94.91%	0.41%	0.93%	0.93%	2.82%
2024	94.17%	0.40%	1.00%	1.05%	3.38%
2025	93.43%	0.39%	1.06%	1.17%	3.96%
2026	92.96%	0.37%	1.10%	1.26%	4.31%
2027	92.51%	0.36%	1.14%	1.34%	4.65%
2028	92.08%	0.35%	1.17%	1.42%	4.97%
2029	91.67%	0.35%	1.20%	1.50%	5.29%
2030	91.26%	0.34%	1.23%	1.56%	5.61%
VMT Change from Previous Year					
2019-20	-0.55%	-0.01%	0.07%	0.07%	0.43%
2020-21	-0.57%	-0.01%	0.09%	0.09%	0.40%
2021-22	-0.71%	-0.01%	0.09%	0.12%	0.51%
2022-23	-0.74%	-0.01%	0.08%	0.12%	0.54%
2023-24	-0.74%	-0.01%	0.07%	0.12%	0.56%
2024-25	-0.74%	-0.01%	0.06%	0.12%	0.57%
2025-26	-0.47%	-0.01%	0.04%	0.09%	0.35%
2026-27	-0.45%	-0.01%	0.04%	0.08%	0.33%
2027-28	-0.43%	-0.01%	0.03%	0.08%	0.33%
2028-29	-0.41%	-0.01%	0.03%	0.07%	0.32%
2029-30	-0.40%	-0.01%	0.03%	0.07%	0.32%

Using the 2019-2020 data as an illustration, Table 4.4 reorganizes the 2020 information from Table 4.2 to distinguish between vehicles with continued usage from the previous year (2019) and those representing new usage. The calculation of average AOC change assigns weight to vehicles with continued usage, as these will experience changes in auto operating costs between the two years. For new usage, their travel patterns are not affected by the changes in AOC.

Table 4.4 Vehicle Usage by Fuel Types for SCAG Region (2019-2020 example)

	Gas/ Diesel		Electricity			
Year	Gas	Diesel	PhEV (gas)	PhEV (ev)	EV	Sum
2019	97.48%	0.44%	0.61%	0.52%	0.95%	100.00%
2020	96.93%	0.43%	0.68%	0.59%	1.37%	100.00%
Continued to Use from 2019	96.93%	0.43%	0.61%	0.52%	0.95%	99.44%
Shift to Other Modes	0.55%	0.01%				0.56%
New Usage			0.07%	0.07%	0.43%	0.56%

Building upon the earlier discussion, Table 4.5 reorganizes Table 4.2 to differentiate between vehicles with continued usage from the previous year and those representing new usage. The percentage of VMT attributed to continued vehicle usage from the previous year will serve as the weight for composite AOC calculation. Conversely, for new usage, as discussed earlier, travel patterns remain unaffected by AOC changes and are therefore excluded from the AOC calculation.

able 4.5 Vehicle Usage by Fuel Types for SCAG Region (2019-2030)

	% VMT for Vehicles Continued Use from Previous Year					% VMT for New Usage			
	Gas/ Diesel			Electricity		PHEV / EV			Sum
Year	Gas	Diesel	PhEV (gas)	PhEV (ev)	EV	PhEV (gas)	PhEV (ev)	EV	
2019									
2020	96.93%	0.43%	0.61%	0.52%	0.95%	0.07%	0.07%	0.43%	100.00%
2021	96.36%	0.42%	0.68%	0.59%	1.37%	0.09%	0.09%	0.40%	100.00%
2022	95.64%	0.42%	0.77%	0.68%	1.77%	0.09%	0.12%	0.51%	100.00%
2023	94.91%	0.41%	0.86%	0.80%	2.28%	0.08%	0.12%	0.54%	100.00%
2024	94.17%	0.40%	0.93%	0.93%	2.82%	0.07%	0.12%	0.56%	100.00%
2025	93.43%	0.39%	1.00%	1.05%	3.38%	0.06%	0.12%	0.57%	100.00%
2026	92.96%	0.37%	1.06%	1.17%	3.96%	0.04%	0.09%	0.35%	100.00%
2027	92.51%	0.36%	1.10%	1.26%	4.31%	0.04%	0.08%	0.33%	100.00%
2028	92.08%	0.35%	1.14%	1.34%	4.65%	0.03%	0.08%	0.33%	100.00%
2029	91.67%	0.35%	1.17%	1.42%	4.97%	0.03%	0.07%	0.32%	100.00%
2030	91.26%	0.34%	1.20%	1.50%	5.29%	0.03%	0.07%	0.32%	100.00%

4.5 Composite AOC Calculation

Lastly, Table 4.6 illustrates the final calculation of the average auto operating costs. Each year, the composite AOC change from the previous year (% $AOC_{y_1-y_2}$) is determined as the weighted average of AOC changes by fuel types (% $AOC_{i,\ y_1-y_2}$ from Table 4.2), with weights assigned based on vehicle usage continuing from the previous year (%VMT_{i,y_2} from Table 4.5) by fuel types.

Since the AOC for the base year 2019 has been calculated, the AOC for 2020 is determined by multiplying the 2019 AOC by the calculated AOC growth from 2019 to 2020. The AOC for the following year follows the same calculation. Once the average AOC change from the previous year is computed, the AOC for the current year can be determined, starting from the model-validated base year, 2019.

Table 4.5 Auto Operating Cost by Fuel Types for SCAG Region (2019-2030)

	% $AOC_{i,y1-y2}$ × % $VMT_{i,y2}$					Sum	Avg. AOC
	Gas/ Diesel			Electricity			
Year	Gas	Diesel	PhEV (gas)	PhEV (ev)	EV	% AOC_{y1-y2}	
2019							20.371
2020	-10.03%	-0.04%	-0.06%	0.02%	0.06%	-10.05%	18.325
2021	15.90%	0.05%	0.12%	0.03%	0.04%	16.14%	21.283
2022	13.94%	0.09%	0.09%	0.00%	-0.05%	14.07%	24.277
2023	-8.64%	-0.04%	-0.06%	0.07%	0.16%	-8.51%	22.212
2024	2.51%	0.01%	0.03%	0.02%	0.07%	2.64%	22.799
2025	0.49%	0.00%	0.01%	0.00%	0.00%	0.50%	22.912
2026	0.57%	0.00%	0.01%	0.02%	0.05%	0.65%	23.060
2027	0.51%	0.00%	0.01%	0.02%	0.07%	0.62%	23.202
2028	0.62%	0.00%	0.01%	0.01%	0.04%	0.69%	23.361
2029	0.75%	0.00%	0.01%	0.02%	0.08%	0.87%	23.564
2030	1.13%	0.00%	0.02%	0.02%	0.06%	1.23%	23.853

5 Summary

This document outlines the approach to improve the modeling procedure, aiming to address issues related to accurately reflecting travel behavior and VMT response to changes in AOC components. Specifically, the focus is on fuel price, fuel efficiency, and EV usage.

Appendix B1.1: Fuel Efficiency Adjustment Procedure

The adjusted fuel efficiency will serve as an input for calculating fuel cost or auto operating cost within the travel demand model. This adjustment is implemented to ensure that the resulting VMT rebound and elasticity align with the findings observed in literature reviews.

1). VMT Elasticity with Respect to Fuel Efficiency

Based on the literature review, it is assumed that VMT elasticity with respect to fuel efficiency is 0.01.

The percentage change in VMT is calculated as:

% VMT change = {[FE(f) / FE(b)] – 1} × 0.01

Where:
% VMT change: Percentage change in VMT between base year and forecast year.
FE(b): Fuel efficiency for the base year, measured in miles per gallon.
FE(f): Fuel efficiency for the future year, measured in miles per gallon.

2). Adjusting Future-Year Fuel Efficiency in the Travel Demand Model

To ensure consistency with the literature review, the fuel efficiency for the future year needs adjustment within the travel demand model. This adjustment aligns the model outcomes with the literature review findings.

The percentage VMT change can be represented as:
% VMT change = % Fuel Cost change × elasticity = {[FC(fa) / FC(b)] – 1} × e = {[FE(b) / FE(fa)] – 1} × e

Where:
e: Elasticity of VMT with respect to fuel cost, determined through sensitivity tests.
FC(b): Fuel cost for the base year, measured in cents per mile.
FC(fa): Fuel cost with adjusted fuel efficiency for the future year, measured in cents per mile.
FP(b): Fuel price for the base year, measured in cents per gallon.
FP(f): Fuel price for the future year, measured in cents per gallon.
FE(b): Fuel efficiency for the base year, measured in miles per gallon.
FE(fa): Adjusted fuel efficiency for the future year, measured in miles per gallon.

3). Fuel Efficiency Adjustment Formula

Based on the assumptions and procedures, given the same VMT change:

{[FE(f) / FE(b)] – 1} × 0.01 *(from literature review)* = {[FE(b) / FE(fa)] – 1} × e *(from the travel demand model)*

Simplifying the equation further:
{[FE(f) / FE(b)] – 1} × 0.01 = {[FE(b) / FE(fa)] – 1} × e
{[FE(f) / FE(b)] – 1} × (0.01/e) = [FE(b) / FE(fa)] – 1
{{[FE(f) / FE(b)] – 1} × (0.01/e)} + 1 = [FE(b) / FE(fa)]
Let K = {[FE(f) / FE(b)] – 1} × (0.01/e)} + 1
FE(fa) = FE(b) / K

Appendix B1.2: Annual VMT Comparison by Fuel Types

The following charts provide a summary of the comparison of annual VMT by fuel types based on the recently released 2022 NHTS data. Due to the unavailability of detailed geography at this time, the study area is concentrated on the Pacific MSA/CMA (near 2,000 vehicle samples). Overall, the data reveals no significant difference in annual VMT between fuel types when examining the data based on household characteristics.

