SAN DIEGO ASSOCIATION OF GOVERNMENTS

ABM3 MODEL CALIBRATION AND VALIDATION REPORT

Report | March 21, 2024

PREPARED FOR

San Diego Association of Governments

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LIST OF FIGURES

LIST OF TABLES

1.0 INTRODUCTION

The San Diego Association of Governments serves as the forum for regional decision-making for the San Diego region. SANDAG is governed by a Board of Directors composed of mayors, councilmembers, and county supervisors from each of the region's 19 local governments. SANDAG also serves as the Metropolitan Planning Organization (MPO) for San Diego County, whose role is to prioritize spending on transportation projects to improve efficiency, promote safety, increase equity, and address other transportation planning objectives. The regional travel demand model is a key tool in SANDAG's toolbox used to analyze transportation and land-use projects and investments, quantify their impacts, and assess their performance relative to these objectives.

In 2009, SANDAG began development of an activity-based travel demand model, in the family of travel models referred to as CT-RAMP (Coordinated Travel Regional Activity-Based Travel Modeling Platform). The model was completed in 2013 and used for the 2015 RTP. The model was updated several times since the initial development - calibrated to new survey data, enhanced for additional sensitivities, expanded to consider emerging transportation technologies, etc. The latest version of the SANDAG ABM is referred to as ABM2+. The objective of this project is to develop Activity-Based Model 3 (ABM3) for the 2025 Regional Plan (2025 RP). The ABM3 development for the 2025 RP includes model estimation using recent surveys, ABM software update to ActivitySim, model calibration and validation, sensitivity tests, policy analysis enhancements, streamlining processes, risk evaluation, and general ABM support.

The ABM3 model calibration and validation report describes the data used for model calibration, the calibration of choices in each model to match observed data, and the validation of auto and transit assignment results against traffic counts and transit boardings. The base year for model calibration is 2022.

2.0 CALIBRATION AND VALIDATION DATA

Household Travel Survey Data

The 2022 SANDAG Household Travel Survey (HTS) Wave 1 was the main data used for ABM3 model calibration and was augmented with American Community Survey (ACS) 2021 data (specifically for the auto ownership model), the DMV data (specifically for the vehicle type choice model), and the 2015 onboard survey data for transit trips. The 2022 HTS data collection for this effort used a modern research approach to collect demographic and travel pattern information from residents throughout San Diego County in California in two waves of data collection. The highlights of this modern approach include a two-part survey (recruit survey and travel diary), use of multiple modes of data collection (app-based, online survey, call centers), and address-based sampling augmented by a non-probability sample frame to better reach hard-to-reach populations. We refer the reader to the SANDAG HTS Final Report document for more detail on the data collection approach. The first wave, which was the data referenced in this report, was conducted in 2022, and the second wave was conducted in 2023, whose data was not available in time for use in ABM3 model calibration.

The rMove app was the primary mode for travel data collection, which offered significant benefits for data quality and quantity (e.g., detailed trip paths, and lower degrees of underreporting). The survey employed American Community Survey (ACS) data, along with RSG’s market research experience and expertise, to develop the sampling plan and data weighting approaches.

The survey collected a rich set of demographic and travel behavior data from a representative sample of 2,800 households in San Diego County. The survey collected data from 5,290 persons, representing 45,962 trips across 11,543 complete person-days from May 2 through June 10, 2022. The data was further weighted to adjust for survey non-response, survey participation mode, and geographic bias due to oversampling and other factors. In addition, RSG adjusted trip rates between the participation methods offered for the survey: online, call center, or smartphone app.

One issue with the 2022 HTS data was around how the survey instrument restricted participation to persons aged 18 and older to protect the confidentiality of child travel. Travel for persons under age 18 was reported by proxy. Investigation of the survey data indicated that proxy reporting for child travel is problematic, particularly for the rMove app data. On the proxy days in the rMove data, parents/guardians reported that 91% of children went to school but we only have trips for 25% of the children. If someone says that their child went to school but didn't report a school trip, we prompt them to add it, but a parent can bypass this and clearly many chose to do that. For the online survey, approximately 85% of children have a reported school trip. This is lower than historical levels but is closer to the 88% average daily attendance seen during the 2021-2022 post-pandemic period. RSG, therefore, developed a procedure to impute the missing joint and school escorting trips. This trip imputation process was able to impute a substantial number of missing trips for both children and adults, but due to some data challenges, not all missing joint trips were imputed.

At the time of model calibration and validation, the 2023 SANDAG onboard survey (OBS) data was not yet available. RSG, therefore, used the 2015 SANDAG onboard data in conjunction with the 2022 HTS data to develop the transit targets for calibration purposes. This procedure adjusted the 2022 HTS transit data to: (1) replicate the 2015 OBS distribution of transit trips by access mode, and (2) match the total 2023 ridership data. The adjusted transit targets were then used in resident tour and trip mode choice model calibration steps. To provide a more clear picture on the transit targets used for the overall model, Table 1 shows the distribution of the adjusted transit trip targets by model and access mode. The total transit trip target count for all models is 207,445. Assuming a 1.35 boarding rate for each transit trip, calibrating to these targets should result in approximately 278K boardings.

TABLE 1 TRANSIT TRIP TARGETS USED FOR MODEL CALIBRATION

TRANSIT MODE BY ACCESS	RESIDENT	VISITOR	CROSSBORDER	SAN AIRPORT	CBX AIRPORT	TOTAL
Walk transit	136453	10000	25000	14	20	**171487**
PNR transit	9798	0	0	0	56	**9854**
KNR transit	25558	0	0	129	184	**25871**
TNC transit	0	0	0	25	36	**61**
Total	**171809**	**10000**	**25000**	**396**	**240**	**207445**

The San Diego region is divided into eight districts for the modeling and analysis discussed below. The districts are reflected in Figure 1, and include 1) Downtown, 2) Central, 3) North City, 4) South Suburban, 5) East Suburban, 6) North County West, 7) North County East, 8) East County.

Map of Districts

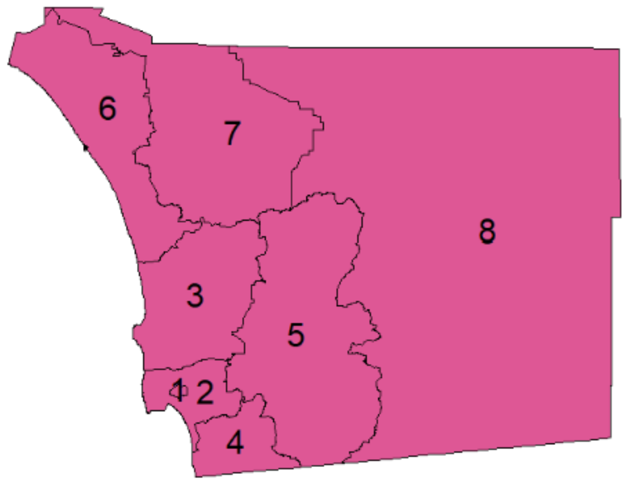


FIGURE 1: MAP OF DISTRICTS

3.0 CALIBRATION RESULTS

ActivitySim model components are shown in Figure 2. The first model in the sequence is disaggregate accessibilities. This is a recent addition to ActivitySim in which the tour destination choice model is run for a prototypical sample population covering key market segments and destination choice logsums from the model are written out for each tour in the population. These destination choice logsums are then merged with the actual synthetic population and used as accessibility variables in downstream models such as auto ownership, coordinated daily activity patterns, and tour frequency. The next step involves the mandatory location choice models that are run for all workers and students regardless of whether they attend work or school on the simulated day. Next, a set of long-term and mobility models are run. The first model in the sequence predicts whether an autonomous vehicle is owned by the household. This model conditions the next model, which predicts the number of autos owned. If an autonomous vehicle is owned, multiple cars are less likely. Next, the mandatory (work and school) location choice models are run. The work location choice models include a model to predict whether the worker has a usual out-of-home work location or exclusively works from home. If the worker chooses to work from home, they will not generate a work tour. An external worker identification model determines whether each worker with an out-of-home workplace location works within the region or external to the region. If they work external to the region, the external station is identified. Any primary destination of any work tours generated by the worker will be the external station chosen by this model. A work location choice model predicts the internal work location of each internal worker, and a school location choice model predicts the school location of each student.

Next, a set of models predicts whether workers and students have subsidized transit fares and if so, the percent of transit fare that is subsidized, and whether each person in the household owns a transit pass. A vehicle type choice model then runs, which predicts the body type, fuel type, and age of each vehicle owned by the household; this model was extended to predict whether each vehicle is autonomous, conditioned by the autonomous vehicle ownership model. Next, we predict whether each household has access to a vehicle transponder which can be used for managed lane use. We assume that all vehicles built after a certain year (configurable by the user) are equipped with transponders. Next, we predict whether each worker has subsidized parking available at work. Finally, we predict the telecommute frequency of each worker, which affects downstream models including the daily activity pattern model, the non-mandatory tour frequency model, and stop frequency models.

Next, the daily and tour level models are run. The first daily model is the coordinated daily activity pattern, which predicts the general activity pattern type for every household member. Mandatory tours are then generated for workers and students, the tours are scheduled (their location is already predicted by the work/school location choice model), a vehicle availability model is run that predicts which household vehicle would be used for the tour, and the tour mode is chosen. After mandatory tours are generated, a school pickup/dropoff model forms half-tours where children are dropped off and/or picked up at school. The model assigns chaperones to drive or ride with children, groups children together into “bundles” for ride-sharing, and assigns the chaperone task to either a generated work tour or generates a new tour for the purpose of ridesharing. Fully joint tours – tours where two or more household members travel together for the entire tour - are generated at a household level, their composition is predicted (adults, children or both), the participants are determined, the vehicle availability model is run, and a tour mode is chosen. The primary destination of fully joint tours is predicted, the tours are scheduled, the vehicle availability model is run, and a tour mode is chosen. Next, non-mandatory tours are generated, their primary destination is chosen, they are scheduled, the vehicle availability model is run, and a tour mode is chosen for each. At-work subtours are tours that start and end at the workplace. These are generated, scheduled (with constraints that the start and end times must nest within the start and end time of the parent work tour), a primary destination is selected, the vehicle availability model is run, and a tour mode is chosen.

At this point, all tours are generated, scheduled, have a primary destination, and a selected tour mode. The next set of models fills in details about the tours: number of intermediate stops, location of each stop, the departure time of each stop, and the mode of each trip on the tour. Finally, the parking location of each auto trip to the central business district (CBD) is determined.

After the model is run, output files (households, persons, vehicles, tours, joint tour participants, and trips) are created. The trip lists are then summarized into origin-destination matrices by time period and vehicle class or transit mode and assigned to the transport network. Skims are created based on congested times, and the model system is iterated multiple times until either some convergence threshold is attained, or a predetermined number of iterations is reached.

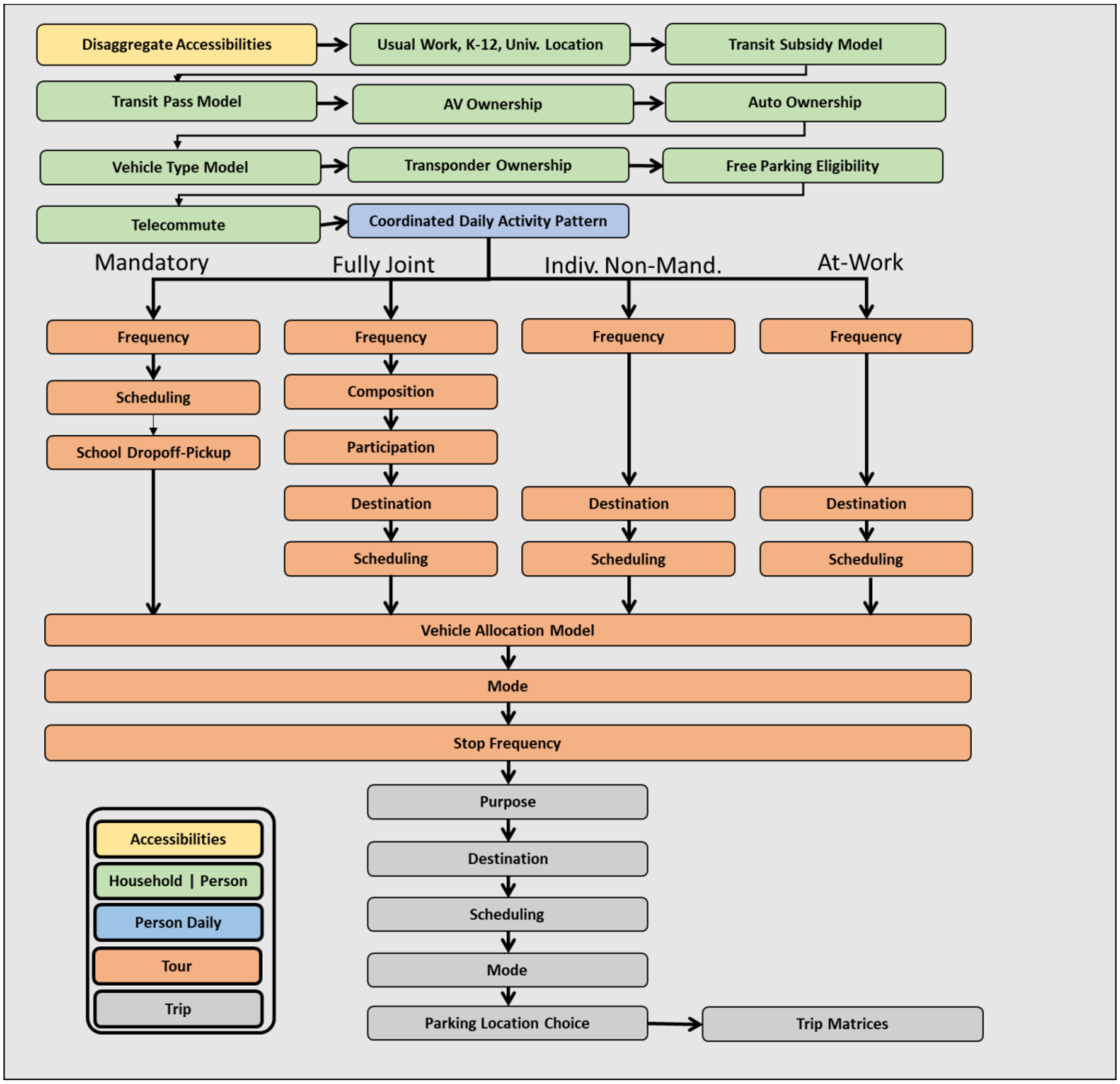


FIGURE 2 MODEL COMPONENTS

ActivitySim is used to represent all internal travel made by residents of the SANDAG region (modeled area). The decision-makers in the model system include both persons and households. These decision-makers are created (synthesized) for each simulation year and land-use scenario, based on Census data and forecasted distributions of households and persons by key socio-economic categories. The decision-makers are used in the subsequent discrete-choice models in a microsimulation framework where a single alternative is selected from a list of available alternatives according to a probability distribution. The probability distribution is generated from a logit model which considers the attributes of the decision-maker and the attributes of the various alternatives. The application paradigm is referred to as Monte

Carlo simulation, since a random number draw is used to select an alternative from the probability distribution. 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.

A key advantage of using the micro-simulation approach is that there are essentially no computational constraints on the number of explanatory variables that can be included in a model specification. However, even with this flexibility, the model system will include some segmentation of decision-makers. Segmentation is a useful tool to both structure models (for example, each person type segment could have their own model for certain choices) and to characterize person roles within a household. Segments can be created for persons as well as households.

Component models that were re-estimated for ABM3 are discussed in the ABM3 Model Development Report[1]. The output of each component model was examined and compared to the observed data, and calibrated as necessary. An overview of the modeled versus reference data stops, tours, trips and VMT and percent difference between the two are provided in Table 2. For the remainder of the calibration section of this report, each component will be discussed, calibration constants will be presented if applied, and the results comparing model output and observed data are presented.

TABLE 2: MODELED AND OBSERVED STATISTICS

Variable	Reference	Model	% Difference
Households	1,175,732	1,160,472	-1.3%
Population	3,262,207	3,166,044	-2.9%
Stops	4,112,956	3,837,898	-6.7%
Tours	4,760,939	4,512,239	-5.2%
Trips	13,783,608	12,862,376	-6.7%
VMT	48,825,633	47,743,022	-2.2%

[1] SANDAG ABM3 Model Development Report https://app.box.com/s/2npugxfpb9pl5a41tp4rj0zgsiqn2n7v

The Table below shows an overall summary of the models that were either estimated or calibrated.

TABLE 3 OVERVIEW OF MODELS IN ABM3

MODEL NAME	DESCRIPTION
Disaggregate Accessibility	New model component in ABM3, uses tour mode and destination choice models
Aggregate Accessibility	MTC TM1 disaggregate accessibility calculations. Many have been replaced with disaggregate accessibilities
AV Ownership	Asserted model (no AVs owned currently)
Auto Ownership	Estimated using 2016 & 2022 HTS data and calibrated to 2022 ACS
Work From Home	Estimated using 2016 & 2022 HTS data and calibrated to 2022 ACS
External Worker Identification	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
External Workplace Location	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
School Location	Estimated using 2004 HTS and calibrated to 2022 HTS data
Workplace Location	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
Transit Pass Subsidy	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
Transit Pass Ownership	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
Vehicle Type Choice	Estimated using 2017 NHTS data, constants for San Diego County
Transponder Ownership	Estimated using 2022 HTS data, calibrated to 2022 HTS
Free Parking	Estimated using 2004 HTS and calibrated to 2022 HTS data
Telecommute Frequency	Estimated using 2016 & 2022 HTS data and calibrated to 2022 ACS
CDAP	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS and asserted shares for students
Mandatory Tour Frequency	Estimated using 2004 HTS, calibration unnecessary
Mandatory Tour Scheduling	Estimated using 2015 HTS for Southeast Michigan Council of Governments, calibration unnecessary
School Escorting	Estimated using 2008 NHTS add-on for Maricopa Association of Governments, not calibrated due to issues with 2022 HTS school travel
Joint Tour Frequency Composition	Estimated using 2004 HTS and calibrated to 2022 HTS data
External Joint Tour Identification	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
Joint Tour Participation	Estimated using 2004 HTS and calibrated to 2022 HTS data

Joint Tour Destination	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
External Joint Tour Destination	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
Joint Tour Scheduling	Estimated using 2015 HTS for Southeast Michigan Council of Governments, calibration unnecessary
Non-Mandatory Tour Frequency	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
External Non-Mandatory Identification	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
Non-Mandatory Tour Destination	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
External Non Mandatory Destination	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
Non-Mandatory Tour Scheduling	Estimated using 2015 HTS for Southeast Michigan Council of Governments, calibration unnecessary
Vehicle Allocation	Estimated using 2017 NHTS data, not calibrated
Tour Mode Choice	Estimated using 2004 HTS and calibrated to 2022 HTS data and adjusted 2015 OBS data
At-work Subtour Frequency	Estimated using 2004 HTS and calibrated to 2022 HTS data
At-work Subtour Destination	Estimated using 2004 HTS and calibrated to 2022 HTS data
At-work Subtour Scheduling	Estimated using 2015 HTS for Southeast Michigan Council of Governments, calibration unnecessary
At-work Subtour Mode Choice	Estimated using 2004 HTS and calibrated to 2022 HTS data and adjusted 2015 OBS data
Stop Frequency	Estimated using 2016 & 2022 HTS data, calibrated to 2022 HTS
Trip Purpose	Frequencies from 2022 HTS
Trip Destination	Estimated using 2004 HTS and calibrated to 2022 HTS data
Trip Scheduling	Estimated using combined data from SANDAG, Chicago Metropolitan Agency for Planning, Metropolitan Washington Council of Governments, and Southeast Michigan Council of Governments
Trip Mode Choice	Estimated using 2004 HTS and calibrated to 2022 HTS data and adjusted 2015 OBS data
Parking Location	Estimated using 2004 HTS, not calibrated

Mobility Models

Disaggregate Accessibilities

The disaggregate accessibility model is an extension of the base accessibility model. While the base accessibility model is based on a mode-specific decay function and uses fixed market segments in the population (i.e., income), the disaggregate accessibility model extracts the actual destination choice logsums by purpose (i.e., mandatory fixed school/work location and non-mandatory tour destinations by purpose) from the actual model calculations using a user-defined proto-population. This prototypical population is run through the mandatory location and non-mandatory destination choice models (*Usual work, K12, Univ. location* and *destination* model steps in Figure 2) to create accessibility logsums representing household accessibility to zones throughout the region, by all modes. These destination choice logsums are then used in downstream models including auto ownership, coordinated daily activity pattern, and tour frequency models. The disaggregate accessibility measures utilize the actual tour mode and destination models; therefore, this component is not calibrated per se.

Autonomous Vehicle Ownership

Because there is no base-year autonomous vehicle ownership, there is nothing to calibrate in this model.

Auto Ownership

The auto ownership model estimates the number of autos owned by a household. Alternatives include 0, 1, 2, 3 and 4+ autos. The model was estimated using household travel survey data and calibrated to 2021 American Community Survey data. The coefficients that were changed were the alternative specific constants for 0, 2, 3 and 4+ autos, and are provided in

Table 4.

TABLE 4: AUTO OWNERSHIP CALIBRATION CONSTANTS

COEFFICIENT	CONSTANT
asc_allhhs_0_autos	-0.2050
asc_allhhs_2_autos	0.1031
asc_allhs_3_autos	0.2177
asc_allhhs_4plus_autos	0.1785

The resulting distribution for the number of household vehicles is provided in Figure 3. The model is very close to the reference data for all categories.

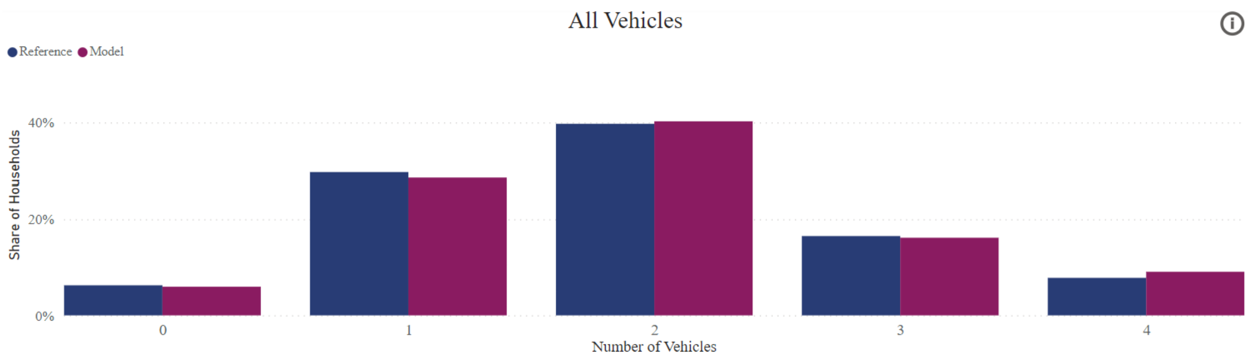


FIGURE 3: AUTO OWNERSHIP

Work From Home

The work from home model estimates whether an individual works from home or not. This is a binary choice model where 0 means the worker has a usual out of home workplace location and, 1 indicates working from home. This model was estimated for the SANDAG region using household travel survey data.

The calibration target for this model was based on the survey data, but was adjusted to the share of workers whose 'usual mode to work' was home according to 2022 ACS data. We assume that workers who report that their usual mode to work is home includes all workers whose usual workplace location is home, plus workers who telecommute at least 3 days per week. RSG scaled the work from home and telecommute frequency targets so that the sum of those who work from home, those who telecommute 4+ days/week, and 50% of those who telecommute 2-3 days/week (categories defined in the survey) match the 18.1% work from home share in the ACS 2022 data.

RSG calibrated this model only at the regional-level, and refrained from adding county-level constants to the model in the final calibration effort. Table 5 shows the regional-level calibration constant for the model.

TABLE 5 CALIBRATION CONSTANTS FOR WORK FROM HOME MODEL

CALIBRATION CONSTANT DEFINITION	VALUE
Regional-level constant	-0.820

The work from home share is provided in Figure 4. Overall, the model predicted 9.82% work from home share, while the reference data had a 9.36% share. The biggest discrepancy between the model and reference data was in East County, where there was no reference data on which to base a comparison, due to the relatively low number of survey responses in this area. Note that the estimated work from home share is relatively higher in East County due to the relatively lower accessibility of East County households to employment as compared to the rest of the county.

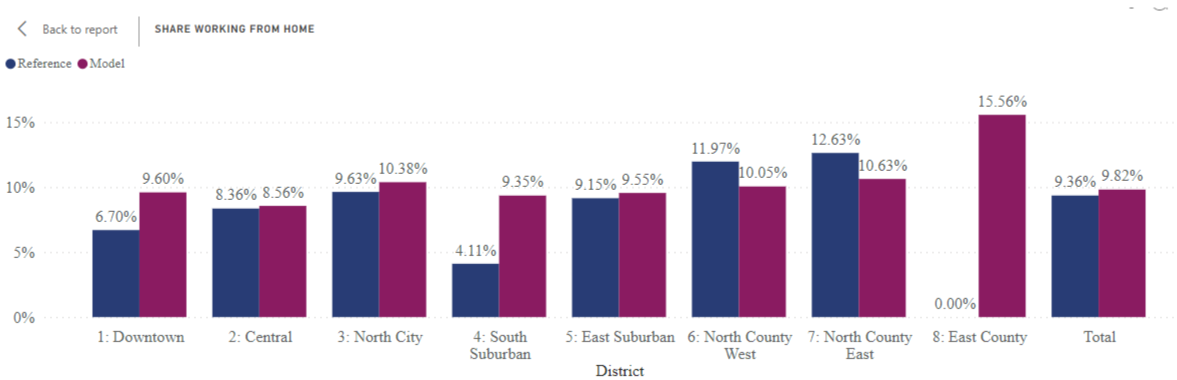


FIGURE 4: WORK FROM HOME SHARE

External Worker Identification

The external worker identification model is used to identify for those who have a regular out of home workplace, whether the workplace is outside of the region. If a worker has an external place of work, the work tour if generated will be assigned an external station.

RSG calibrated this model to effect a modest increase in the share of external workers. Table 6 shows the calibration constant.

TABLE 6 CALIBRATION CONSTANTS FOR EXTERNAL WORKER IDENTIFICATION MODEL

CALIBRATION CONSTANT DEFINITION	VALUE
Generic constant	0.350

The estimated external work location result is very close, with a 1.74% share of external workers, compared with a 1.63% share of participants with an external work location in the observed data.

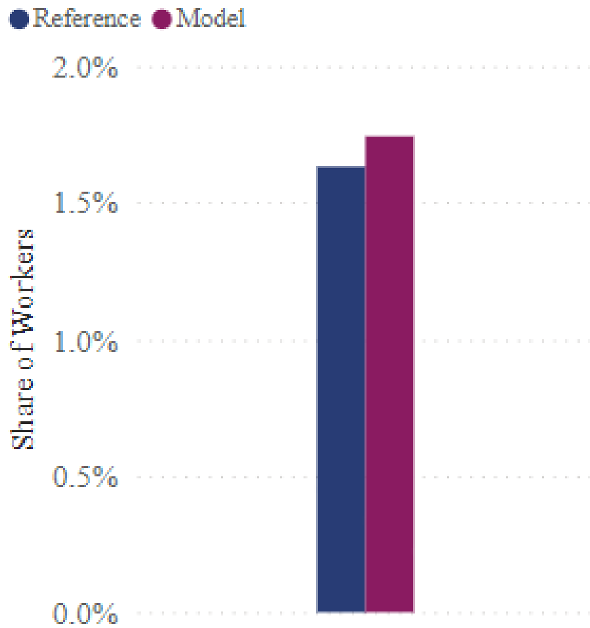


FIGURE 5: EXTERNAL WORKER IDENTIFICATION MODEL

External Workplace Location

The external workplace location model estimates the external station location of those workers who are assigned as external workers in the aforementioned model. This model was estimated for the SANDAG region.

This model was not calibrated.

Results of the model estimation and observed data are provided in Figure 6. Results indicate that the model slightly underpredicts the average distance across all districts by 6 miles or approximately 15%. It is important to note that external workers sample size in the 2022 HTS data was a total of 707 workers, and there were no external workers in the observed data for the downtown district (district 1), and the largest discrepancy between the model and observed was for South Suburban which the model overestimated by over 12 miles.

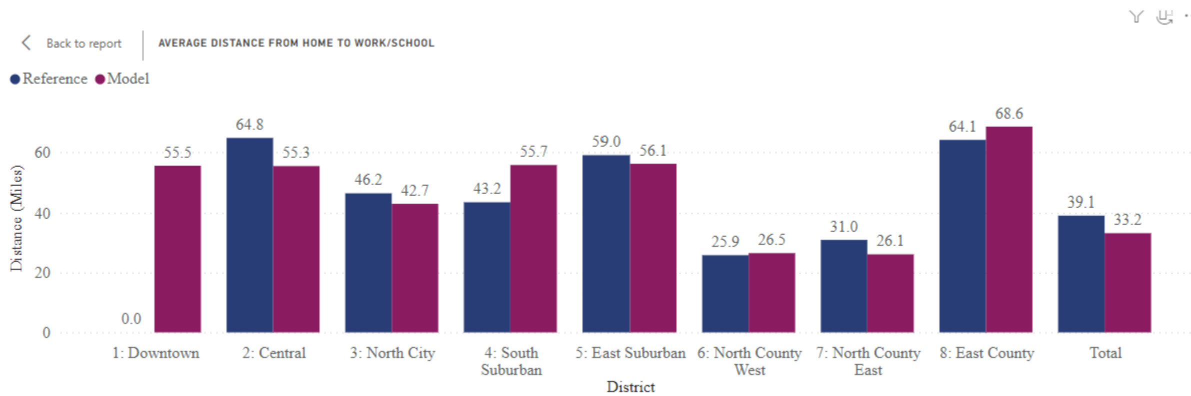


FIGURE 6: AVERAGE DISTANCE FROM HOME TO WORK: EXTERNAL TOURS

Usual work, K-12, University Location

A workplace/school location choice model assigns a workplace/school zone (MGRA) for every employed person or student in the synthetic population. Every worker/student is assigned a regular work/school location zone according to a multinomial logit destination choice model. Since mode choice logsums are required for each destination, ActivitySim uses a two-stage procedure for all destination choice models in ActivitySim to reduce computational time (it would be computationally prohibitive to compute a mode choice logsum for each of the approximately 24.3K zones and every worker in the synthetic population). In the first stage, a simplified destination choice model is applied in which all zones are alternatives. The variables in this model are the distance to the zones, distance interaction terms and the size term of the zones. The logsum term is not used in the simple model used to sample alternatives. This model creates a probability distribution for all possible alternatives (zones with no employment are not sampled). A set of thirty alternatives are sampled from the probability distribution and these alternatives constitute the choice set in the full destination choice model. Mode choice logsums are computed for these alternatives and the destination choice model is applied. A discrete choice of zones is made for each worker/student from this more limited set of alternatives (the same general structure is used for all destination choice models).