Chart 1: Annual VMT by Fuel Types – U.S. sample

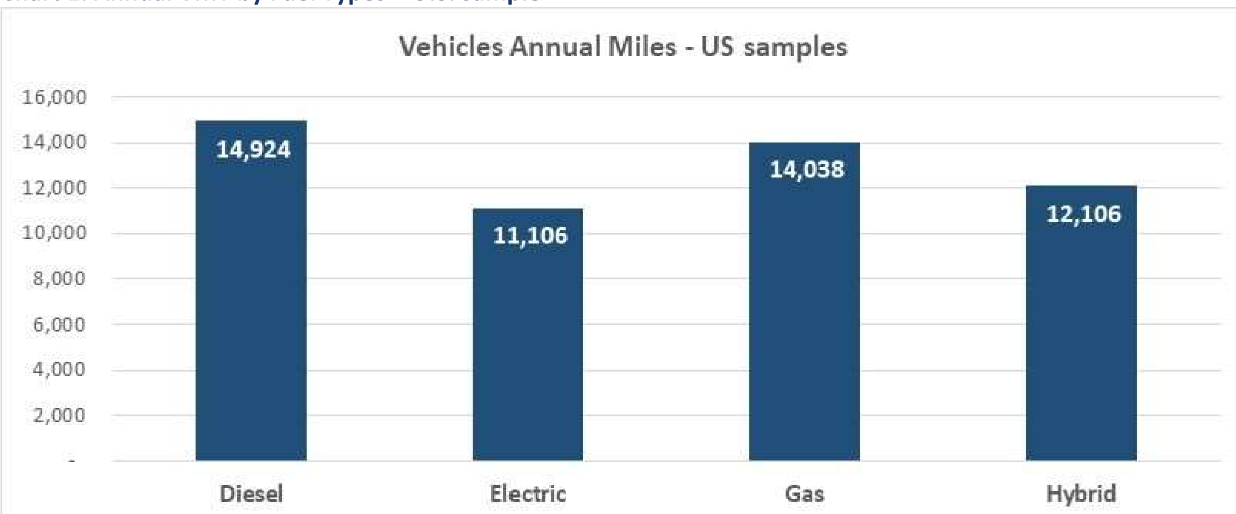


Chart 2: Annual VMT by Fuel Types – U.S. and Pacific MSA

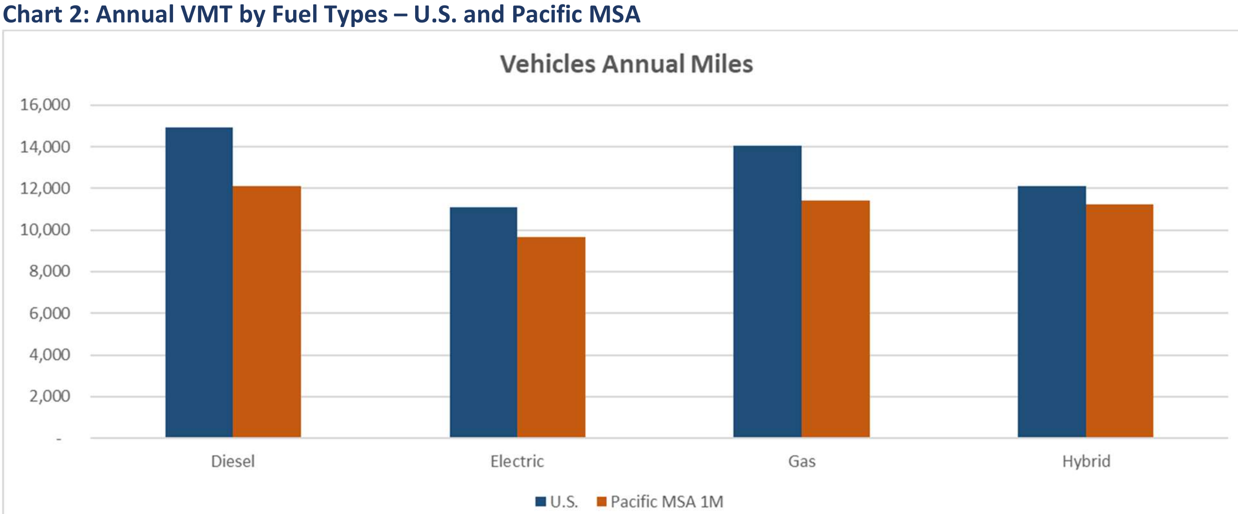


Chart 3: Annual VMT by Fuel Types (Pacific MSA) – by Vehicle Age

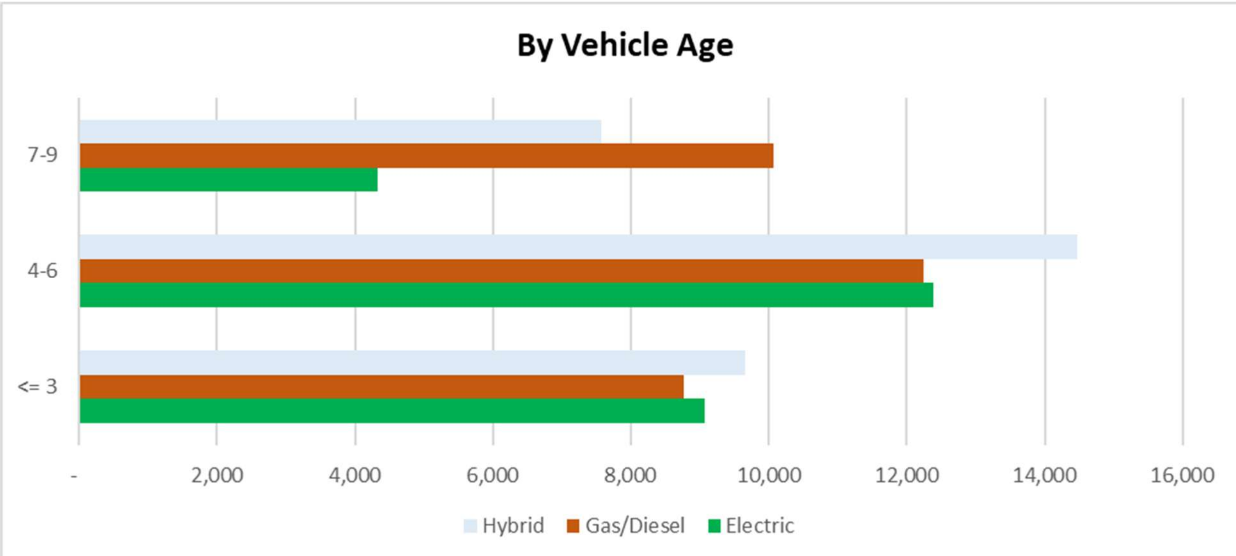


Chart 4: Annual VMT by Fuel Types (Pacific MSA) – by Household Income

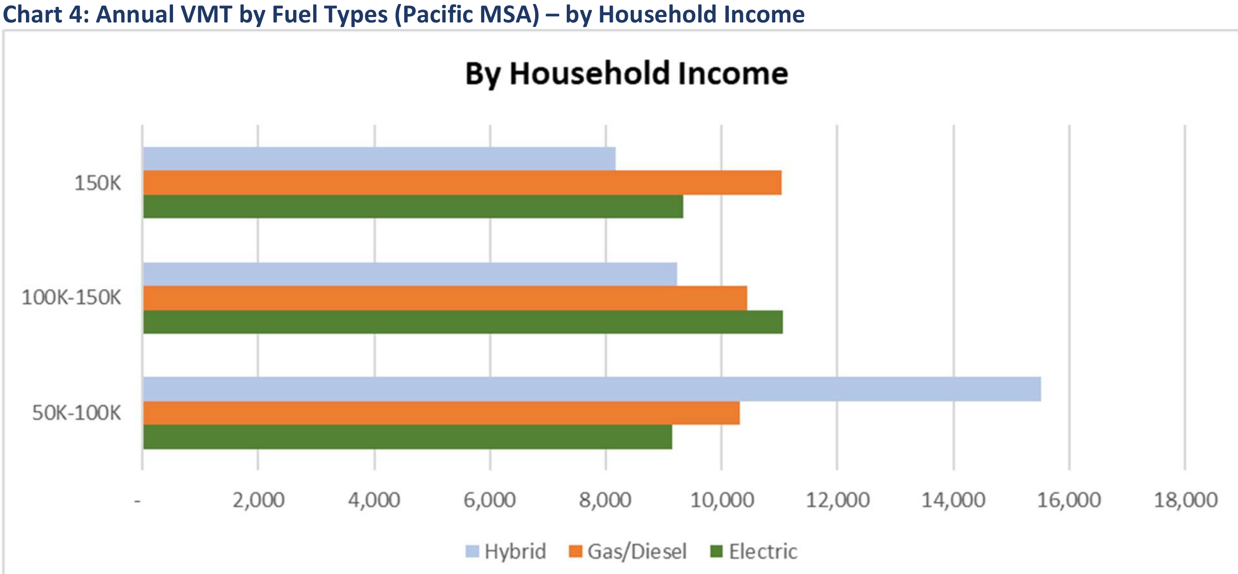


Chart 5: Annual VMT by Fuel Types (Pacific MSA) – by Household Size

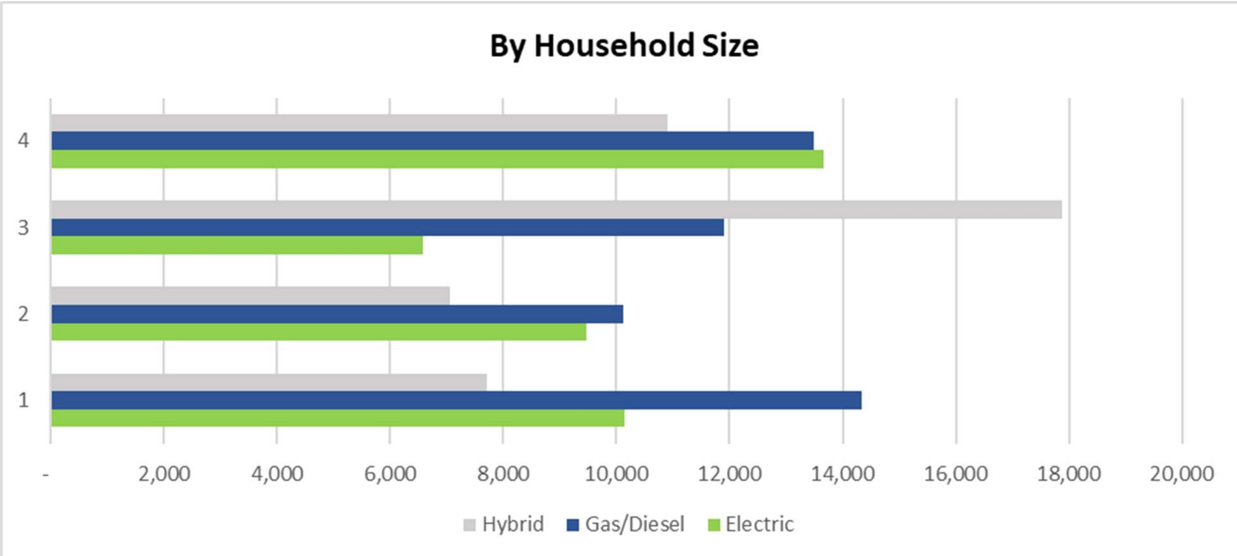


Chart 6: Annual VMT by Fuel Types (Pacific MSA) – by Household Workers

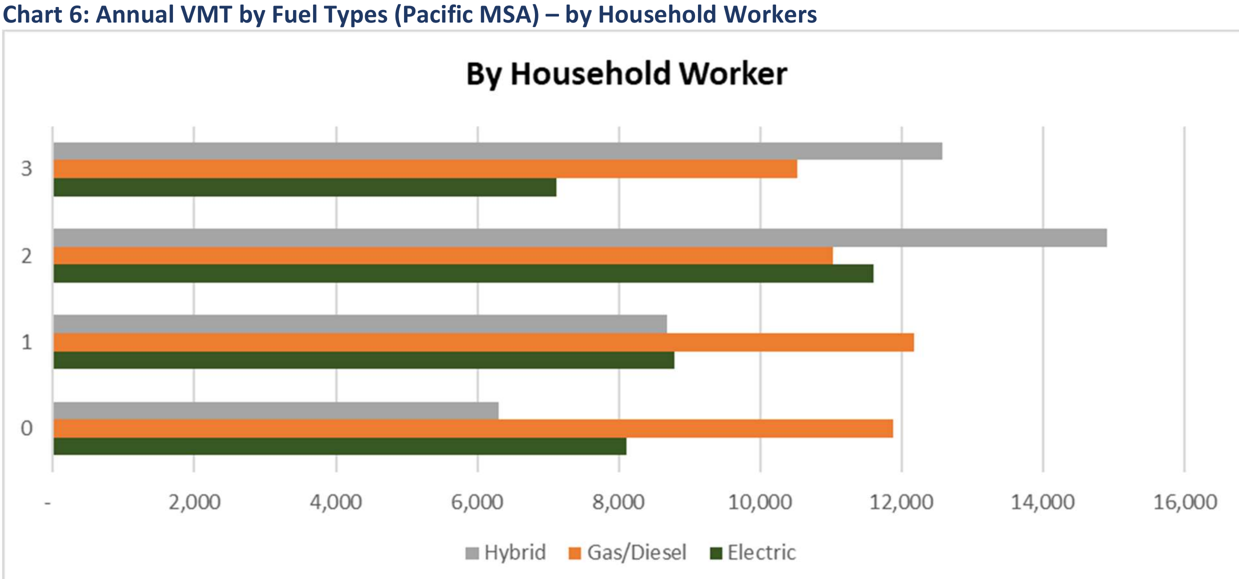
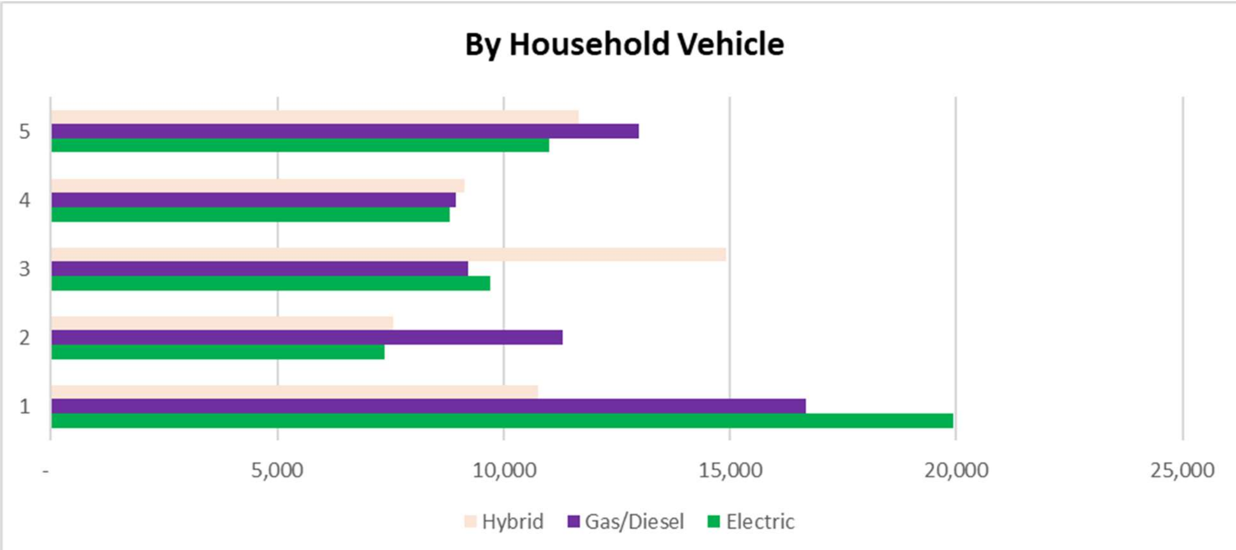


Chart 7: Annual VMT by Fuel Types (Pacific MSA) – by Household Vehicles



Regression Analysis

A linear regression model was employed to assess the variation in annual VMT among New EVs (vehicle age <= 3 years), Old EVs, Hybrid, and ICVs. The analysis controlled for factors such as household size (separated by the number of household workers and non-workers), the number of household vehicles, and household income (high income).

The findings indicate no statistically significant difference among vehicles based on fuel types, including new EVs.

The SAS System

The REG Procedure
Model: MODEL1
Dependent Variable: ANNMILES Self-reported annualized mile estimate

Number of Observations Read	1928
Number of Observations Used	1928

Weight: WTHHFIN 7-day natl household weight

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	4.130082E14	5.900117E13	5.03	<.0001
Error	1920	2.253585E16	1.173742E13		
Corrected Total	1927	2.294886E16			

Root MSE	3425992	R-Square	0.0180
Dependent Mean	12332	Adj R-Sq	0.0144
Coeff Var	27781		

Parameter Estimates						
Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	15540	1554.09081	10.00	<.0001
NewEV		1	-1906.88046	3632.25199	-0.52	0.5997
OldEV		1	583.97631	5738.85384	0.10	0.9190
HB		1	-1073.59789	2446.45028	-0.44	0.6608
WRKCOUNT	Count of workers in household	1	945.73612	668.86423	1.41	0.1575
Nonworker		1	1539.22823	500.04253	3.08	0.0021
Hinc		1	-3863.20820	1308.43599	-2.95	0.0032
HHVEHCNT	Total number of vehicles in household	1	-1952.36193	444.17980	-4.40	<.0001

Independent Variables: ANNMILES: Self-reported annualized mile

Variable:
New EV: EV vehicle age <= 3 years
OldEV: EV vehicle age > 3 years
HB: Hybrid Vehicles (plug-in and non plug-in)
WRKCOUNT: Number of household workers
Nonworker: Number of non-workers in a household
(HHSIZE = wrkcount + nonworker)
Hinc: household income between $100,000 and $200,000

Appendix B2: Work from Home Data Analysis and Assumptions

In recent years, the travel patterns for workers have undergone a transformative shift by the unprecedented COVID-19 pandemic. This change has been driven by the widespread adoption of remote work arrangements as a response to health concerns. To accommodate the altered travel dynamics, it is important to incorporate the impact of working from home into the analysis of SCAG's long-range transportation plan. The objective of this report is to describe the assumptions, methodology, and procedure to estimate work from home within the framework of regional travel demand.

1. Work from Home (WfH) Modes

We incorporate two primary modes of work-from-home (WfH) into SCAG model analysis:

1. Remote Work or Home Office: This mode involves individuals who are working from home on a daily basis. It is most common among those who do not have a permanent workplace. Historically, most of these individuals worked from home offices prior to the pandemic. In the SCAG model, which simulates travel for an average weekday (Monday-Friday), a remote worker is considered to spend a full day working from home.
2. Hybrid or Telework: In this mode, individuals split their workweek between working at home and a physical workplace. A hybrid worker in the SCAG model spends between 0.2 weekdays (equivalent to 1 day per week) and 0.8 weekdays (equivalent to 4 days per week) working from home.

These distinctions allow us to accurately model the variations in work-from-home practices and their impacts on travel demand.

2. Historical Data and Trend Projection

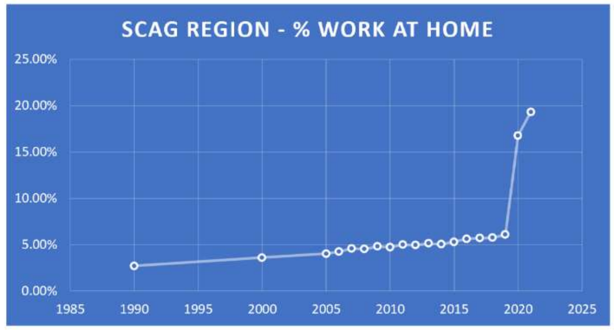
To project the trend of the two WfH modes, SCAG utilized two primary sources of data:

2.1 American Community Survey (ACS)

The ACS provides useful data into workers' primary means of transportation to work. Specifically, the "Work at Home" category represents remote and home office workers. To estimate the percentage of workers engaged in remote or home office work for future projections, we collected ACS data for SCAG region. A straightforward linear regression model was employed to estimate and apply future projections (data before 2019). The table and chart below show the historical trends in the "work at home" category, derived from annual ACS data for the SCAG region.

Table 1 & Chart 1: Percentage of "work at home" Workers of SCAG Region (ACS data)

Annual Data	% W@H
1990	2.71%
2000	3.60%
2005	4.02%
2006	4.23%
2007	4.60%
2008	4.52%
2009	4.81%
2010	4.74%
2011	4.99%
2012	4.93%
2013	5.13%
2014	5.04%
2015	5.30%
2016	5.63%
2017	5.69%
2018	5.76%
2019	6.08%
2020	16.77%
2021	19.30%



2.2 Travel Surveys

Our analysis of telework data drew from multiple sources, including the 2009 and 2017 National Household Travel Survey (NHTS), as well as SCAG's add-on survey conducted in conjunction with the 2011-12 California Household Travel Survey (CHTS). These surveys encompassed questions related to telework, such as eligibility for telework and the frequency of telework days in the past month. The table below presents summary data from the three household travel surveys, which are based on samples of the SCAG region.

Table 2: Summary Data of NHTS and CHTS

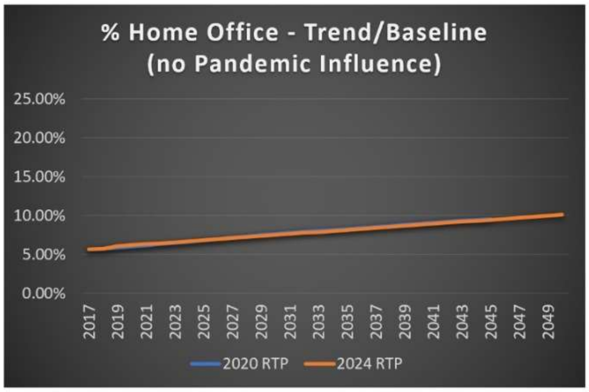
	Year	2009 NHTS	2011 CHTS SCAG add-on	2017 NHTS	Note
% Home Office Workers	of All Workers	4.8%	5.0%	5.7%	ACS
% Non Home Office Workers	of All Workers	95.2%	95.0%	94.3%	calculate
% Workers Allowed Telework	of Non Home Office Workers	10.6%	11.1%	12.5%	NHTS*
% Teleworker	of Workers Allowed Telework	70%	72%	78%	NHTS*
% Teleworking of a Weekday	of Teleworkers	22%	25%	27%	NHTS & CHTS
% Teleworks of a weekday	**of All Workers**	**1.54%**	**1.94%**	**2.44%**	

** Using NHTS 2009 and 2017 to interpolate 2011 data*

2.3 Trend Projection Update

Before we delve into the analysis of how the pandemic will shape future commuting patterns, particularly work from home, we initiated a trend projection update. This trend projection data serves as a baseline against which we will evaluate the pandemic's impact. By applying linear regression techniques to the ACS data and calculating growth rates from travel surveys, we projected trends for both work-from-home (WfH) modes up to the year 2050 for 2024 RTP. The charts below illustrate the consistency of 2024 RTP projection with the WfH estimates from 2020 RTP.

Charts 2 & 3: Percentage of Workers on an Average Weekday by WfH Modes, for 2020 RTP and 2024 RTP (draft)



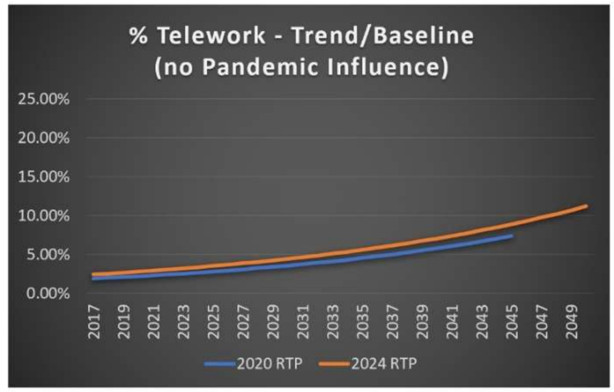
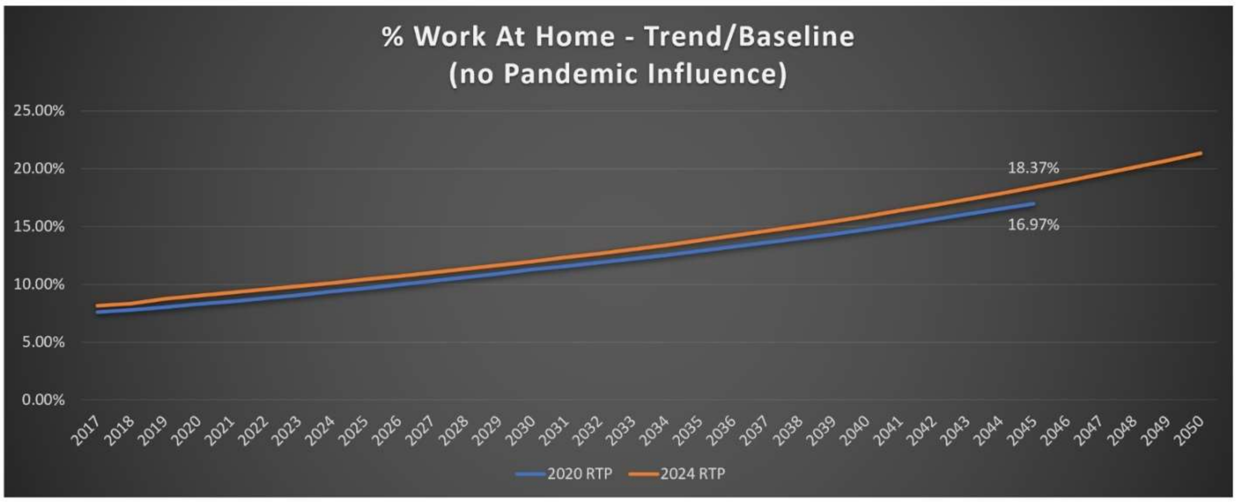


Chart 4: Percentage of WfH Workers (combined WfH modes), for 2020 RTP and 2024 RTP (draft)



3. Analysis of Work-from-Home Data for During and Post-Pandemic

To formulate post-pandemic work-from-home assumptions for the 2024 RTP/SCS, SCAG staff analyzed two surveys that include questions about working from home both during the pandemic and its future expected results after the pandemic. The surveys in question are: 1) UC Davis Transportation Survey, and 2) US Survey of Working Arrangement and attitudes (SWAA). Both surveys contain samples collected for SCAG region.

3.1 UC Davis Transportation Survey

To better understand the impact of the COVID-19 pandemic on mobility, SCAG partnered with UC Davis to launch a two-phase survey aimed at investigating the evolving effects of the pandemic on transportation within the SCAG region. The survey gathered data on workers' workplace locations, categorizing them into three workplaces, which are office, remote, and hybrid. These categorizations were based on responses to questions about their workplace situations before the pandemic, during the pandemic, and their expectations after the pandemic. The survey was conducted in the summer of 2021 and collected responses from 2,533 workers in the SCAG region. It's important to note that responses related to other work locations and temporary locations were not included in the analysis due to small sample sizes. The table below illustrates the survey questions and the resulting categorization of workplaces.

Table 3: UC Davis Survey Question to Workplaces

6. In the **months just prior to the pandemic (before March 2020)**, please indicate how often you generally went to each of the following places for work or school.

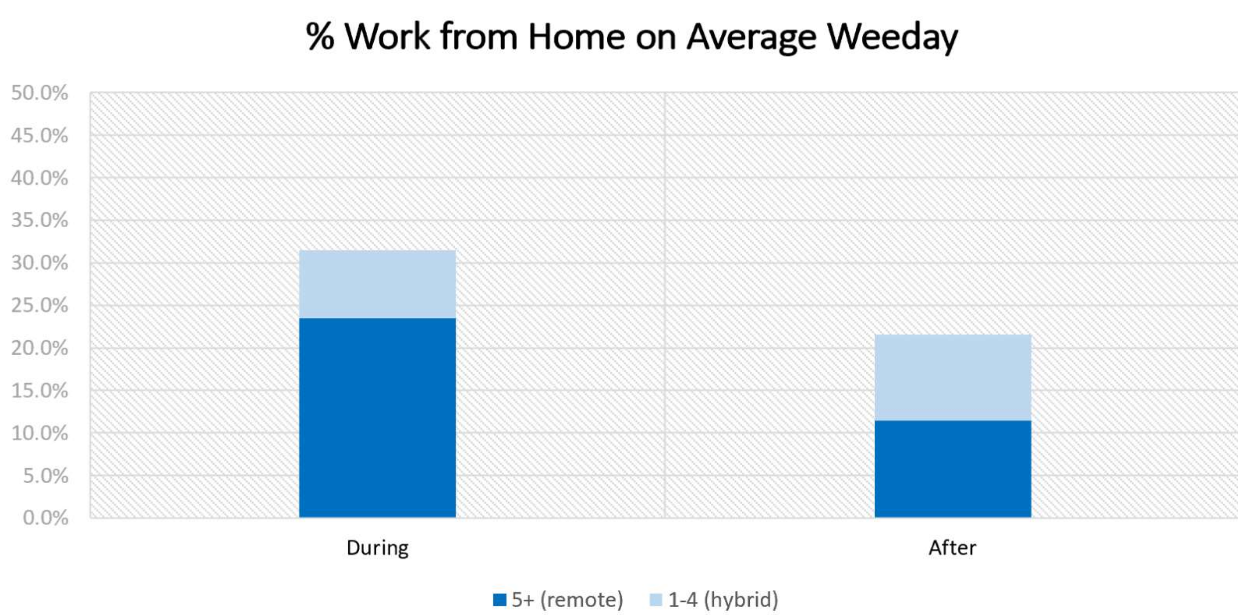
	Just prior to the pandemic, I used to work/study at…	*Never*	*Less than once a **month***	*1-3 times a **month***	*1-2 times a **week***	*3-4 times a **week***	*5 or more times a **week*** 1
a.	… primary workplace/school location	$\square_0$	$\square_1$	$\square_2$	$\square_3$	$\square_4$	$\square_5$
b.	… other workplace/school location/ customer location	$\square_0$	$\square_1$	$\square_2$ 4	$\square_3$	$\square_4$ 3	$\square_5$ 2
c.	… home	$\square_0$	$\square_1$	$\square_2$	$\square_3$	$\square_4$	$\square_5$
d.	… temporary locations (*e.g.*, coffee shops, parks, public library)	$\square_0$	$\square_1$	$\square_2$	$\square_3$	$\square_4$	$\square_5$

Office Remote Hybrid

<u>Analysis</u>

The initial result of analyzing the data shows that the survey tends to over-represent remote workers, an issue also addressed by the UCD research team. Nonetheless, the survey offers valuable insights into the dynamics of work-from-home patterns during and after the pandemic. The data suggests a significant shift among remote workers during the pandemic are expected to return to office work, either in a hybrid or full-time capacity. Furthermore, our analysis predicts a reduction in the average frequency of work from home and remote work after the pandemic, with a corresponding increase in hybrid work as shown in Chart 5.

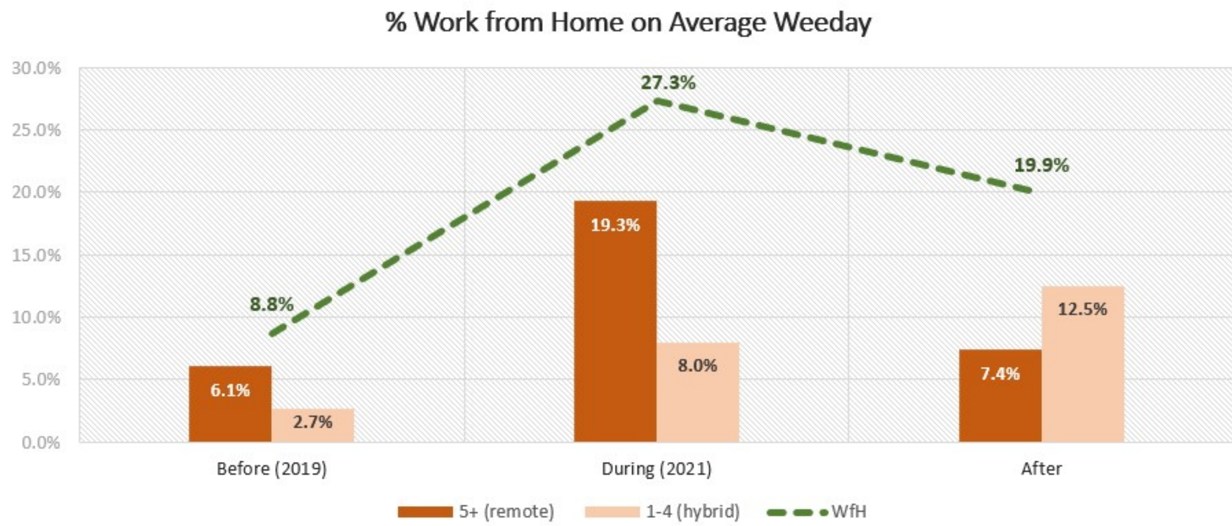
Chart 5: % of Work from Home on An Average Weekday (during vs. post pandemic)



Finally, based on the observed changes in work-from-home patterns between the pandemic period and the post-pandemic projections derived from the UCD survey, coupled with our trend analysis from historical data prior to and during the pandemic, we refined the UCD survey results as presented in the chart below.

Chart 6 indicates a significant shift in workplace dynamics during the pandemic, with many workers transitioning from office settings to remote work arrangements, either fully remote or hybrid. As the pandemic gradually recedes, it is anticipated a return of remote workers to office spaces, assuming hybrid work arrangements. Notably, the percentage of total working from home on an average weekday is considerably higher post-pandemic than it was before the pandemic.

Chart 6: % of Work from Home on An Average Weekday (based on UCD Survey)



3.2 US Survey of Working Arrangement and Attitudes (SWAA)

The WfH (Work From Home) Research and the SWAA initiative emerged in response to the profound impact of COVID-19 on work arrangements. The SWAA is a collaborative, monthly online survey conducted jointly by the University of Chicago, ITAM (Mexico), MIT, and Stanford University. This extensive survey dataset, encompassing more than 140,000 samples, is updated monthly and available for free download. To ensure its accuracy and representativeness, the data undergoes validation and weighting to align with worker demographics in age, sex, education, and earnings, as per the Current Population Survey (CPS). Results, microdata, survey instruments, and additional resources can be freely accessed at its homepage: www.WFHresearch.com.

SWAA survey asks questions for each day of a week about work status for 1) did not work, 2) work from home, and 3) worked on employer or client premises. This question design is very useful to accurately count for each worker's working as remote (if respondents work at home between Monday and Friday), or 2) Hybrid (if respondents worked for at least one weekday not at home.