The workplace location choice model was calibrated using the 2022 target data. The focus of the calibration was better matching the work tour length distribution of the target data. To do so, tour distances were binned into 6 categories: 0-2miles, 2-5miles, 5-10miles, 10-20miles, 20-30miles, and greater than 30miles. Calibration constants were computed so that the modeled share of tours in each bin match the target data. The original model was predicting shorter work tours compared to the target data. The distance calibration constants are provided in Table 7.

TABLE 7: WORKPLACE LOCATION CALIBRATION CONSTANTS

DISTANCE	CONSTANT
0-2 miles	-0.7700
2-5 miles	-0.8700
5-10 miles	0.0270
10-20 miles	0.7200
20-30 miles	0.8520
30 plus miles	0.2310

Work locations by district shows that the model predicts district locations for workplace closely for most districts.

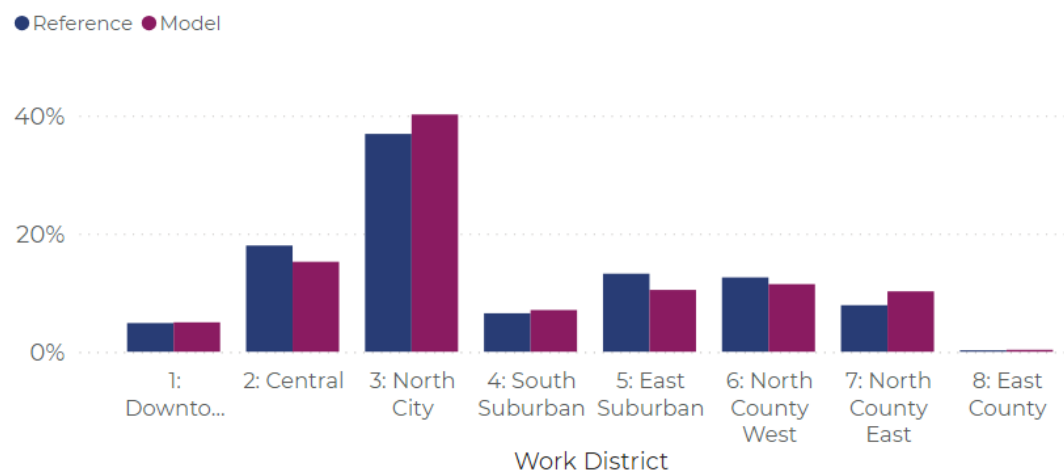
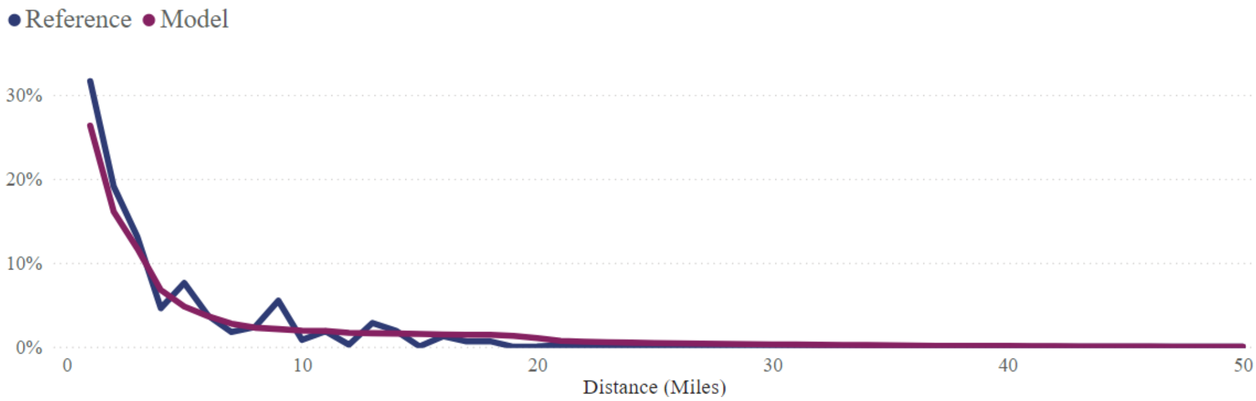
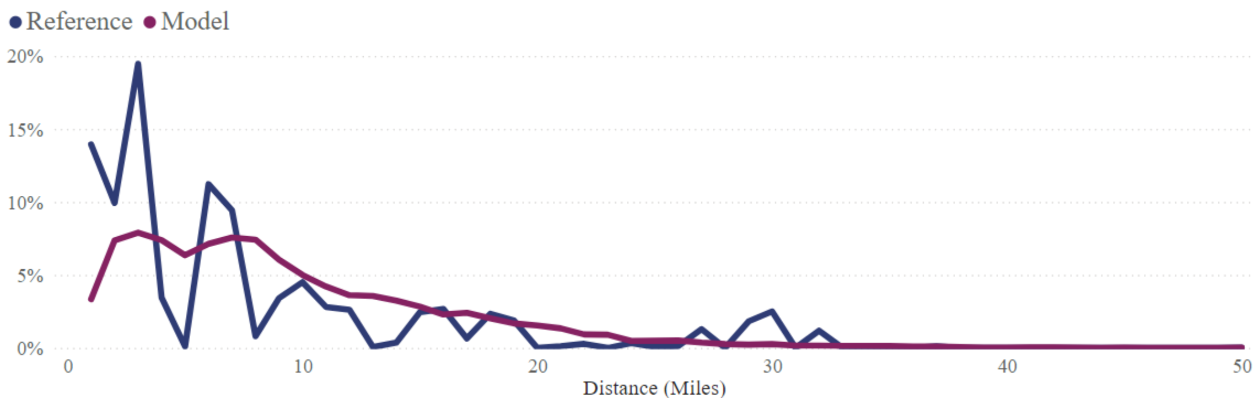


FIGURE 7: WORK LOCATIONS BY DISTRICT

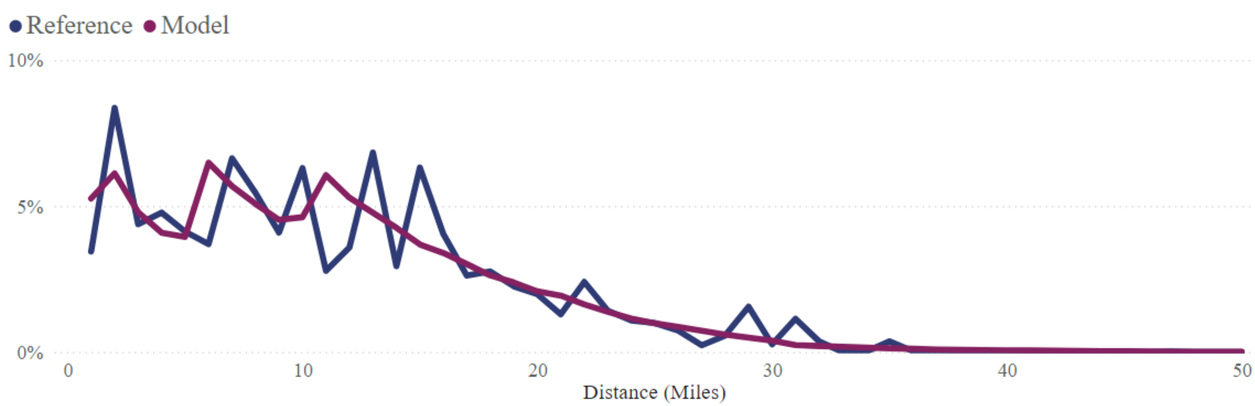
Figure 8 shows the distance distribution from home to mandatory activity locations. The average home to work distance in the model is 10.8 miles, which is very close to the 11.1 miles average in the data. The average home to university distance is 9.0 miles in the model, which is higher than the 7.4 mile average in the target data. Similarly, the average home to school distance is 6.3 miles which is higher than the 3.6 mile average in the data. Although RSG did an initial effort at calibration of the school and university location models, we suggest revisiting these models again for better matching of distances. According to the distance distributions, these models need to have a higher share of half tours within the 0-5 mile distance category.



(a) Distance distribution from home to K-12 school



(b) Distance distribution from home to university



(a) Distance distribution from home to work

FIGURE 8 DISTANCE DISTRIBUTION TO MANDATORY ACTIVITY LOCATIONS

Transit subsidy/ Transit Pass Models

The transit subsidy model predicts which workers have transit subsidized by their employer, while the transit pass ownership model predicts which persons own a transit pass. Both models were calibrated to observed shares in the household travel survey.

Table 8 and Table 9 show the calibration constants for these two models.

TABLE 8 CALIBRATION CONSTANTS FOR TRANSIT SUBSIDY MODEL

CALIBRATION CONSTANT DEFINITION	VALUE
Full-time worker	-0.240
Part-time worker	-0.250
University student	0.300

TABLE 9 CALIBRATION CONSTANTS FOR TRANSIT PASS OWNERSHIP MODEL

CALIBRATION CONSTANT DEFINITION	VALUE
Full-time worker	-0.240
Part-time worker	-0.250
University student	0.300
Retired/non-worker	1.650
Driving-age student	1.000
Non-driving age student	-2.000
preschoolers	-2.000

The results of the transit subsidy model are shown by person type in Figure 9. It shows a close match with some difference by person type though the shares are generally very small.

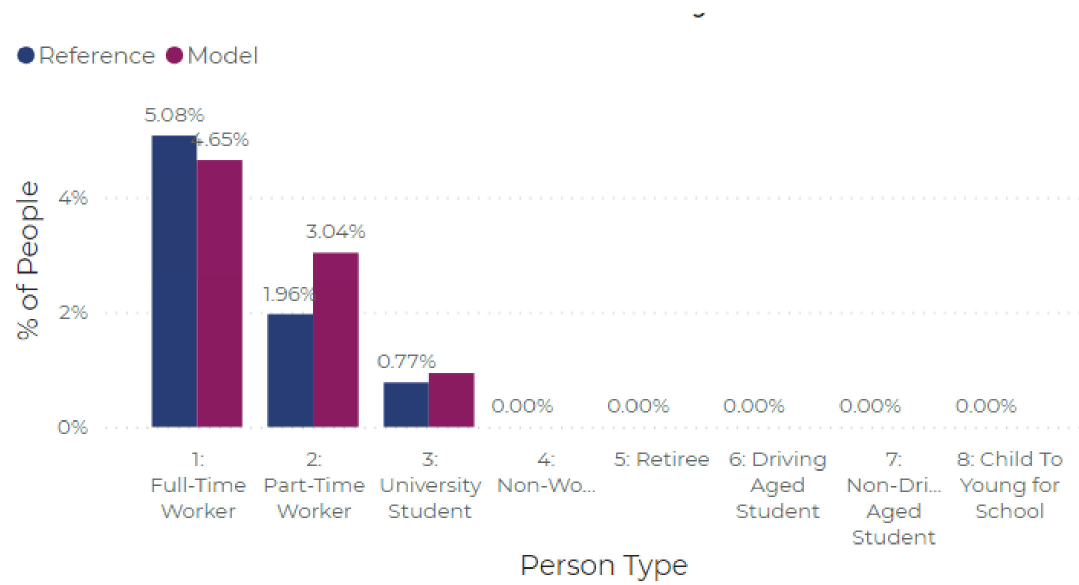


FIGURE 9: TRANSIT SUBSIDY MODEL RESULTS BY PERSON TYPE

The transit pass ownership results are shown by person type in Figure 10. It shows that the model generally follows the right distribution of transit pass ownership by person type with the biggest discrepancy being for university students. Note there are only 108 university students who own a transit pass in the survey data.

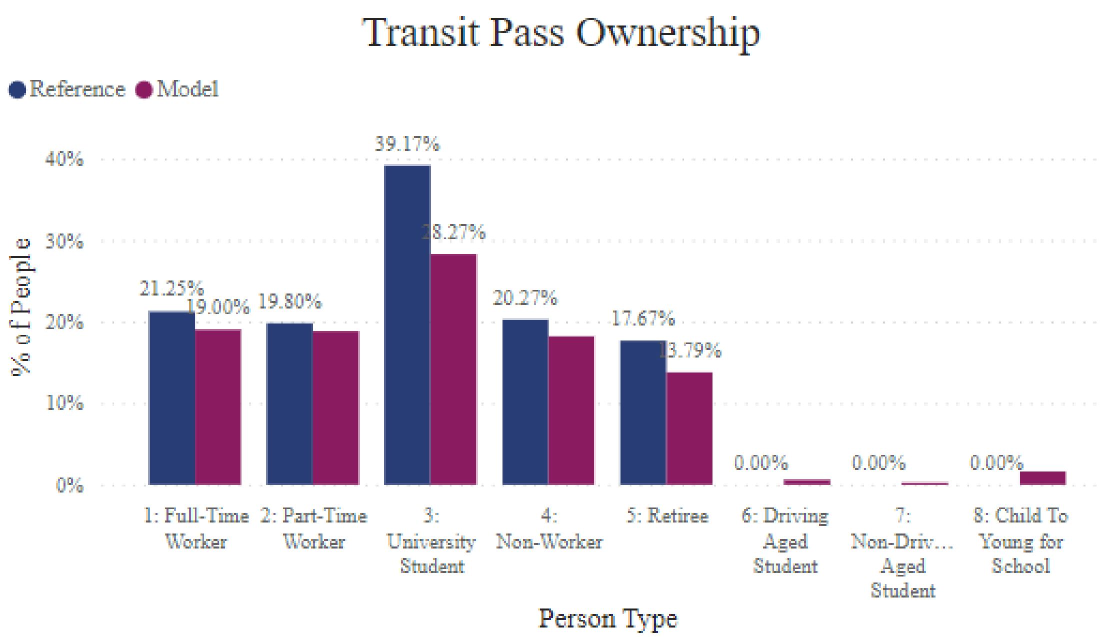


FIGURE 10: TRANSIT PASS OWNERSHIP RESULTS BY PERSON TYPE

Vehicle Type Model

The vehicle type model assigns attributes to each of the household vehicles assigned in the Auto Ownership.

The target data for this model originated from the California Department of Motor Vehicles (DMV). In 2023 SANDAG began receiving data from the California DMV. This included data on every vehicle registered in San Diego County. This dataset allowed for the calculation of distributions of fuel type, body type, and age that the vehicle type choice model could be calibrated to. Distributions were created based on a report from October 2023. It should be noted that the fuel and body type categories in the DMV data did not perfectly line up with the categories from ActivitySim, so some effort was needed to reconcile the two.

Results of the model prediction indicate that the model performed well in predicting the body type of the vehicle fleet for all vehicles from 1 to 20 years of age. Additionally, the fuel type distribution matches the distribution of the observed data. The vehicles by age for the model has a decent fit with the target, although the 20+ year old cars appear to be underpredicted in the model compared with the target DMV data.