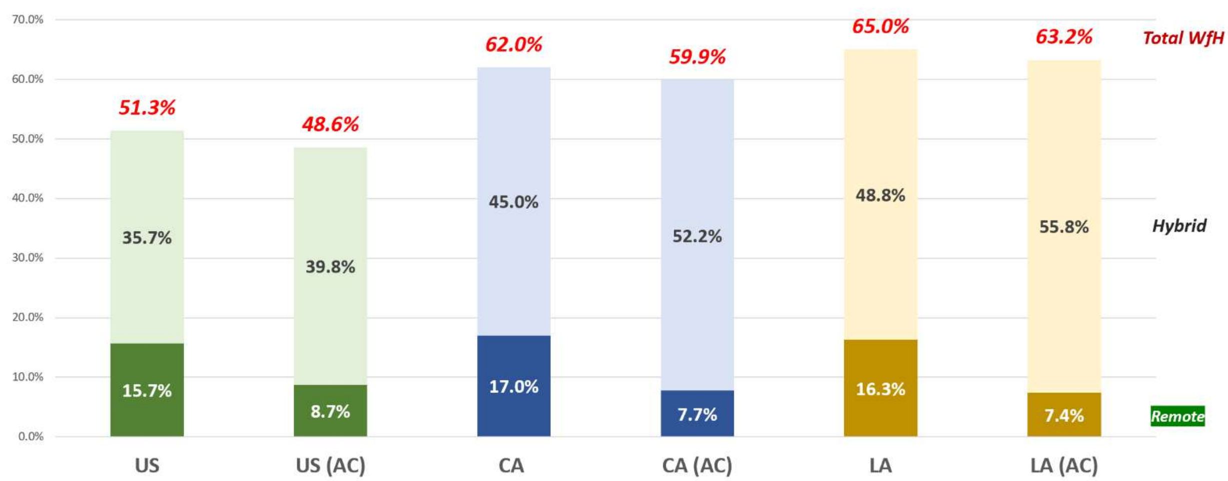
The SWAA survey includes questions for each day of the week regarding work status, categorized into 1) did not work, 2) worked from home, and 3) worked on employer or client premises. This question design is particularly useful as it allows for precise classification of each worker's status as either remote (if they respond "worked at home" between Monday and Friday) or hybrid (if they respond "worked" for at least one weekday away from home). SWAA also covers a question about "Employer's planned number of paid WfH days after COVID", which provides a valuable information to estimate work-from-home status after the pandemic.

Analysis

SCAG downloaded SWAA data for analysis, focusing on 1) the percentage of workers by two WfH modes: remote or hybrid, 2) the average WfH days per week for hybrid workers, and 3) the percentage of WfH workers on an average weekday. The analysis covered three geographical areas: the U.S., California, and the Los Angeles Region (Combined Statistical Area). To ensure relevance, the data analyzed during the pandemic spanned from Nov. 2021

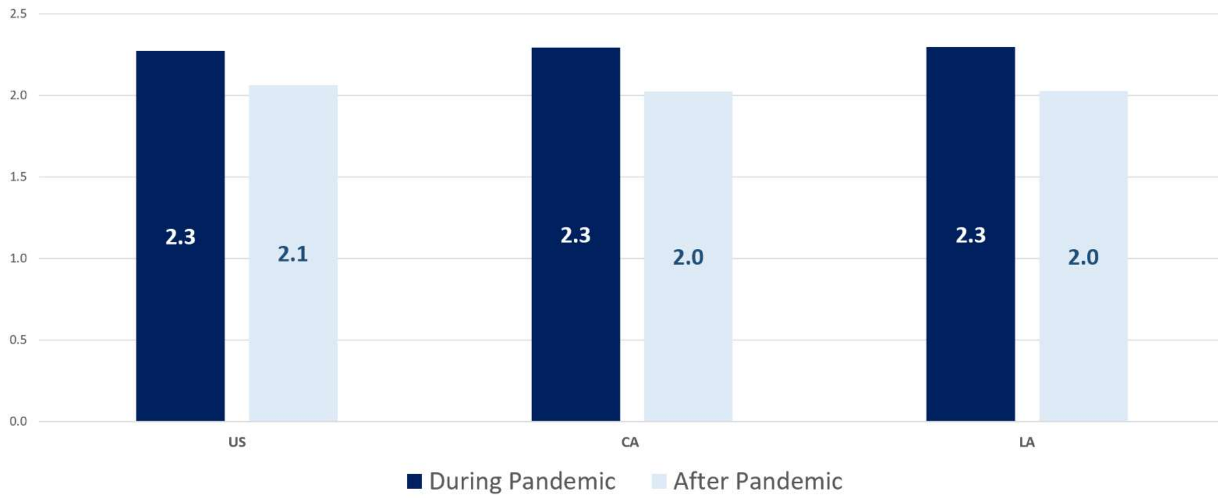
to Feb. 2023. For post-pandemic analysis, the most recent four months were considered from Oct. 2022 to Feb. 2023. to provide insights into how employers may plan for work-from-home arrangements after the pandemic. As shown below, charts 7 and 8 present the percentage of remote and hybrid workers during pandemic (as current) and post-pandemic in the three areas. Overall, the percentage of total work-from-home workers reduce slightly to post-pandemic, but a significant drop for remote workers and increase in hybrid workers. The share of total work-from-home workers is about 10 percent higher for the two California areas than the U.S. The average work-from-home days per week is 2.3 days during pandemic and reduce slightly to 2 days after pandemic.
Also, charts 7 and 8 depict the percentages of workers engaged in remote and hybrid work arrangements during the pandemic (current) and post-pandemic periods across the three study areas. On the whole, the percentage of total work-from-home workers experiences a slight reduction in the post-pandemic phase, with a noticeable decrease in remote workers and a concurrent rise in hybrid workers. It's worth noting that the share of total work-from-home workers is approximately 10 percent higher in the two California areas compared to the U.S. The average work-from-home days per week for hybrid workers reduces from 2.3 days during the pandemic to 2 days after the pandemic.

Chart 7: % of Workers Working from Home – Current vs. After Covid (AC)



Current/During Pandemic (11/2011-01/2023); After Pandemic: 10/2022-01/2023)

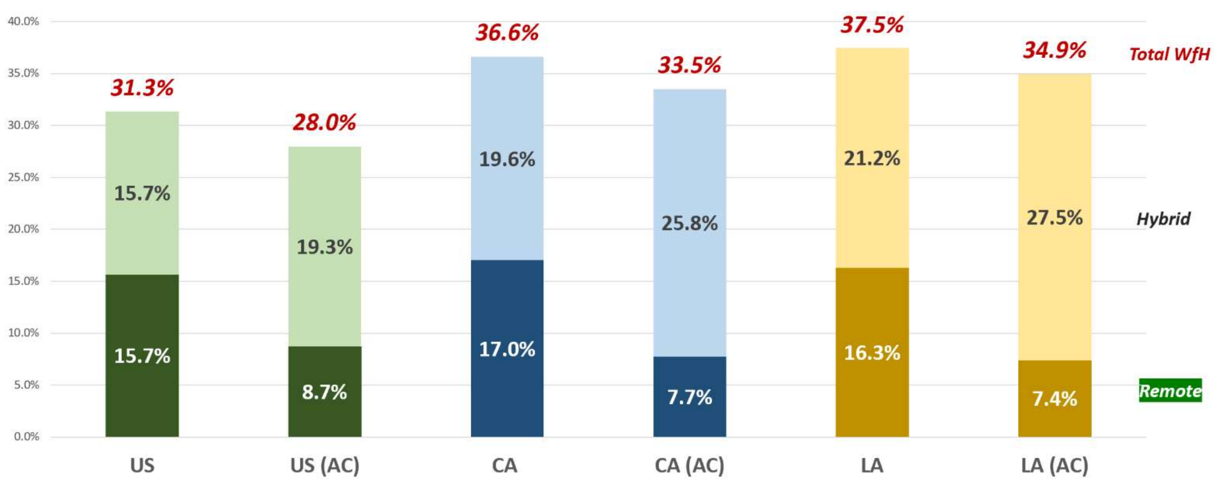
Chart 8: Average Work-from-Home Days for Hybrid Workers



Current/During Pandemic (11/2011-01/2023); After Pandemic: 10/2022-01/2023)

To assess the travel impact of work-from-home arrangements, hybrid workers were converted to an average weekday basis. For instance, two days of working from home were converted to 0.4 average weekdays for model analysis. Chart 9 illustrates the percentage of work from home on an average weekday across the three study areas. The patterns closely mirror those in Chart 7. During the pandemic, 31.3% of U.S. workers worked from home on an average weekday, and this is expected to decrease slightly to 28% post-pandemic (AC). The two California areas exhibit similar patterns, albeit with approximately 5% higher work-from-home rates.

Chart 9: % of Work from Home on An Average Weekday



Current/During Pandemic (11/2011-01/2023); After Pandemic: 10/2022-01/2023)

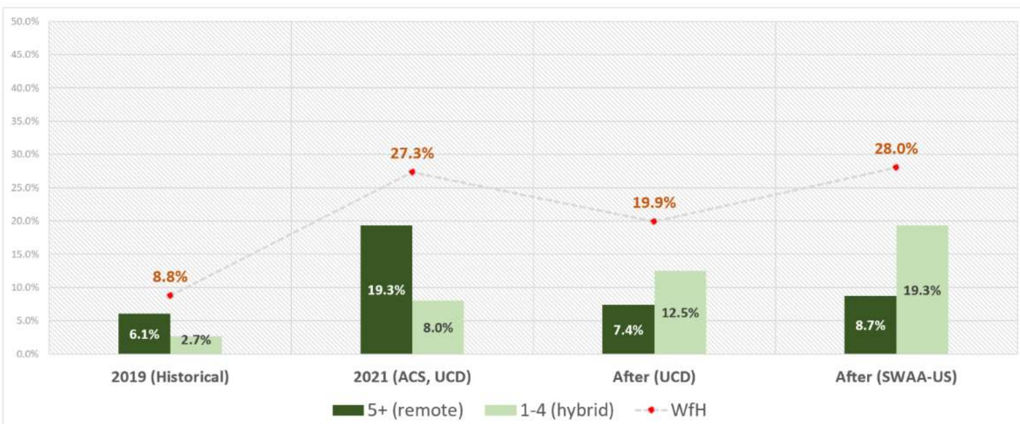
3.3 Summary of Work from Home Data Analysis

Based on the data analysis, work-from-home arrangements can be summarized across three time periods associated with the pandemic:

- Before the Pandemic (2019): 2019 data from ACS (remote) and travel surveys (hybrid).
- During the Pandemic (2021): 2021 data from ACS (remote) and travel survey/UC Davis survey (hybrid).
- Post-Pandemic: Leveraging data from the UC Davis survey (lower bound) and SWAA US sample (higher bound), with a conservative choice of using US data due to uncertainties about future work-from-home statuses.

Chart 10 shows work-from-home status during these time periods. As previously discussed, the data highlights a significant shift in workplace dynamics during the pandemic, with many workers transitioning from office settings to remote work arrangements in response to health concerns. This transition includes both fully remote and hybrid work modes. As the pandemic gradually subsides, the expectation is that remote workers will increasingly return to office settings, assuming hybrid work arrangements. Notably, the share of workers engaged in total work-from-home practices on an average weekday is considerably higher post-pandemic than it was before the pandemic.