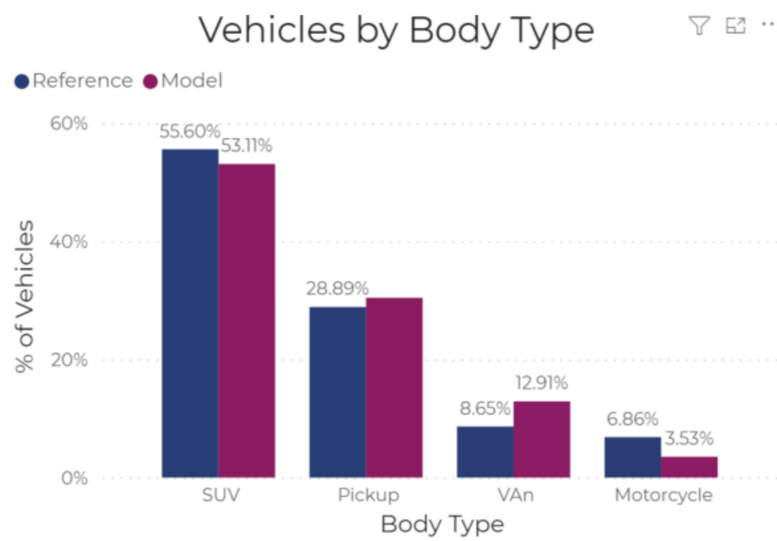


FIGURE 11: VEHICLES BY BODY TYPE

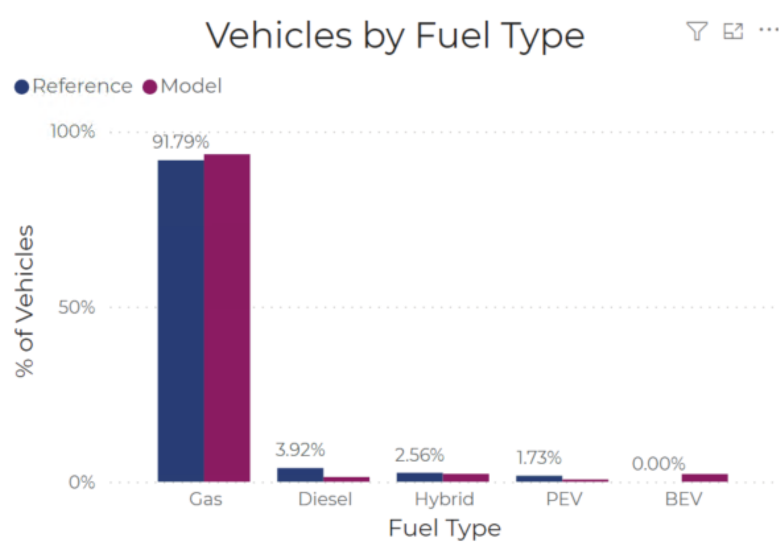


FIGURE 12: VEHICLES BY FUEL TYPE

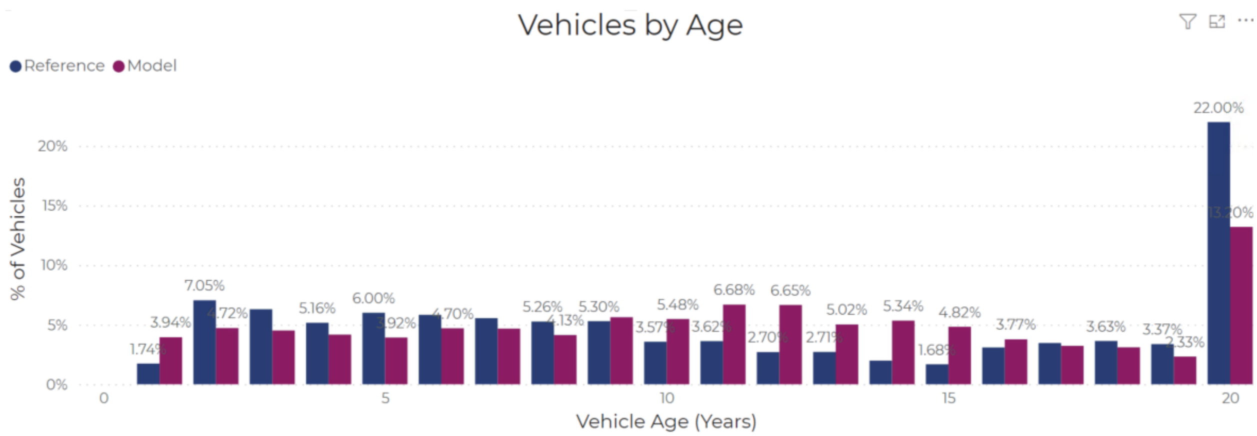


FIGURE 13: VEHICLES BY AGE

Transponder Ownership

The toll transponder ownership model predicts which households own a FasTrak toll transponder, which is required to utilize the I-15 managed lanes as a drive-alone vehicle. This model was estimated and is used to segment the drive-alone trips in terms of whether they can use I-15 managed lane or not. Travelers in households without a transponder are prohibited from using I-15 managed lanes and their mode choice decisions are based on skims that do not include I-15 managed lane in the auto path.

Results of the model are shown in Figure 14. Ownership of transponders as estimated by the model is slightly higher at 21% than the observed data at 18%.

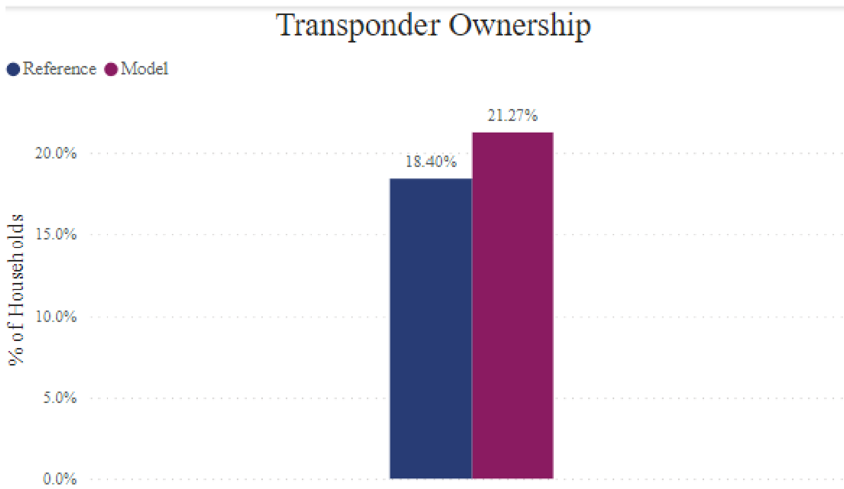


FIGURE 14: TOLL TRANSPONDER OWNERSHIP

Free Parking Eligibility

The free parking eligibility model predicts whether each worker has free parking provided at their workplace by their employer. The purpose of the model is to adequately reflect the cost of driving to work in subsequent models, particularly in mode choice. Considering that only a select few person types may be workers, and hence may get free parking from their employer, the results shown in Figure 15 involve full-time and part-time works in addition to college students and driving-age students. Figure 15 presents the share of each of these person types that receive free parking at work, showing a close match to observed data.

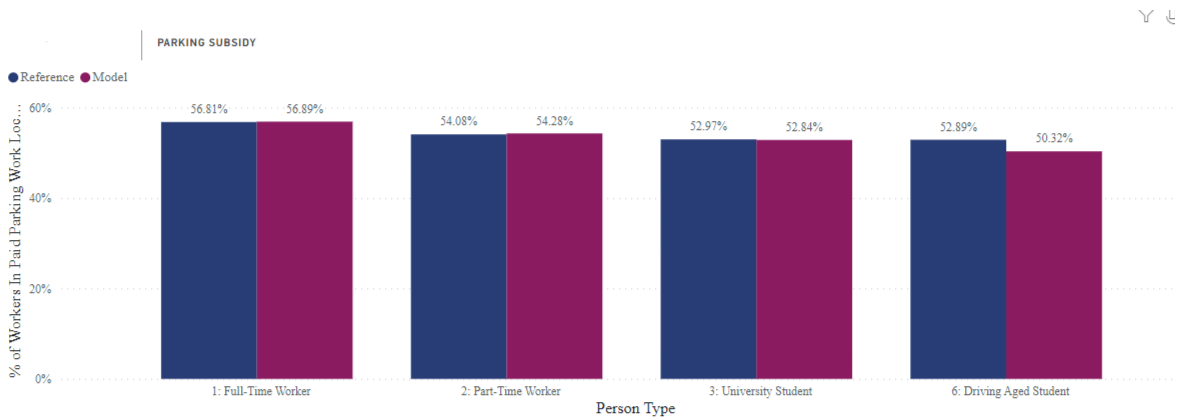


FIGURE 15: PERCENT OF WORKERS IN PAID PARKING WORK LOCATION

Telecommute frequency model

The telecommute frequency model predicts the number of days in which a worker telecommutes from home. The alternatives for this model are no telecommuting/telecommutes less than 1 day per week, 1 day per week, 2-3 days per week or 4+ days per week.

Similar to the work from home model, the calibration target for this model was also based on the survey data, but was adjusted to the share of workers whose 'usual mode to work' was home according to 2022 ACS data. We assume that workers who report that their usual mode to work is home includes all workers whose usual workplace location is home, plus workers who telecommute at least 3 days per week. RSG scaled the work from home and telecommute frequency targets so that the sum of those who work from home, those who telecommute 4+ days/week, and 50% of those who telecommute 2-3 days/week (categories defined in the survey) match the 18.1% work from home share in the ACS 2022 data.

Table 10 shows the calibration constants for this model.

TABLE 10 CALIBRATION CONSTANTS FOR TELECOMMUTE FREQUENCY MODEL

CALIBRATION CONSTANT DEFINITION	VALUE
1-day frequency category	-2.549
2-3 day frequency category	-1.534
4+ day frequency category	-1.948

Telecommute frequency results in Figure 16 indicate that the model has been calibrated closely to observed data.

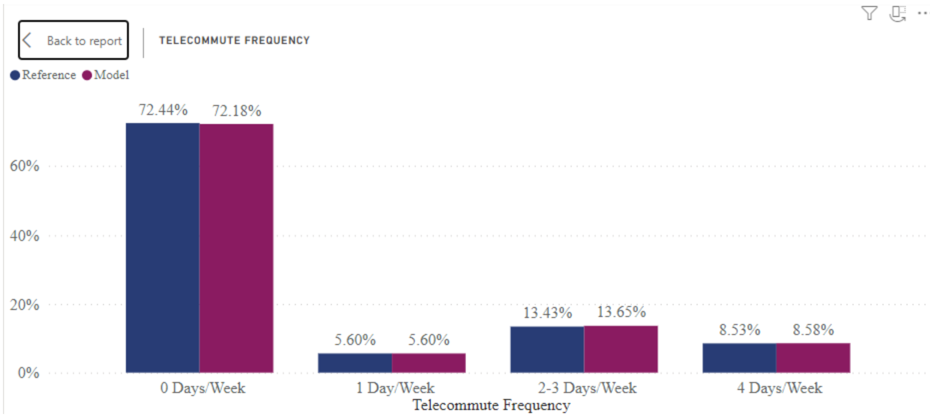


FIGURE 16: TELECOMMUTE FREQUENCY

Coordinated Daily Activity Pattern

The Coordinated Daily Activity Pattern predicts the overall daily activity pattern of each person in the household, simultaneously across household members. The alternatives are mandatory (denoted by “M”, which means that the worker or student has at least one work or school activity), non-mandatory (denoted by “N”, which indicates that the individual has at least one non-mandatory activity) or stay at home (denoted by “H”). Additionally, the model predicts whether a fully joint tour is generated by the household. This option is only the case where there are at least two persons in the household who are assigned an active (M or N) activity pattern. The distribution of fully joint tours by household size in the model and survey data is presented in Figure 17. As this Figure shows, there is a close match between model predictions and survey targets, although the fit may be improved for household size ==3.

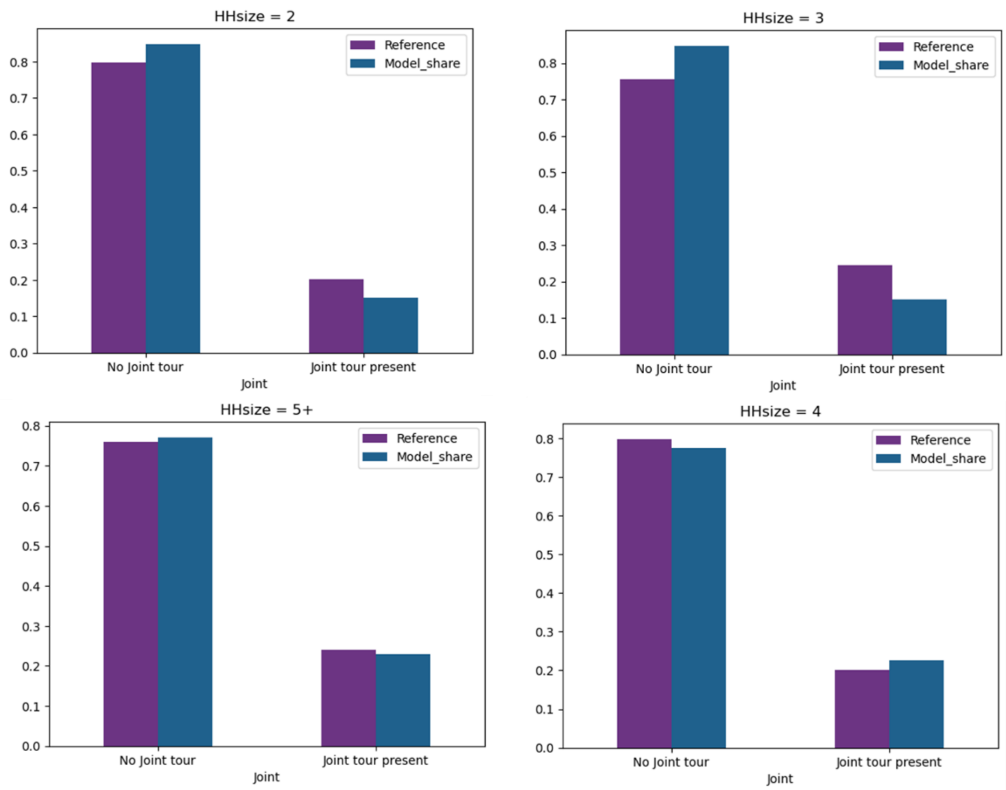


FIGURE 17 FULLY JOINT TOUR DISTRIBUTION BY HOUSEHOLD SIZE

Calibration coefficients include alternative specific constants for each of the 8 person types for mandatory, non-mandatory and stay at home alternatives, which are provided in Table 11.

TABLE 11: CDAP CALIBRATION CONSTANTS

COEFFICIENT	M	N	H
ABM3 calibration ASC ptype=1 (Full time worker)	0.5540	-0.2180	-0.4270
ABM3 calibration ASC ptype=2 (Part time worker)	-0.1070	0.02760	0.2230
ABM3 calibration ASC ptype=3 (University Student)	0.4270	-0.1980	-0.1640
ABM3 calibration ASC ptype=4 (Non-working adult)	0.0000	-0.02900	0.0889
ABM3 calibration ASC ptype=5 (Retired)	0.0000	0.1140	-0.2270
ABM3 calibration ASC ptype=6 (Driving age child)	3.650	-0.2410	0.2980
ABM3 calibration ASC ptype=7 (Non-driving age child)	2.000	-0.1710	0.09600
ABM3 calibration ASC ptype=8 (Preschool child)	0.4360	0.4540	-0.7310

Daily activity patterns are shown in Figure 18 for all person types, and Figure 19 by person type. Results of the model indicate an overall overprediction of mandatory tours, and an underprediction of non-mandatory and stay at home activity patterns for all person types compared to the observed data. However, when examining daily activity patterns by person type, it becomes clear that the model closely follows the distribution of activity patterns of retired and non-working individuals, and has the most divergence from the observed for driving age and non-driving age individuals. This discrepancy is due to the under-reporting of school activities for children in the household survey. As a result, the project team decided to calibrate the model to a much higher rate of school attendance (90%) for K-12 students than is observed in the survey.

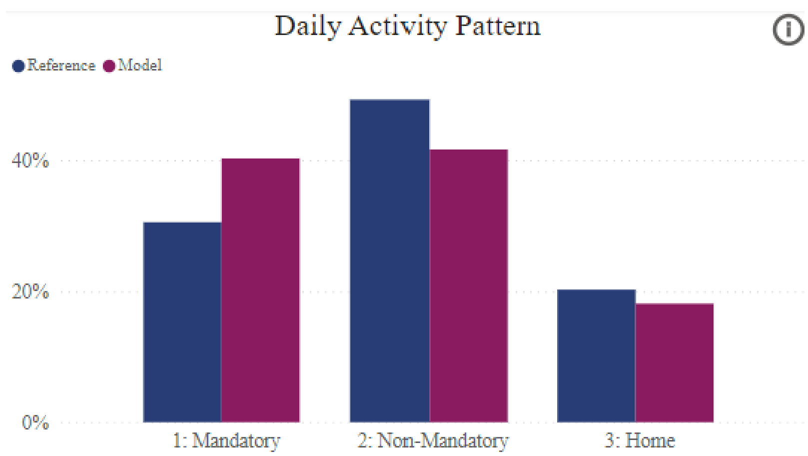


FIGURE 18: DAILY ACTIVITY PATTERNS (ALL PERSONS)

FIGURE 19: DAILY ACTIVITY PATTERN BY PERSON TYPE

Day and Tour Level/Primary Activity Models

Mandatory Tour Frequency

The coordinated daily activity pattern model is used to assign each person a pattern of activities for whether there will be travel for mandatory activities, non-mandatory activities, or no travel/ external travel. Following this model, the mandatory tour frequency model assigns each worker and student an exact number of mandatory tours. It is important to note that it is impossible for non-working adults and retired adults to have mandatory tours, as the mandatory tour category consists of work and school trips.

Results are provided in Figure 20. The model underpredicts instances where there is one work tour, and overpredicts instances where there is one school tour. Conversely, the 2+ work tours are slightly overpredicted and 2+ school tour frequencies are slightly underpredicted compared to the observed data. Person type results, provided in Figure 21, indicate that the disaggregate results are similar to the aggregate results, in that the model slightly underpredicts one work tour frequencies for full time workers and slightly overpredicts 2+ work tours. This is similar for part time workers as well as for university students. Frequency distribution for school trips for university students are predicted close to the observed data, as is the case for driving age students. The model underpredicts the one tour frequency for non-driving age students, and overpredicts 2+ tours.

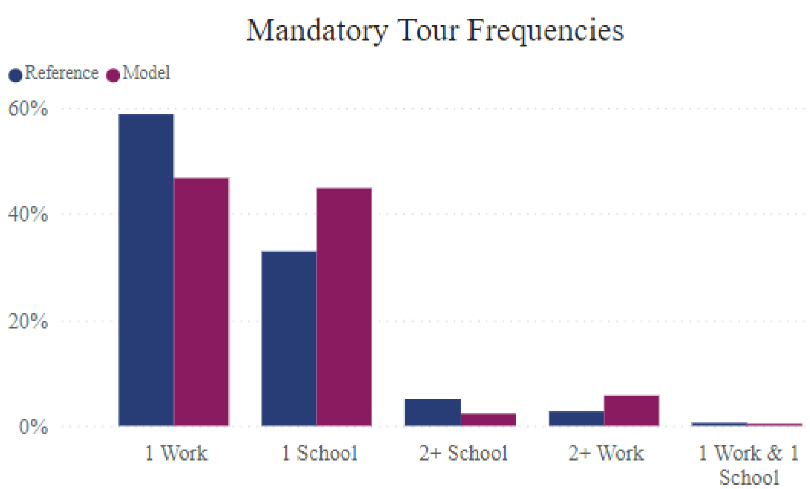


FIGURE 20: MANDATORY TOUR FREQUENCY- ALL PERSON TYPES

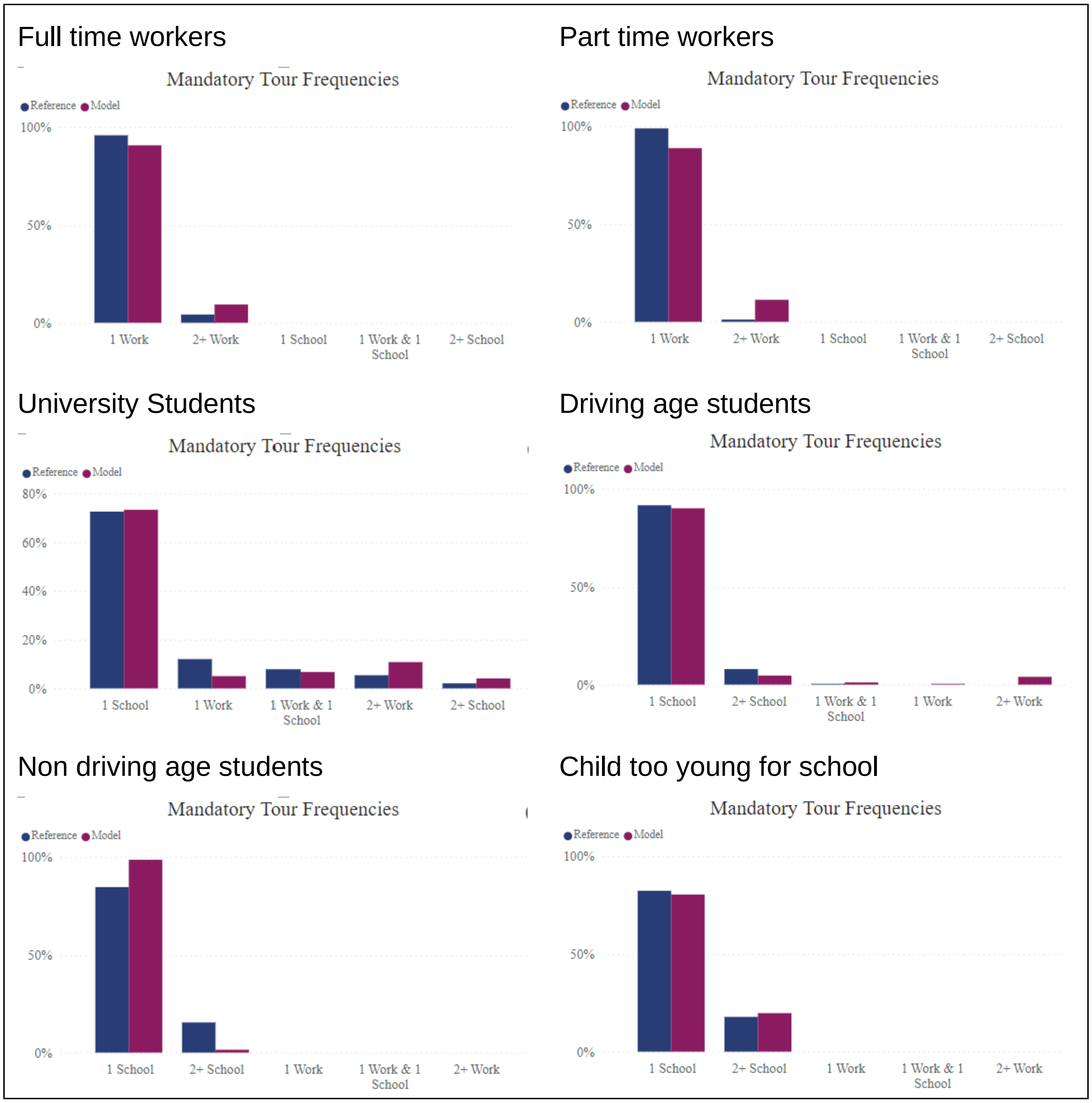


FIGURE 21: MANDATORY TOUR FREQUENCIES BY PERSON TYPE

Mandatory Tour Scheduling

The mandatory tour scheduling model assigns each work and school tour a start and end period simultaneously. There are 48 half-hour periods in the model, starting and ending at 3 A.M.

No calibration was done on work, school or university tours.

The resulting model and observed data comparisons are provided in Figure 22 for work tours, Figure 23 for university tours, and Figure 24 for school tours. The fit statistic (R or coefficient of correlation) for work departures and arrivals and school departures indicates that the model closely aligns with the observed data for these tour types and attributes. University (both departure and arrival) tour attributes do not align as closely between modeled and observed values, with an r of 0.560 for departure and 0.477 for arrival. This is likely related to the lack of data for university student person type. Additionally, the school arrival profile also indicates some divergence from the observed data. This again could be due to the sparsity of data.