Chart 10: % of Work from Home on An Average Weekday



4. SCAG Post-pandemic Work-from-Home Baseline Projection

To incorporate future work-from-home dynamics to SCAG's RTP/SCS through 2050, the following procedure and assumptions are outlined:

1. Short-term projection: Estimating the percentage of work-from-home workers for the year 2024, assumed to be the beginning of the post-pandemic era when travel patterns stabilize as the new normal.
2. Long-term projection between 2025 to 2050: projection by remote and hybrid modes
3.

4.1 Short-term Projection: 2024

Drawing on monthly data from SWAA, the share of work-from-home arrangements has exhibited a consistent decline. Chart 11 illustrates this decline in both the current WfH status and the expected employer's plan. Chart 12 further demonstrates a clear descending trend with a rate of -1.1% calculated from the 3-month moving average.

Chart 11: SWAA % Work from Home on Avg. Weekday

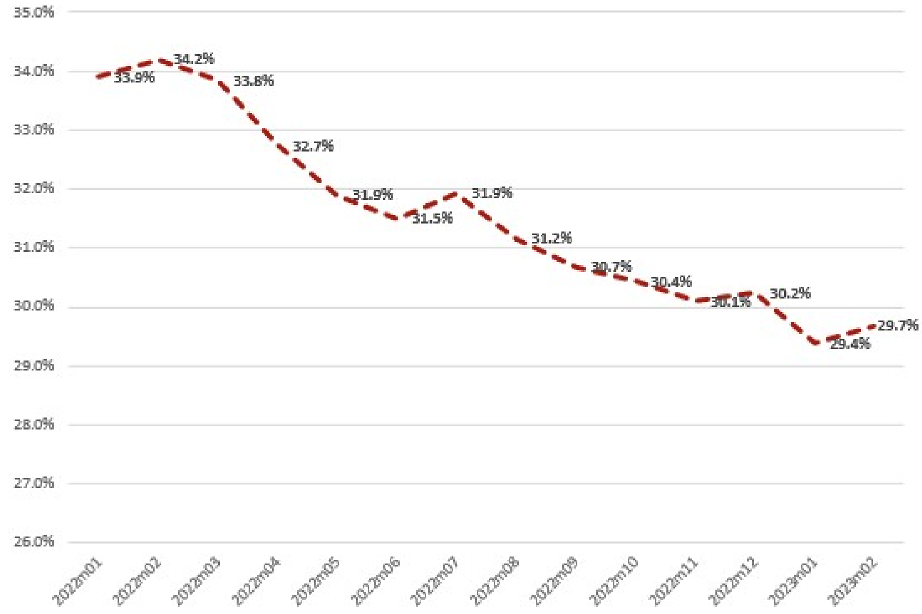
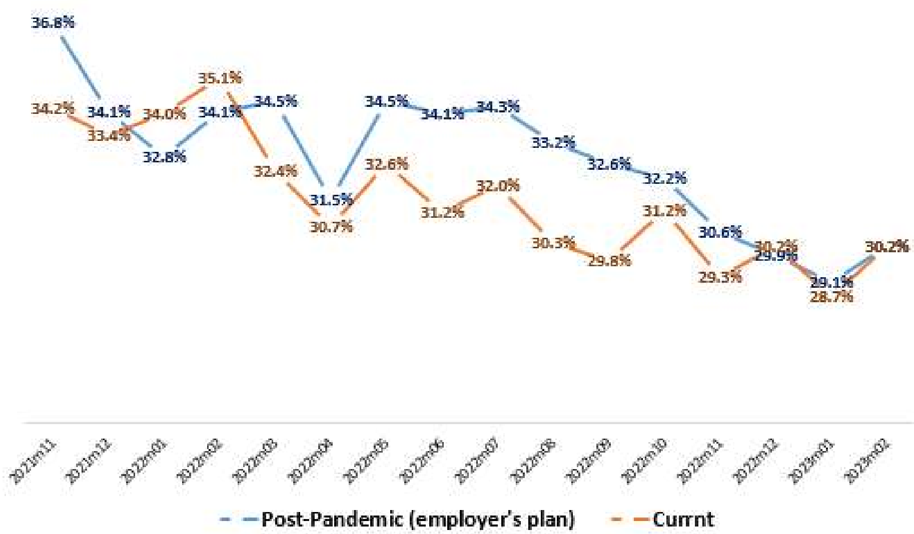
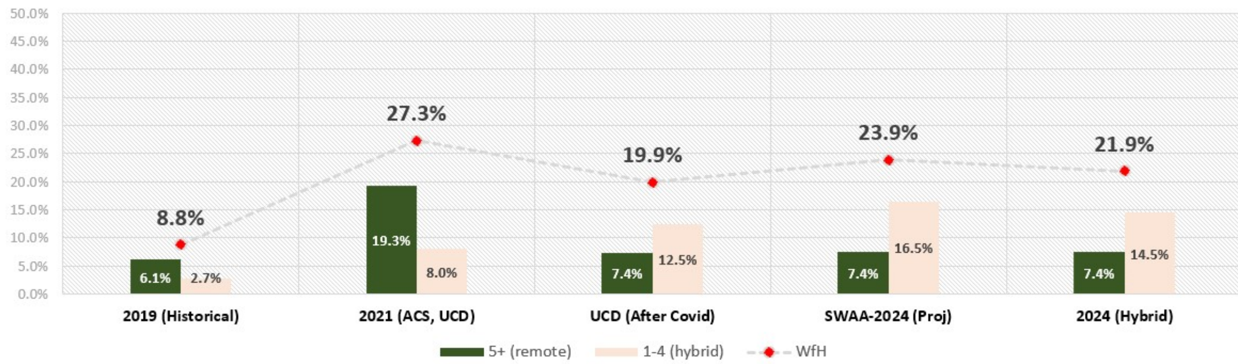


Chart 12: % Work from Home 3-month Average



By applying this declining rate from SWAA (-1.1%), we estimated the total work from home for the year 2024. This total was then divided by the two modes based on early SWAA analysis. The final estimate for 2024 represents an average of the SWAA estimate and the UC Davis estimate, as displayed in Chart 13 below.

Chart 13: % Work from Home on Avg. Weekday



4.2 Long-term Projection: 2025 - 2050

Assumptions for long-term projection (2025 to 2050) are as follows:

1. Remote Workers: Following growth patterns derived from the updated trend projection, as described in section 2.3.
2. Hybrid Workers: Due to future uncertainty, a constant rate of 14.5% is assumed from 2024 to 2050.

Chart 14 illustrates the final analysis of the percentage of workers working from home on an average weekday.

Chart 14: % Work from Home on Avg. Weekday for SCAG 2024 RTP/SCS

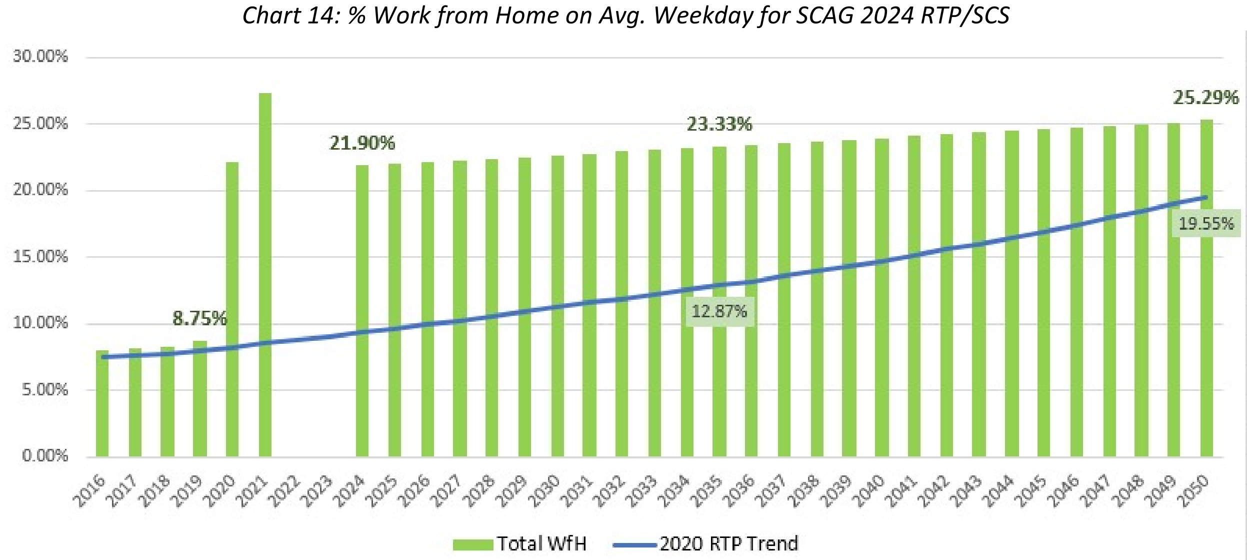
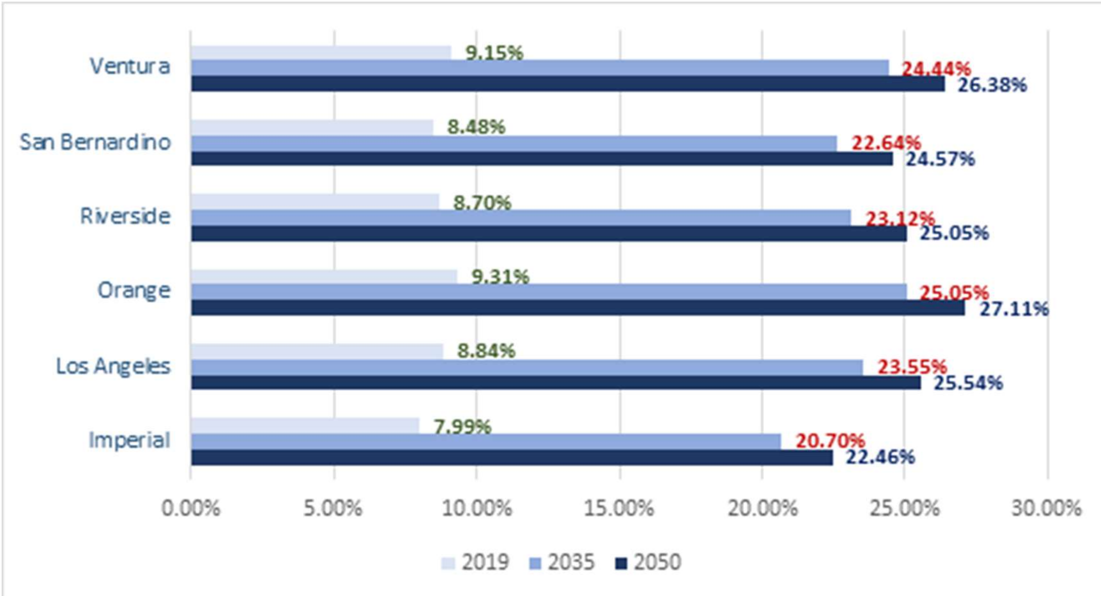


Chart 15: % Work-from-Home Workers by County

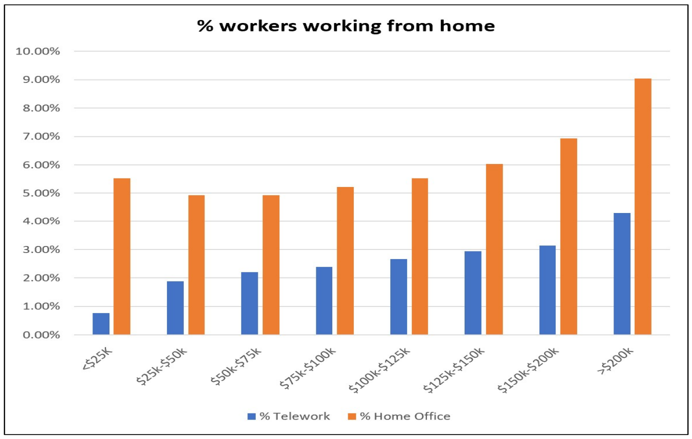


5. SCAG Model and VMT Rebound

5.1 Model Input

Due to the inherent differences between remote/home-office workers and hybrid/telework workers, we used worker's household income as a proxy, as it can reflect these variations. This choice was made because future forecast data on each worker's job industry and occupation is not readily accessible.
Chart 15 illustrates the distribution of workers working from home based on workers' income for the 2019 base year. According to the analysis of ACS data, remote/home-office workers tend to exhibit relatively higher work-from-home percentages among workers with very low incomes and those with higher incomes. This trend is closely linked to their occupation and job industry. In contrast, for hybrid/telework workers, the work-from-home percentage tends to be higher among those with higher incomes. SCAG has converted model input to represent the percentage of work from home within eight income categories, as shown in the chart.