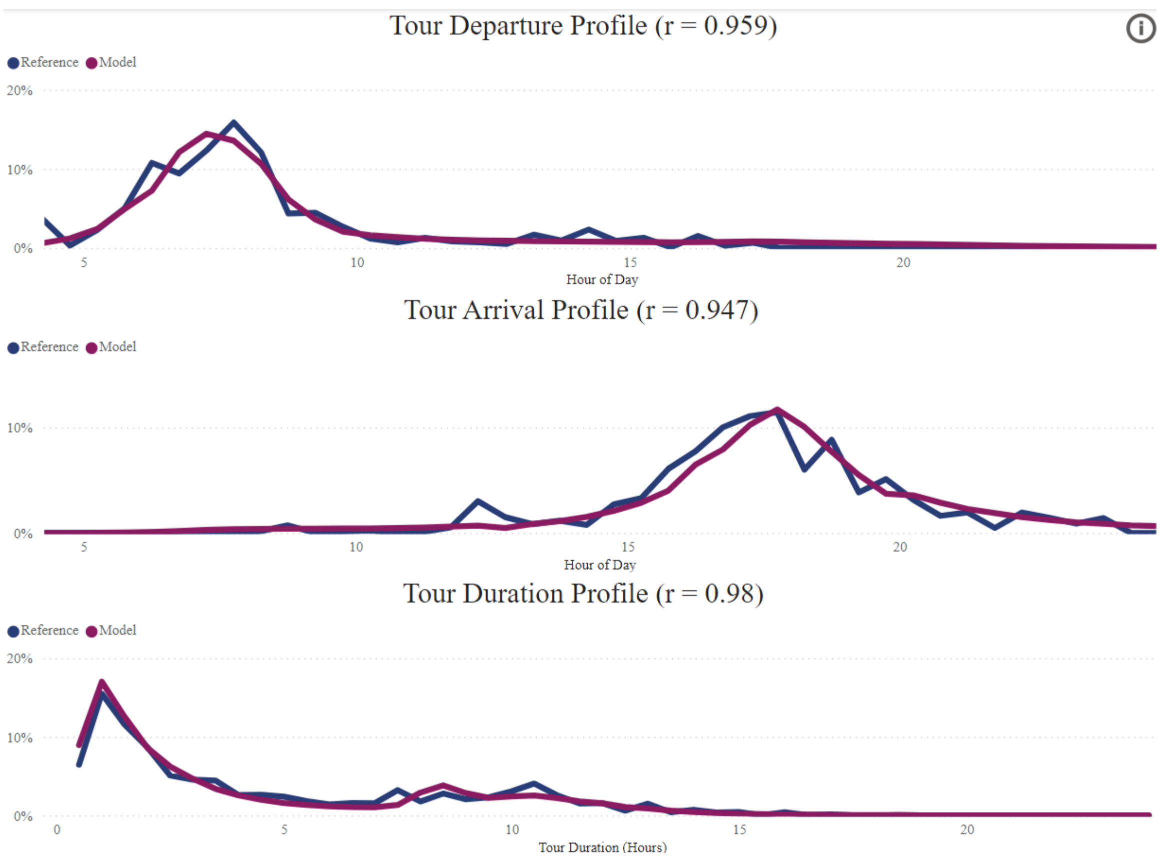


FIGURE 22: WORK TOUR SCHEDULING

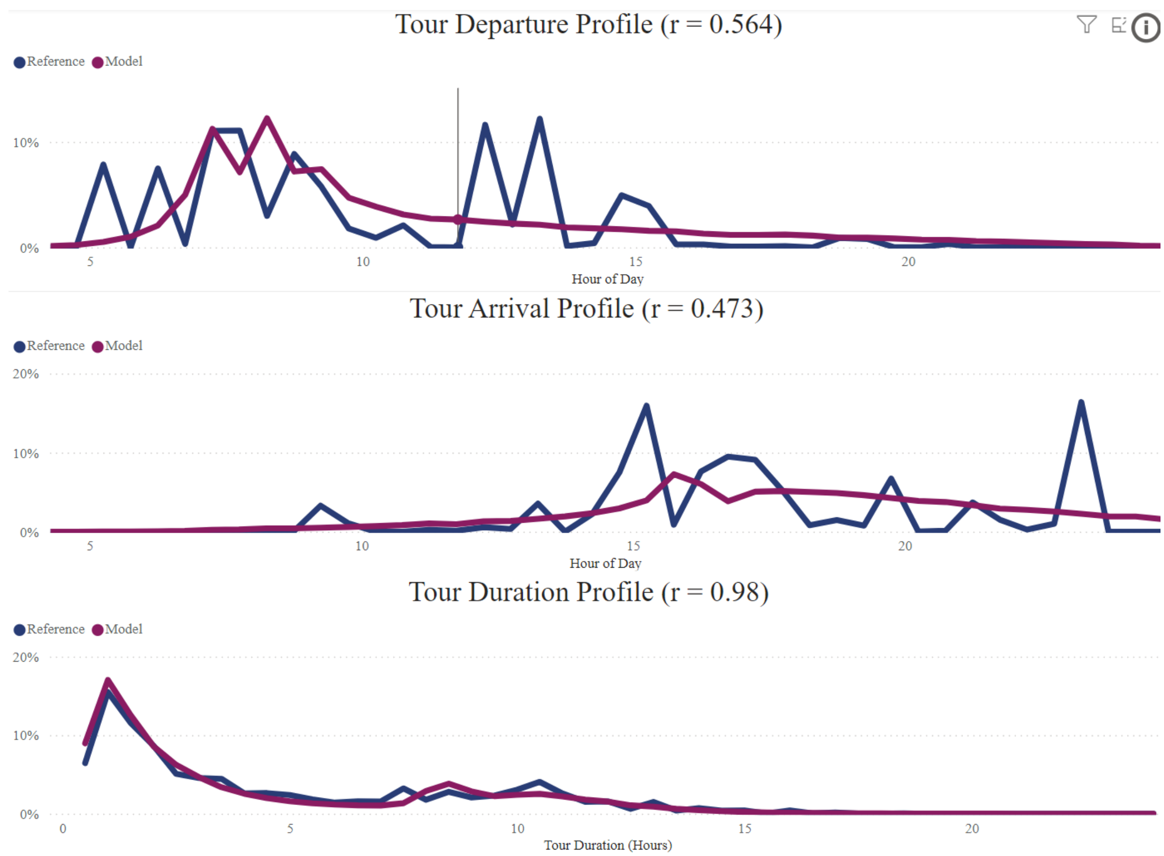


FIGURE 23: UNIVERSITY TOUR SCHEDULING

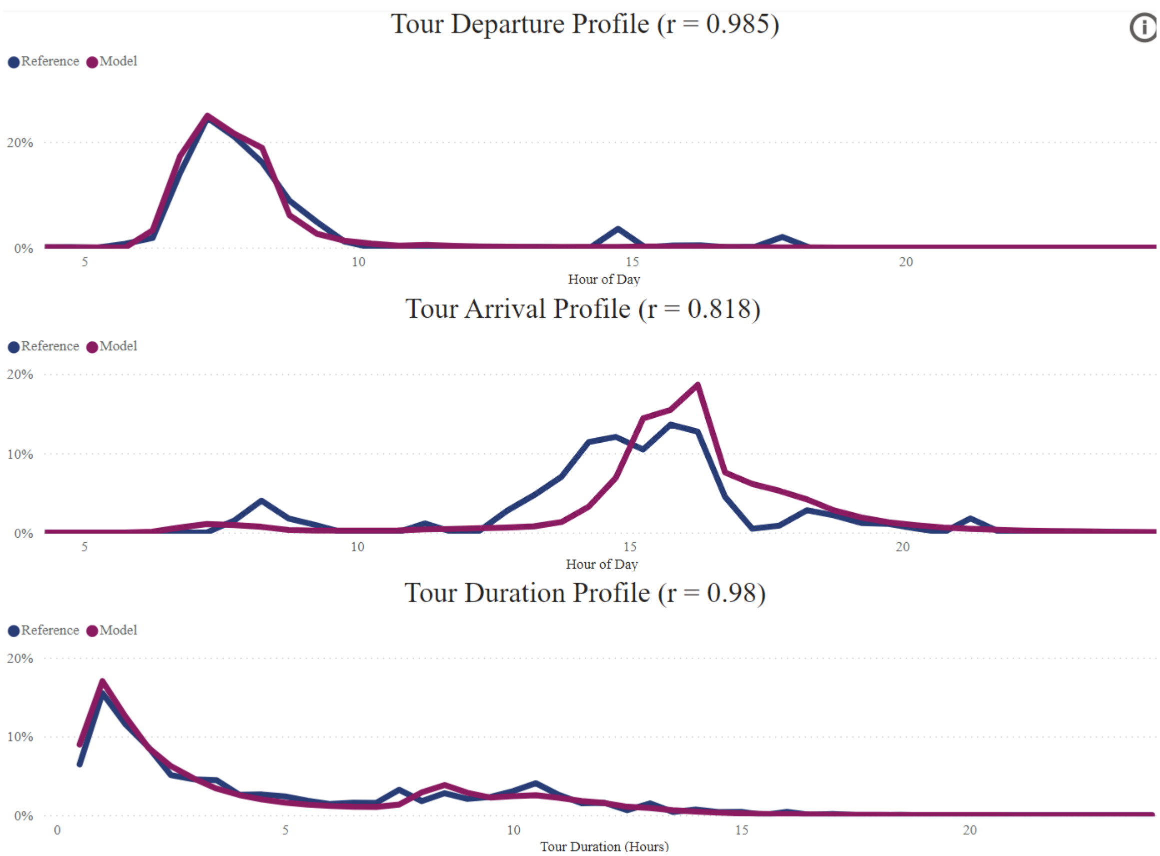


FIGURE 24: SCHOOL TOUR SCHEDULING

Mandatory School Dropoff- Pickup

The school dropoff-pickup model identifies which student's school tours are candidates for ride-sharing/joint travel, and which adults are chaperones for that travel. It either links an adult's work tour with one or more child's school tours where the dropoff/pickup activities occur as stops on the adult's tour ("rideshare" tours), or generates a new tour for the adult specifically for the purpose of dropping off or picking up the child or children ("pure escort" tours). The model is applied by direction; for cases where the adult chaperones the child as part of their work tour, drop-offs at school are assumed to be outbound stops, while pickups at school are assumed to occur in the inbound direction.

This model was not calibrated due to lack of reliable data in the household travel survey, as nearly 100% of the observations were tours with no escort. We know that this is not the case in reality as evidenced by the long line of cars at schools in the morning and afternoon to drop-off and pickup kids. Therefore, we assume that the results of the model estimated using data from

Maricopa Association of Governments is a more accurate source of observed data than the household travel survey for this behavior.

The time-of-day profiles for tour departure and arrival for the model and observed are provided in Figure 25. These scheduling models were also not calibrated. As indicated by the goodness of fit statistic, the r values are 0.852 and 0.772 for departure and arrival respectively. The model follows the trendline of the reference data with a large peak matching the morning school drop off window. There is also a noticeable but smaller peak in both the model and observed data in the afternoon for departures and arrivals, showing a smaller percentage of tours that start and end in the afternoon around K-12 school dismissal. Additionally, the afternoon tour departures and arrivals are more spread-out, reflecting the larger distribution of school and daycare end times or pickups. The model smooths the profile, which would be expected if there was a larger sample size for the observed data.

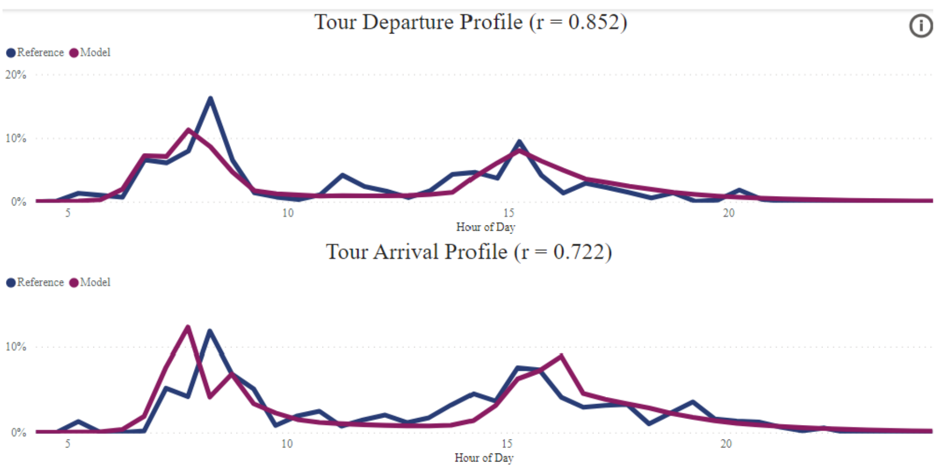


FIGURE 25: ESCORT TOUR SCHEDULING

Joint Tour Frequency and Composition

The joint tour frequency and composition model simultaneously predicts the number of fully joint tours by purpose that will be made by each household, along with the composition of the tour. Fully joint tours are tours in which at least two household members travel together for the entire tour (no drop-offs or pickups of household members). Each alternative is a combination of the number of tours by purpose (up to two maximum) and the composition (adult only, children only, or mixed) of each tour. Joint tours are generated for only non-mandatory purposes whose activities include eating out, shopping, visiting, maintenance and other discretionary. The coordinated daily activity pattern model predicts whether there are zero or at least one fully joint tour generated by the household, so this model is only run in the case that at least one fully joint tour is identified by the coordinated daily activity pattern model. Thus, there is no zero joint tour alternative in the model.

This mode was calibrated to reduce the predicted shares of 2+ joint tours, and better match the tour composition.

TABLE 12 CALIBRATION CONSTANTS FOR JOINT TOUR FREQUENCY AND COMPOSITION MODEL

COEFFICIENT	VALUE
coef_adjustment_for_share_of_2_joint_tours	-1.000
coef_tm2_adjustment_for_children_party	-4.000
coef_tm2_adjustment_for_mixed_party	-1.800
coef_tm2_adjustment_for_share_of_2_joint_tours	0.00
coef_tm2_adjustment_for_share_of_1_joint_tours	1.500
coef_tm2_adjustment_for_share_of_0_joint_tours	-1.000
coef_constant_for_2_shopping_tour	-12.009
coef_constant_for_1_discretionary_tour	-1.200
coef_constant_for_1_eating_out_tour	0.460
coef_constant_for_1_visiting_tour	1.720

The results of the fully joint tour frequency component are provided in Figure 26. The model estimate for the number of joint tours for household is very close to the household though the model estimates approximately 5% higher frequencies for 1 eating out, 1 shopping and 1 maintenance tours than the observed data indicates. The model predicts somewhat lower frequencies for some of the 2+ tour combinations, and higher frequencies than the observed data for others. However, the observed data generally shows infrequent shares for many of the 2+ joint tour, with many of the categories showing 0-500 frequencies.

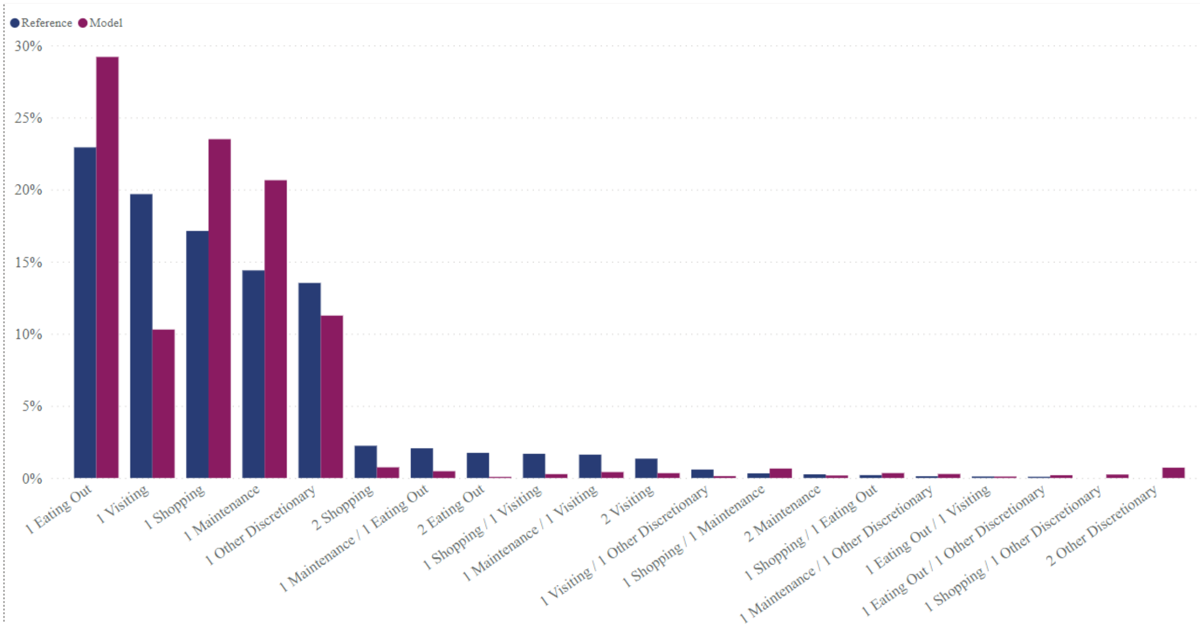


FIGURE 26: JOINT TOUR FREQUENCY

The results of the tour composition model are provided in Figure 27, which demonstrates a close match to observed data. The observed data had no instances of an all-children tour composition.

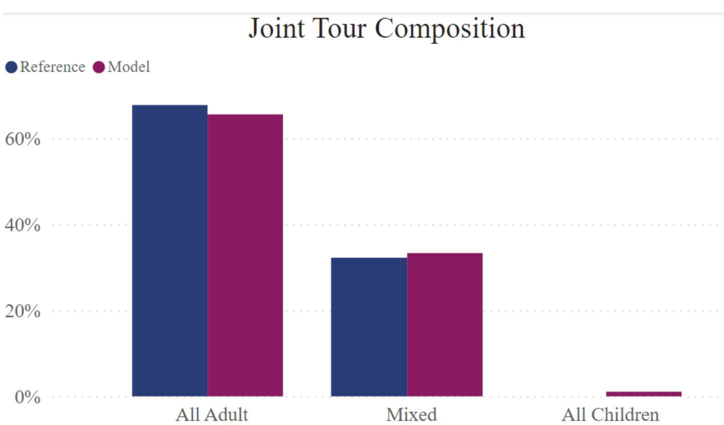


FIGURE 27: JOINT TOUR COMPOSITION- PERSON TYPES

Joint Tour Participation

The joint tour participation model predicts whether each member of the household participates in the joint tour.

Figure 28 compares the party size estimated by the model compared to survey data. The model clearly over-estimates party size for fully joint tours. However, we have found that making the participation constant more negative can result in a model crash. We suggest reformulating this model to be a simultaneous choice across household members who can participate in the tour rather than an iterative person-based participation model. This would require some software development but would be easier to calibrate the model.

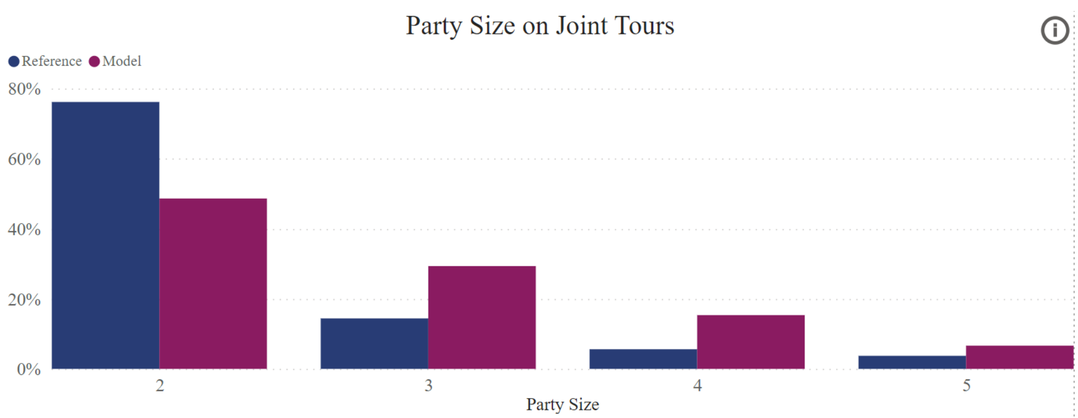


FIGURE 28: JOINT TOUR COMPOSITION- PARTY SIZE

Joint Tour Destination Choice

The fully joint tour destination choice model predicts the primary destination for fully joint tours. This is a two-stage model; first, a sample of alternatives is selected using a simple utility that does not include a mode choice logsum term. Then, the mode choice model is run for sampled alternatives and a final selection is made using the full utility with the mode choice model logsum added to the utility of each sampled alternative.

The fully joint tour destination choice models were not estimated nor calibrated; instead the models were transferred directly from ABM2+ and used in ABM3. Results of the model (Figure 29) indicates that the average distance from home to the primary destination across all non-mandatory tours is within 0.3 miles of the survey data. The distance for joint maintenance tours is underestimated by 1.7 miles, and joint discretionary tour distance is overestimated by 0.7 miles. However, data for joint tours is relatively sparse, as indicated by the lumpiness of the trip length distributions (Figure 30 and Figure 31).