Chart 16: % Work from Home by Workers' Household Income (2019)



5.2 VMT Rebound

The rise of work-from-home (WfH) arrangements can have various impacts on travel patterns: Firstly, WfH workers may directly benefit from reduced commuting distances and saved time between their homes and workplaces. Secondly, the time saved from commuting may lead to increased travel for other activities. This could potentially offset some of the reductions in travel resulting from reduced commuting. Thirdly, a significant number of WfH workers could reduce congestion on the road system, which may encourage other people to travel. It's worth noting that even for WfH workers who don't need to commute to a physical workplace (such as home-office workers), they may still need to travel for work-related or business purposes.

The VMT rebound effect due to working from home is integrated into the SCAG model. With a 10 percent point added in WfH workers compared to the base year 2019 input, VMT for light and medium-duty vehicles is reduced by 3%, reflecting a 32% rebound effect from VMT savings due to reduced commuting. Additionally, SCAG model suggests that there could be an additional 2% increase in overall non-work activities due to the time saved from commuting. Specifically, activities such as school pick-up/drop-off (3%), individual maintenance (3%), dining out or visiting (3%), and discretionary activities (3%) could see an increase.

SCAG staff analyzed with an add-on survey associated with the 2021 CHTS for the last (2020) RTP/SCS. Based on limited survey data, the VMT rebound was estimated to be between 20% and 25%. The SCAG 2020 RTP ABM was calibrated with the estimated rebound effect. With a 10 percent point increase in WfH workers compared to the previous base year 2016 input, VMT for light and medium-duty vehicles is reduced by approximately 3.4%, indicating a 24% VMT rebound.

The rebound effect observed in the SCAG model's work-from-home analysis aligns with recent research findings. According to a study by Obeid et al. (2022), two key findings closely mirror the SCAG model's outcomes:

1. Individuals who telecommute make an average of about one non-commute trip on telecommuting days. The additional distance traveled on this trip is however shorter than the two-way commute distance, as individuals travel significantly shorter distances on telecommuting days relative to commute days.
2. The additional non-commute trip that individuals make on telecommuting days is a newly generated trip, not a trip that has been shifted from other days of the week. The net effect of one additional day of telecommuting per week on weekly distance traveled is also negative, confirming that the newly generated non-commute travel distance does not fully offset the reduction in the two-way commute distance.

As those research studies were conducted using data collected during the pandemic, it becomes imperative to pursue further analysis based on updated data collected after the pandemic. This will allow us to gain a more accurate and up-to-date understanding of the evolving dynamics of work-from-home arrangements and their long-term impacts as the situation stabilizes and transitions into a post-pandemic 'new normal.
Additional information regarding SCAG model sensitivity tests related to work from home will be included in the Model Sensitivity Test report.

6. Conclusion and Next Step

Given the uncertainty surrounding travel patterns in the post-pandemic era, this analysis and modeling assumptions are grounded in the limited information currently available. To address this uncertainty, SCAG's approach leans toward conservative, relying on US samples from SWAA. Despite this study was completed several months ago, the analysis and the patterns remain valid as confirmed through recent checks against the most up to date SWAA report.
Looking ahead, SCAG is committed to ongoing monitoring of the SWAA survey, and will soon initiate a new round of travel surveys that will include inquiries about work-from-home data, which will be subject to thorough analysis.

APPENDIX B3: DATA ANALYSIS AND MODEL ASSUMPTIONS FOR TELEMEDICINE IN SCAG 2024 RTP/SCS

Telemedicine, also known as telehealth, was initially incorporated into the travel analysis for the SCAG 2020 RTP/SCS due to its impact on travel behavior associated with accessing medical services. Given the significant surge in telemedicine adoption during the COVID-19 pandemic, it is both logical and beneficial to retain telemedicine as a baseline input for the 2024 RTP/SCS.

SCAG staff conducted an analysis of survey samples sourced from the California Health Interview Survey (CHIS), focusing on data collected prior to the pandemic. To account for the dynamic shifts in travel patterns resulting from the adoption of telemedicine, SCAG has integrated telemedicine analysis into the SCAG Activity-Based Model (ABM).

This document serves as a technical summary for telemedicine analysis, including data analysis, input assumptions, baseline projection methodology, and model outputs.

1. **Health Care Trips to Personal Maintenance Trips**

Using SCAG samples of the 2017 National Household Travel Survey (NHTS), the share of health care trips to personal maintenance trips was calculated by six age cohorts: under 18, 18-29, 30-44, 45-64, 65-74, and 75 and older. According to NHTS Codebook, health care trips include visits for medical, dental, and therapy; personal maintenance trips include attending childcare or adult care, buy services (dry cleaners, banking, service a car, pet care), religious or other community activities, and health care visits.
To determine the percentage of health care trips in relation to personal maintenance trips, we utilized data from the 2017 National Household Travel Survey (NHTS), specifically focusing on SCAG samples. The calculation was performed for six age cohorts: under 18, 18-29, 30-44, 45-64, 65-74, and 75 and older.
According to the NHTS Codebook, health care trips encompassed visits related to medical, dental, and therapy purposes, while personal maintenance trips included activities such as attending child care or adult care, purchasing services (e.g., dry cleaning, banking, vehicle servicing, pet care), participating in religious or other community activities, as well as health care visits.

Table 1. % of health care trips to personal maintenance trips

Age Cohort	% Health Care Trips / Per Maint. Trips
< 18	33%
18-29	18%
30-44	34%
45-64	36%
65-74	30%
75+	42%
** 2017 NHTS, SCAG samples*	

2. **Telemedicine Usage by Age Cohorts**

We analyzed data from the 2015-2018 California Health Interview Survey (CHIS) to determine the percentage of the population using telemedicine services by age cohorts. Table 2 presents the percentage of individuals who responded to the survey question: 'During the past 12 months, did you receive care from a doctor or health professional through a video or telephone conversation rather than an office visit?' Additionally, we calculated the average annual growth rate for this telemedicine usage.

Table 2. % of people using telemedicine

Age Cohort	2015	2016	2017	2018	Avg. Annual Growth Rate
< 18*	6.4%	7.1%	11.1%	10.9%	21.7%
18-29	5.0%	9.1%	6.5%	10.3%	37.7%
30-44	6.4%	7.1%	11.1%	10.9%	21.7%
45-64	7.7%	8.1%	8.5%	11.3%	14.3%
65-74	7.9%	8.7%	12.2%	11.3%	14.2%
75+	11.8%	6.7%	11.0%	12.2%	10.9%
*Note: 0-17 use 30-44; likely age of parents					
**2015-1018 CHIS, SCAG samples					

3. **Assumption of Healthcare Trips Substitution with Telemedicine**

Based on the CHIS data, it's important to note that a 'Yes' response to the previous survey question merely indicates whether a person used telemedicine, without specifying the number of telemedicine visits. To adopt a conservative approach, we assume only one out of every SCAG region respondent's average number of trips (3.5) is substituted with telemedicine.

Assumption: The percentage of healthcare trips replaced by telemedicine = 1 out of 3.5 trips = 28.57%

4. **Telemedicine Usage During the Pandemic**

Based on the data summary presented in Figure 1 of the NCHS Data Brief[1], it was reported that in 2021, 37.0% of adults had utilized telemedicine services in the past 12 months. Notably, this percentage increased with age. To compare the usage of telemedicine in California vs the U.S. average for the same year, Table 3 illustrates that telemedicine usage in California was approximately 6% higher than the national average.

Figure 1: % of adults used telemedicine in 2021 (past 12 months)

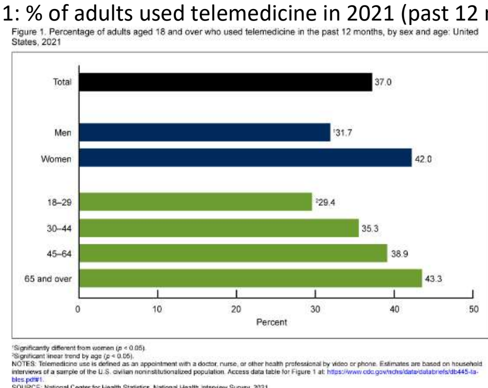


Table 3: Adults who had appointment with health professional over video or phone, last 4 weeks

Survey Perios	California	US	Diff
4/14~4/26, 2021	31.70%	25.70%	6.00%
6/9 ~ 6/21, 2021	29.90%	23.80%	6.10%
9/15 ~ 9/21, 2021	29.10%	20.60%	8.50%
12/1 ~ 12/13, 2021	26.30%	19.70%	6.60%

* U.S. Census Bureau, Household Pulse Survey, 2021-2022
https://www.cdc.gov/nchs/covid19/pulse/telemedicine-use.htm

Since the specific data for the SCAG region was not available, we adopted a conservative approach by adjusted the U.S. data 5% upward for each age cohort as an assumption for SCAG region (Table 4). The telemedicine usage during the pandemic represents the maximum acceptance achievable based on the current state of communication technology and people's perception to telemedicine. Therefore, we consider this adjusted data as a representation of the future capacity.

Table 4: % of adults used telemedicine in 2021 (past 12 months)

Age Cohort	US (Fig 1)	CA (est)
<18	35.3%	40.3%
18-29	29.4%	34.4%
30-44	35.3%	40.3%
45-64	38.9%	43.9%
65-74	43.3%	48.3%
75+	43.3%	48.3%

5. **Telemedicine Usage Projection**

Logistic Growth Model

To project the percentage of people using telemedicine up to the year 2050, we employed a logistic growth pattern commonly used for long-term population growth projections. The logistic growth model illustrates a decreasing rate of population growth as the population surpasses the carrying capacity, which is the point where resources become insufficient to sustain further growth. As discussed earlier, we assumed the telemedicine usage during the pandemic represents the maximum acceptance that is used as carrying capacity.