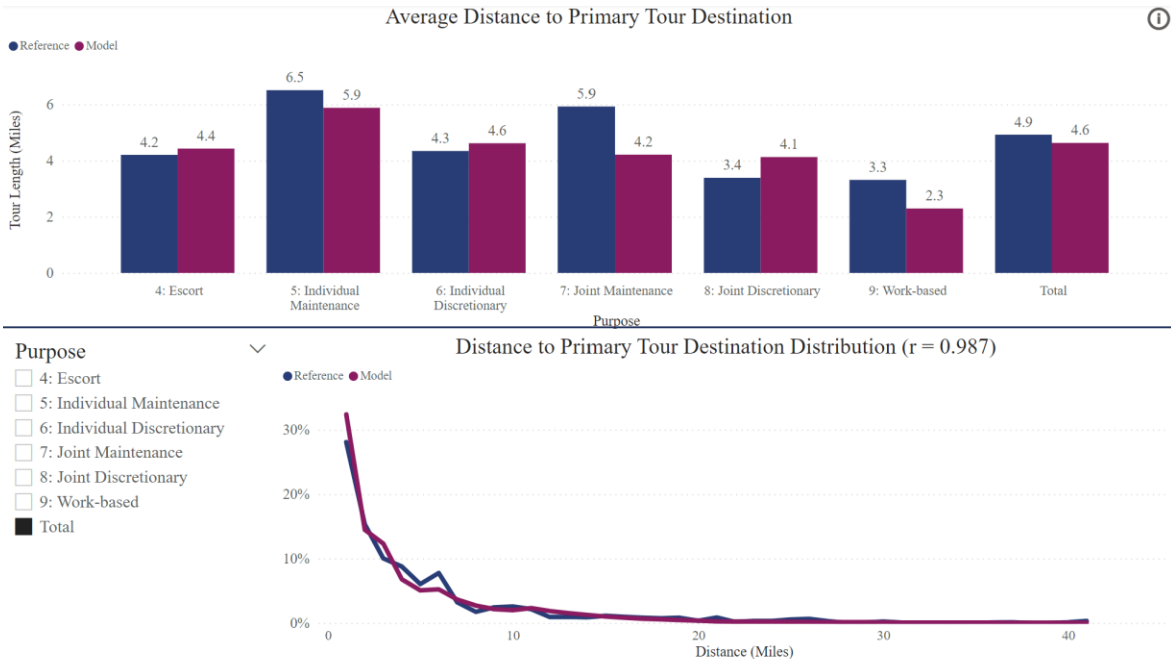


FIGURE 29: DISTANCE TO PRIMARY TOUR DESTINATION- NON MANDATORY JOINT TOURS

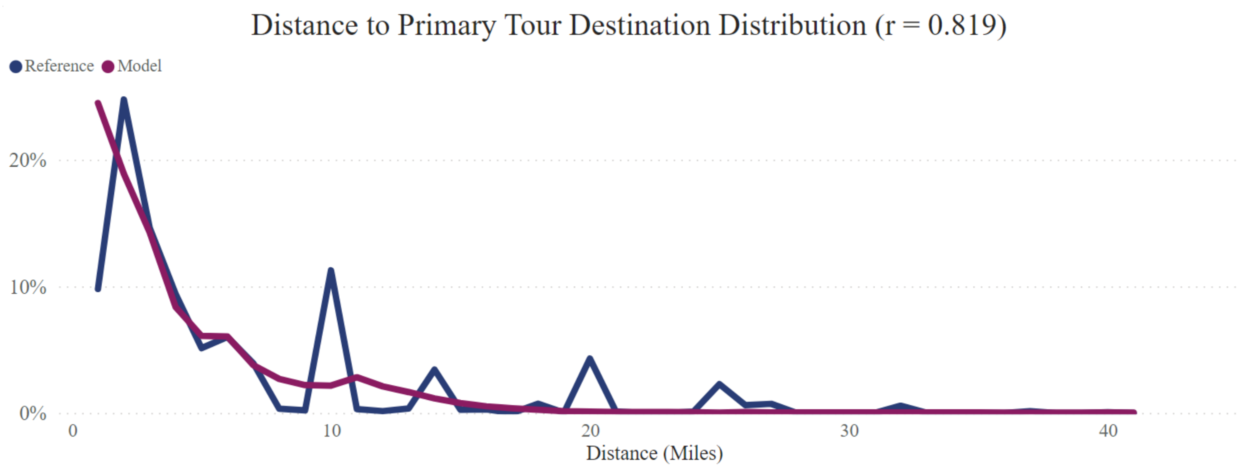


FIGURE 30: JOINT MAINTENANCE DISTANCE TO PRIMARY TOUR DESTINATION

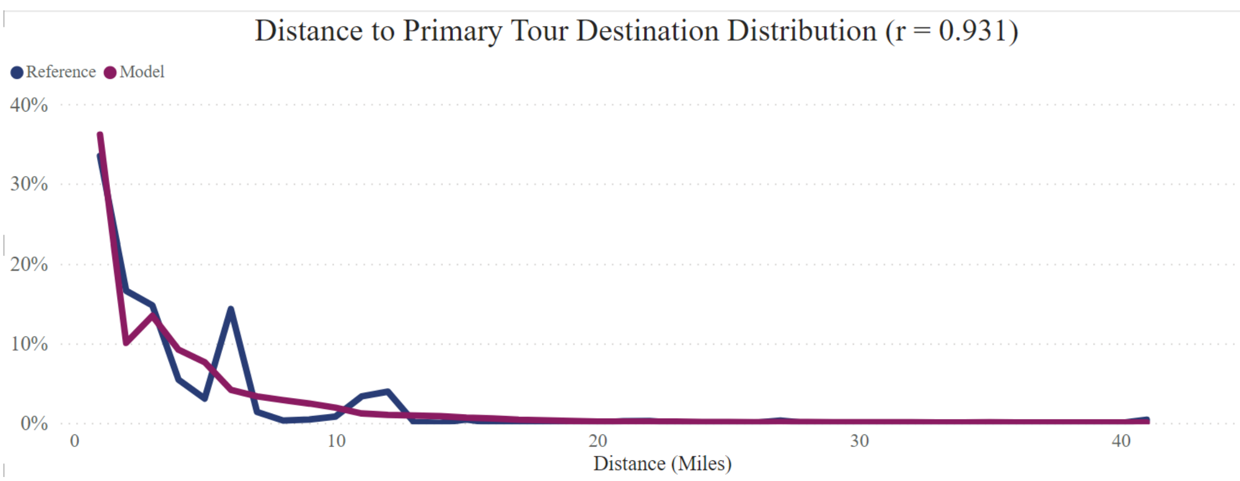


FIGURE 31: JOINT DISCRETIONARY DISTANCE TO PRIMARY TOUR DESTINATION

Joint Tour Scheduling

The joint tour scheduling models predicts the tour departure and arrival periods simultaneously.

Comparisons of the model and observed data show that joint discretionary tours by TOD (Figure 32) and by time period (Figure 33) match the observed data well.

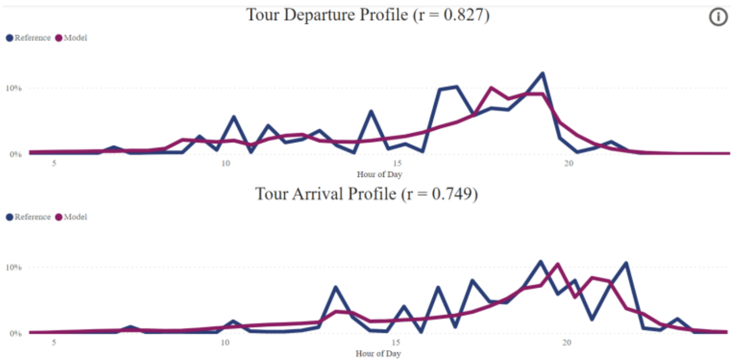


FIGURE 32: JOINT DISCRETIONARY TOURS BY TIME OF DAY

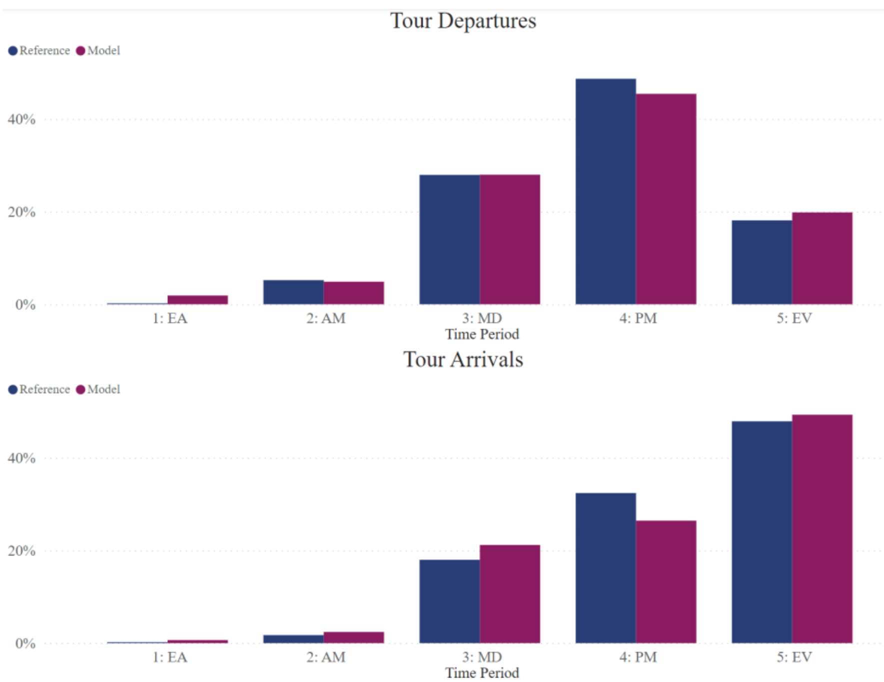


FIGURE 33: JOINT DISCRETIONARY TOURS BY TIME PERIOD

Similar trends for tour departure and arrival for joint maintenance tours by time of day (TOD) (Figure 34) and time period (Figure 35) are observed. Lower goodness of fit statistics are observed compared to the joint discretionary tours. However there is a small sample size for joint tours in the observed data.

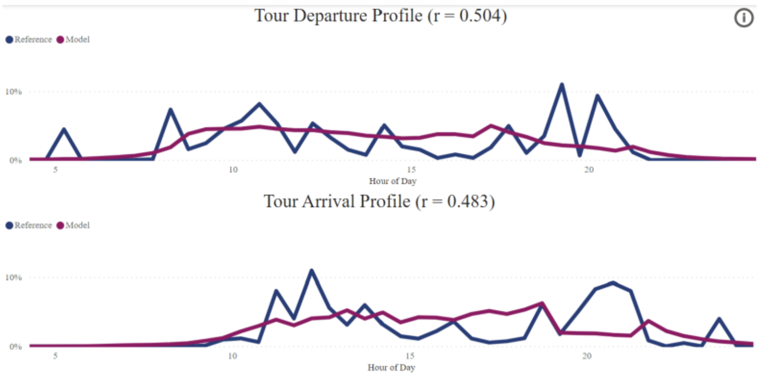


FIGURE 34: JOINT MAINTENANCE TOURS BY TIME OF DAY

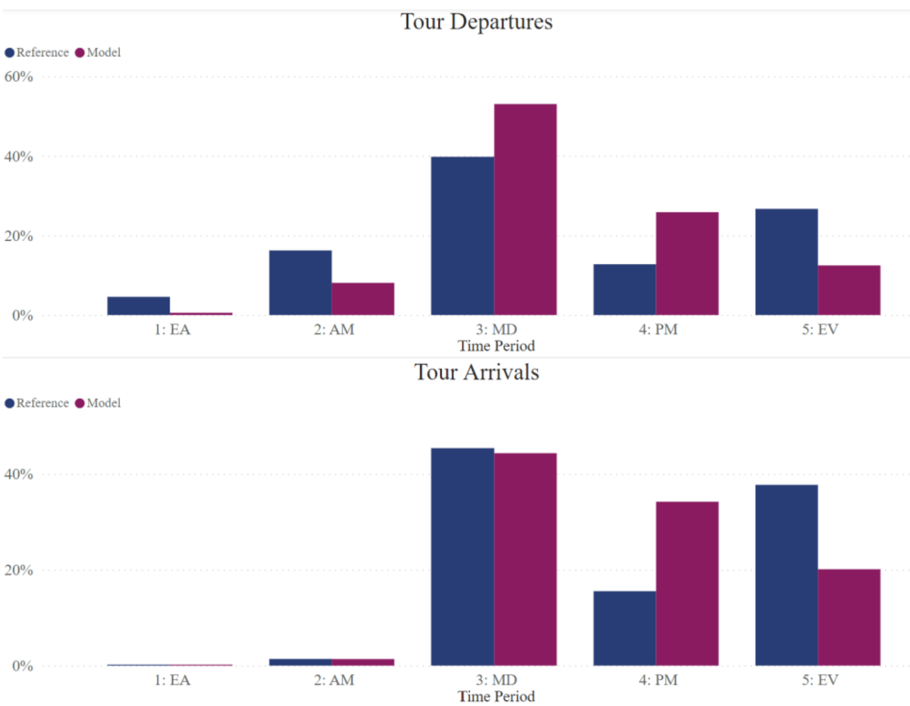


FIGURE 35: JOINT MAINTENANCE TOURS BY TIME PERIOD

Individual Non-Mandatory Tour Frequency

The individual non-mandatory frequency model predicts the number of non-mandatory tours that are taken by each individual. There are separate tour frequency models by person type. Each model predicts the number of non-mandatory tours by tour purpose. Each alternative is therefore a combination of the number of tours (0,1, 2, 2+, or 3+) tours by tour purpose. Any case where an individual selects 2+ or 3+ tours (there are different caps in total tours for each purpose based on observed data) requires an additional model in which a fixed set of probabilities is used in a Monte Carlo simulation to determine the exact number of tours. The six non-mandatory purposes are: escorting, shopping, social, eat out, other discretionary (such as gym, religious services and other activities), and other maintenance (medical, auto repair, etc.). This model was re-estimated for ABM3..

Results of the aggregate non-mandatory tour frequencies for all person types are provided in Figure 36. Results show slight underestimation of 1 non-mandatory tour frequencies, and a slight overestimation of 3+ non-mandatory tour frequencies across all person types.