The equation of the Logistic Growth Model is as follows:

$$P(t) = \frac{P_0 K e^{rt}}{(K - P_0) + P_0 e^{rt}}$$

Where:

P(t): The projected population (in this study, the percentage of people in each age cohort using telemedicine) in year t.
P(0): The projected population in year 0 (in this study, the percentage of people using telemedicine in 2018, in Table 2).
K: The carrying capacity. We determine this value using data in Table 4, reflecting maximum percentage of telemedicine usage.
r: The growth rate. We calculate this annual average growth rate using the data from Table 2.
t: The year, with 2018 represented as *t* = 0.

Projection Results
By applying the logistic growth model, the percentage of people using telemedicine is calculated to year 2050. Table 5 shows the summary of model input and output.

Table 5: Summary of Model Input and Output

Input	Note	< 18	18-29	30-44	45-64	65-74	75+
K	Capacity (CA)	40.3%	34.4%	40.3%	43.9%	48.3%	48.3%
r	Growth rate	21.7%	37.7%	21.7%	14.3%	14.2%	10.9%
P0 =2018	Initial Po	10.9%	10.3%	10.9%	11.3%	11.3%	12.2%
P1 =2019	2019	12.7%	13.2%	12.7%	12.6%	12.6%	13.3%
P17 =2035	2035	37.7%	34.3%	37.7%	35.0%	37.4%	33.0%
P32 =2050	2050	40.2%	34.4%	40.2%	42.6%	46.7%	44.3%

6. **Model Input: Percentage of Telemedicine to Total Personal Maintenance**

Due to the advancement in wireless/communication technology, there is on-going increase in engaging activities at home through on-line access to services, including online shopping and telemedicine. SCAG enhanced ABM by adding an at-home non-mandatory activity choice module. This sub-model tags a fraction of the individual discretionary tasks generated by the discretionary task frequency model as at-home activity and those at-home activities are not scheduled during tour formation model. The expected result would have impact on travel patterns. The needed model input for telemedicine is to input the percentage of telemedicine activities to total personal maintenance activities, by age cohorts. For additional technical information, please refer to Model Validation Report. Below Table 6 presents the results for model input by age cohort.

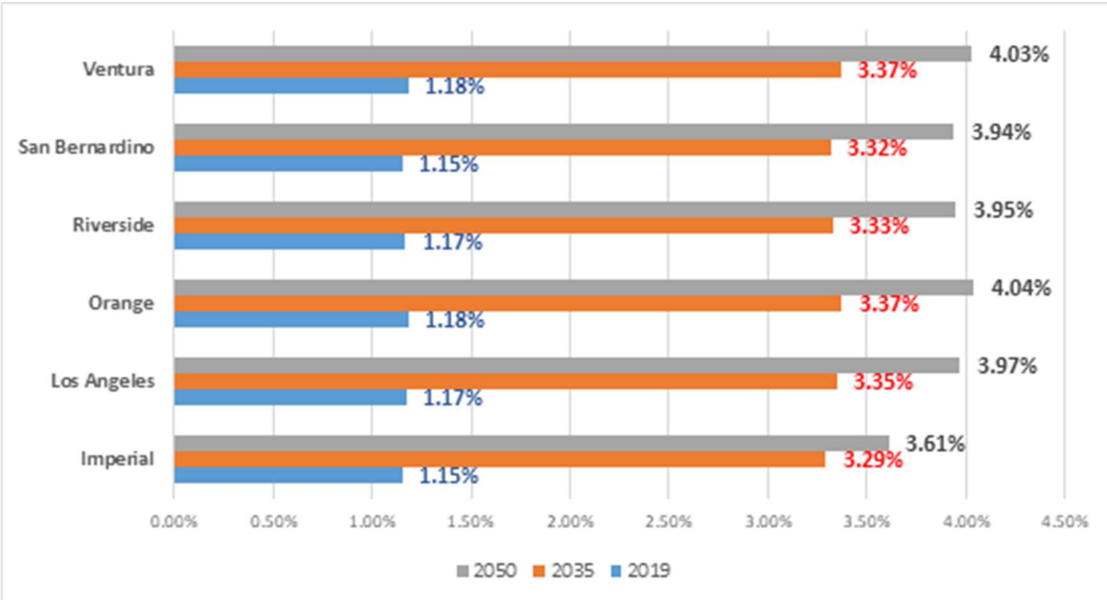
% of telemedicine activities to total personal maintenance activities
= % of health care trips to personal maintenance trips (Table 1)
x % telemedicine trip to healthcare trips (28.57%)
% of people using telemedicine (Table 5)

Table 6: % of telemedicine activities to total personal maintenance activities (model input)

Year	< 18	18-29	30-44	45-64	65-74	75+
2019	1.21%	0.67%	1.25%	1.28%	1.08%	1.59%
2025	2.42%	1.51%	2.49%	2.18%	1.87%	2.44%
2030	3.21%	1.72%	3.30%	2.95%	2.60%	3.22%
2035	3.61%	1.75%	3.71%	3.58%	3.20%	3.96%
2040	3.76%	1.76%	3.87%	3.99%	3.62%	4.57%
2045	3.82%	1.76%	3.93%	4.23%	3.87%	5.01%
2050	3.84%	1.76%	3.95%	4.36%	4.00%	5.32%

Below Figure 2 summarize the percentage of telemedicine activities to total personal maintenance activities for each of SCAG county.

Figure 2: % of telemedicine activities to total personal maintenance activities by counties.



7. **Model Test Results**

To assess the impact of telemedicine on travel behavior, SCAG conducted two model runs for the 2035 baseline:

1. Using 2035 telemedicine input (reflecting trend projection of increased telemedicine adoption)
2. Using 2019 telemedicine input (base case)

The findings indicate that when using the 2035 telemedicine input, there is a marginal reduction of 0.06% in VMT compared to the test with 2019 input. Moreover, total outdoor activities, or tours, decrease by 0.08%. However, these changes do not significantly alter mode share patterns. With a higher prevalence of telemedicine usage in 2035, there is a slight increase of 0.02% in carpooling, while the drive-alone and walk/bike share decreases 0.01%. The model results also highlight a rebound effect resulting from time saved on outdoor travel with telemedicine. There is a 0.9% reduction in maintenance tours (including medical activities) due to in-home telemedicine, which, in turn, prompts increased engagement in other activities, such as eat out (+0.13%), visiting (+0.1%), discretionary (+0.05%), as well as work and school-related activities (+0.02%).

8. **Next Step**

Considering that the projection of future telemedicine adoption was based on CHIS data collected prior to the pandemic, it is anticipated that telemedicine usage will surpass the current projections due to the widespread adoption of telemedicine during the Covid-19 pandemic. Therefore, SCAG will continue the ongoing monitoring and analysis of CHIS and other data to provide a more accurate assessment of telemedicine's evolving impact on travel behavior in the future.

ACRONYMS

Acronym	Definition
ABM	Activity-Based Modeling
ACS	American Community Survey
ADT	Average Daily Traffic
AOC	Auto Operating Cost
AQMP	Air Quality Management Plan
ARB	California's Air Resources Board
ASC	Alternative-Specific Constants
AT	Area Type
BPR	Bureau of Public Roads
BRT	Bus Rapid Transit
CARB	California Air Resource Board
CBD	Central Business District
CEMDAP	Comprehensive Econometric Micro-simulator of Daily Activity-travel Patterns
CIP	Capital Improvement Program
CMAQ	Congestion Mitigation and Air Quality Improvement Program
CMP	Congestion Management Program
CPI	Consumer Price Index
CTPP	Census Transportation Planning Package
DOF	California Department of Finance
DOT	Department of Transportation
EDD	California Employment Development Department
EE	External-External
EPA	Environmental Protection Agency
FHWA	Federal Highway Administration

Acronym	Definition
FIRES	Finance/Insurance/Real Estate/Services
FT	Facility Type
FTA	Federal Transit Administration
FTIP	Federal Transportation Improvement Program
GHG	Greenhouse Gas
GIS	Geographic Information System
GPS	Global Positioning System
GVW	Gross Vehicle Weight
HBCU	Home-Based College and University
HBNW	Home-Based Non-Work
HBO	Home-Based Other Trips
HBSC	Home-Based School
HBSH	Home-Based Shopping Trips
HBSP	Home-Based Serving-Passenger
HBSR	Home-Based Social-Recreational Trips
HBW	Home-Based Work
HBWD	Home-Based Work Direct
HBWS	Home-Based Work Strategic Trips
HCM	Highway Capacity Manual
HDT	Heavy Duty Truck
HH	Household
HHDT	Heavy-Heavy Duty Trucks
HIS	Household Interview Survey
HOT	High Occupancy Toll
HOV	High Occupancy Vehicle
HPMS	Highway Performance Monitoring System

Acronym	Definition
ICTC	Imperial County Transportation Commission
HU	Housing Unit
IE/EI	Internal-External and External-Internal
IMX	Intermodal
ITMS	Intermodal Transportation Management System
IVT	In-Vehicle Time
KNR	Kiss-and-Ride
KSF	Thousand Square Feet
LA Metro	Los Angeles County Metropolitan Transportation Authority
LADOT	Los Angeles Department of Transportation
LHDT	Light-Heavy Duty Trucks
LOS	Levels of Service
LS	Logsum
LTL	Less-Than-Truckload
LU	Land Use
MDAB	Mojave Desert Air Basin
MHDT	Medium-Heavy Duty Trucks
MPO	Metropolitan Planning Organization
MPU	Minimum Planning Unit
MTC	Metropolitan Transportation Commission
NAICS	North American Industrial Classification Standard
NHB	Non-Home Based
NHTS	National Household Travel Survey
NRE	Non-Retail Employment
NTD	National Transit Database
OBO	Other-Based Other Trips

Acronym	Definition
OCTA	Orange County Transportation Authority
OD	Origin-Destination
PA	Production-Attraction
PCEs	Passenger Car Equivalents
PCPLPH	Passenger Car Per Lane Per Hour
PeMS	Performance Measurement System
PNR	Park-and-Ride
PS	Posted Speed
PUMS	Public Use Microsample
QA/QC	Quality Assurance/Quality Control
RCTC	Riverside County Transportation Commission
RE	Retail Employment
RMSE	Root Mean Squared Error
RSA	Regional Statistical Area
RSE	Retail/Service Employment
RTP	Regional Transportation Plan
SACOG	Sacramento Area Council of Governments
SBCTA	San Bernardino County Transportation Authority
SASVAM	Small Area Secondary Variables Allocation Model
SB 375	California's Senate Bill 375
SCAB	South Coast Air Basin
SCAG	Southern California Association of Governments
SCCAB	South Central Coast Air Basin
SCS	Sustainable Communities Strategy
SMT	Subregional Modeling Tool
SP	Stated Preference

Acronym	Definition
SSAB	Salton Sea Air Basin
SSCAB	South Central Coast Air Basin
STCC	Standard Transportation Commodity Classification
TAZ	Transportation Analysis Zone
TCA	Transportation Corridor Agency
TDM	Transportation Demand Management
TIGER	Topographically Integrated Geographic Encoding and Referencing
TL	Truckload
TOD	Time-of-Day
TRB	Transportation Research Board
TSM	Transportation System Management
VCTC	Ventura County Transportation Commission
VDF	Volume-Delay Function
VHT	Vehicle-Hours Traveled
VIUS	Vehicle Inventory and Use Survey
VMT	Vehicle Miles of Travel
VOT	Value of Time
VTRIS	Vehicle Travel Information System
WBO	Work-Based Other Trips
WIM	Weigh In Motion