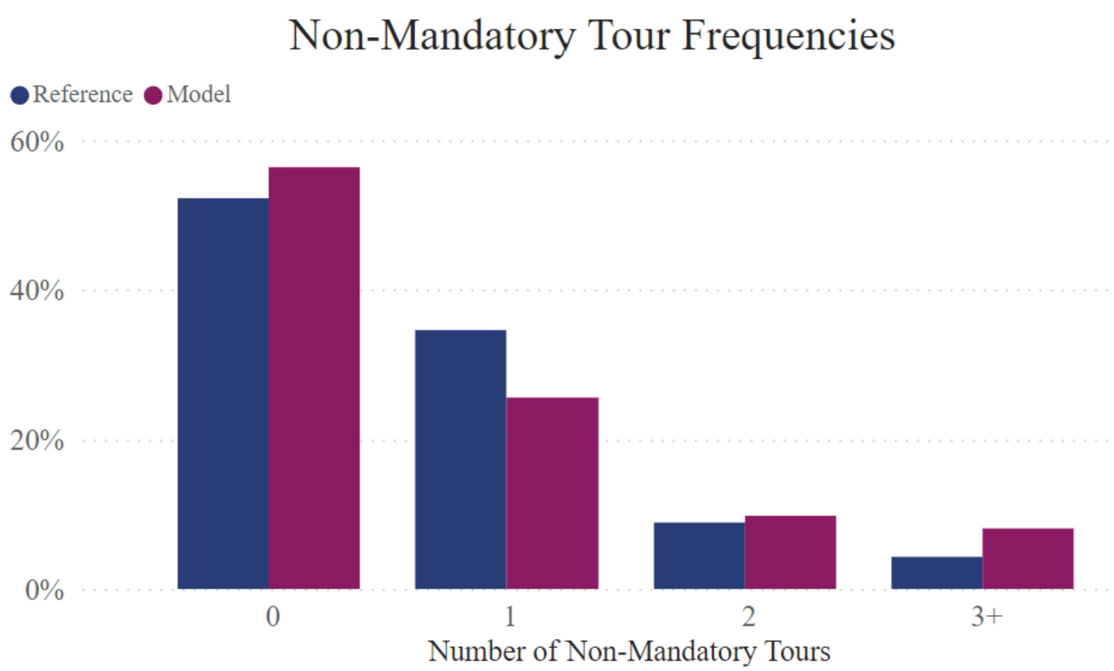


FIGURE 36: NON-MANDATORY TOUR FREQUENCIES FOR ALL PERSON TYPES

When examining the model performance by person type (Figure 37), it is apparent that the model matches observed non-mandatory tour frequency for full time and part time workers and retirees well. The model does not match non-mandatory frequencies for other person types quite as well. Students generally are predicted to have lower shares of non-mandatory tours, which is due to the adjustment we made to the coordinated daily activity pattern model where we increased the rate of students who attend school to compensate for bias in observed data. This has the effect of reducing non-mandatory travel for students. For non-workers, furthermore, we are seeing and overprediction of 3+ tours, which is largely coming at the expense of 1 tour category. We recommend a further calibration of non-mandatory tour frequency for the non-worker person type.

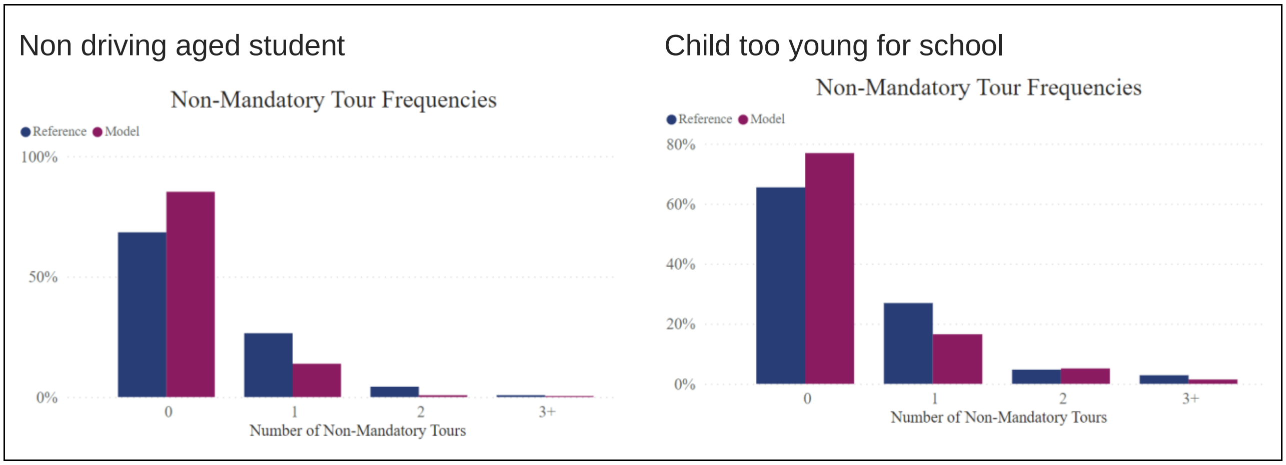


FIGURE 37: INDIVIDUAL NON-MANDATORY TOUR FREQUENCIES BY PERSON TYPE

External Non-Mandatory Tour Identification

The external non-mandatory tour identification model identifies non-mandatory tours that have a destination outside of the region. This model was estimated for ABM3.

The model closely matches the rate of external tours in the observed data (Figure 38).

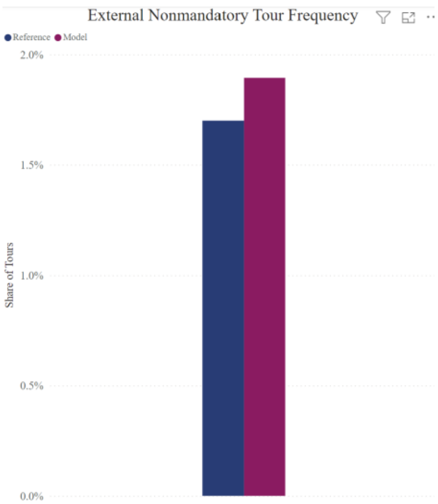


FIGURE 38: EXTERNAL NON-MANDATORY TOUR IDENTIFICATION RESULTS

Individual Non-Mandatory External Destination Choice

The external non-mandatory destination choice model predicts which external station is the primary destination for tours identified as external. The alternatives of the model are the external stations.

Results shown in Figure 39 for average distance to primary tour destination for external tours indicates that the estimated individual maintenance tours are one mile longer than the observed data.

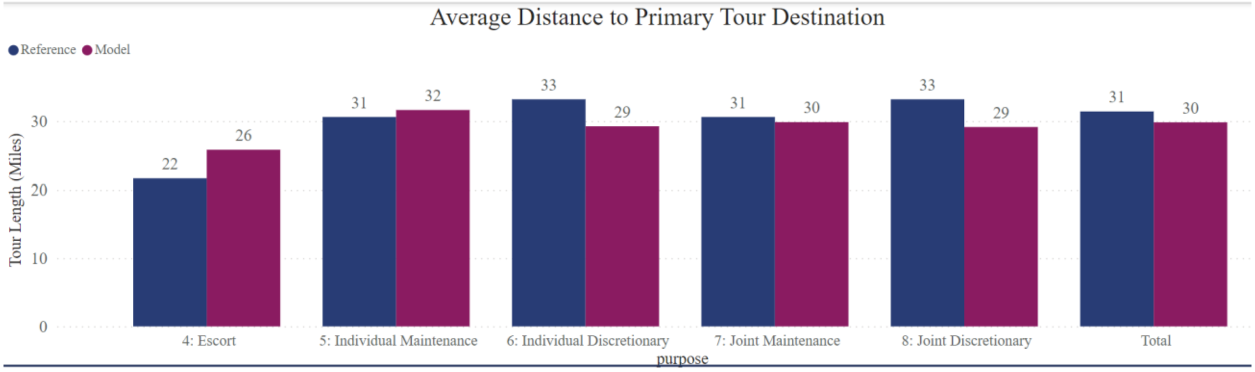


FIGURE 39: AVERAGE DISTANCE TO PRIMARY TOUR DESTINATION FOR EXTERNAL TOURS

The distribution of distances to primary tour destination for non-mandatory external tours shows a high fit statistic at r = 0.987.

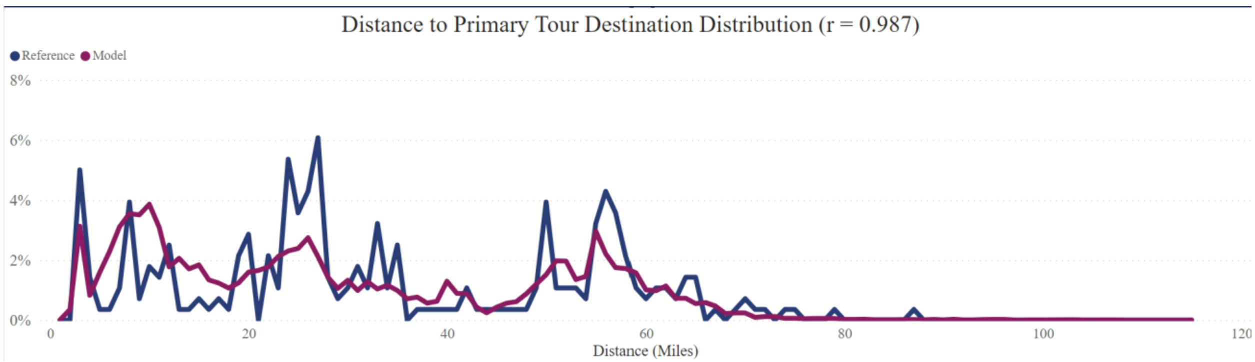


FIGURE 40: DISTANCE TO PRIMARY TOUR DESTINATION FOR NON-MANDATORY EXTERNAL TOURS

Individual Non-Mandatory Internal Destination

Following the external non-mandatory destination choice model, all non-mandatory tours that are identified in the non-mandatory tour frequency model and are internal are assigned a destination via the internal non-mandatory destination choice model. As with other destination choice models in ActivitySim, the two-step process involves a sampling of alternatives model followed by a full model that includes mode choice logsums. Results comparing the model and observed data average distance to primary tour destination by tour type (Figure 41) and the distance distribution for all tours (Figure 42) indicate that the model fits closely with the observed patterns and distribution.

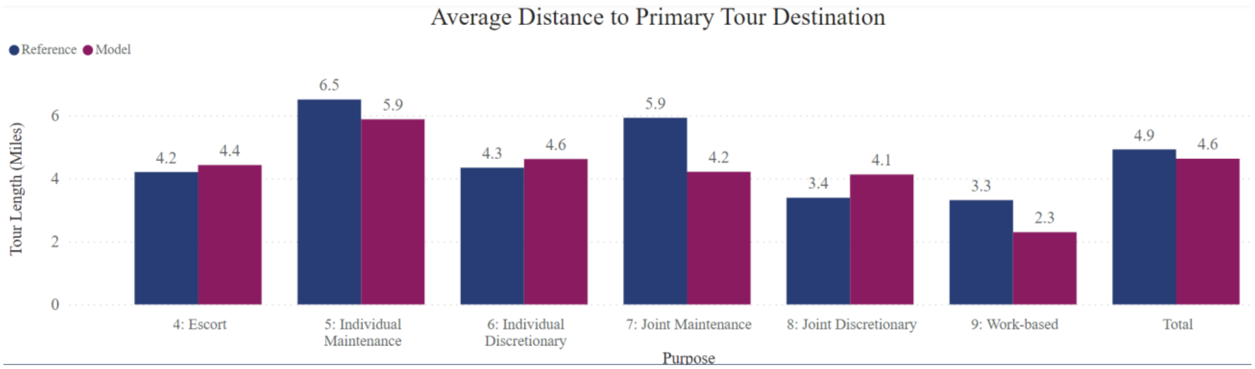


FIGURE 41: AVERAGE DISTANCE TO PRIMARY TOUR DESTINATION BY TOUR TYPE

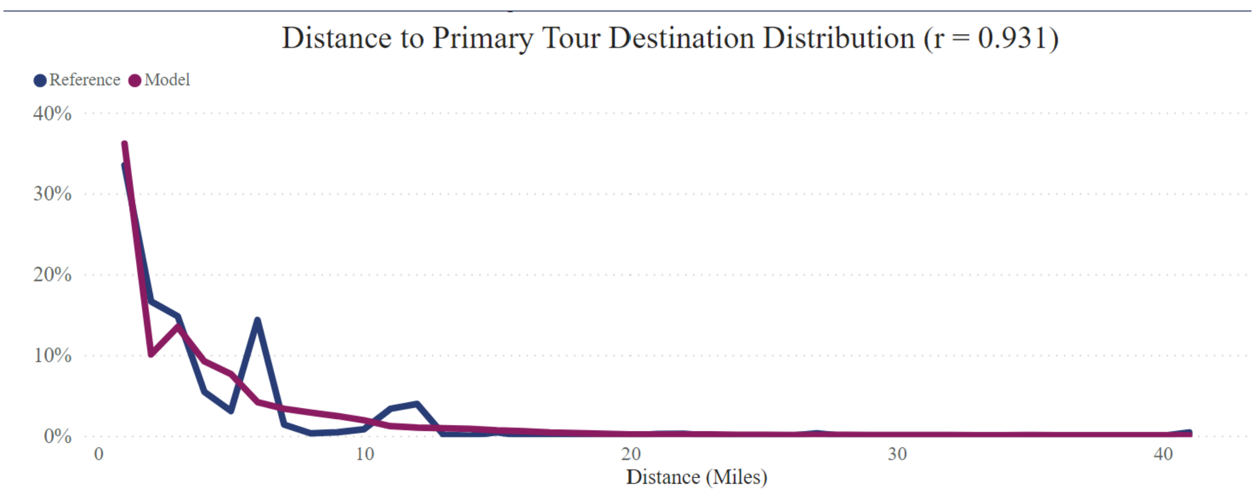


FIGURE 42: DISTANCE TO PRIMARY TOUR DESTINATION

Non-Mandatory Tour Scheduling

The non-mandatory tour scheduling model assigns a tour departure and arrival period to each tour simultaneously. RSG did not do calibration on this set of models.

Results for maintenance tours (Figure 43) and discretionary tours (Figure 44), show a relatively good fit to observed data. The model for discretionary tours estimates a peak of tour departures between the hours of approximately 5pm and 7pm, which is also present in the data.

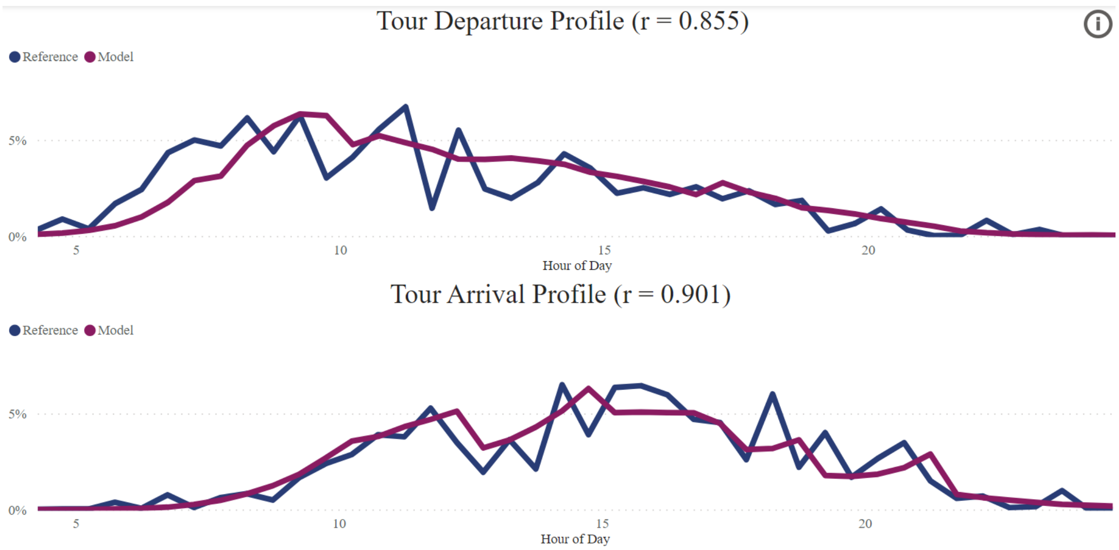


FIGURE 43: INDIVIDUAL MAINTENANCE TOD PROFILE

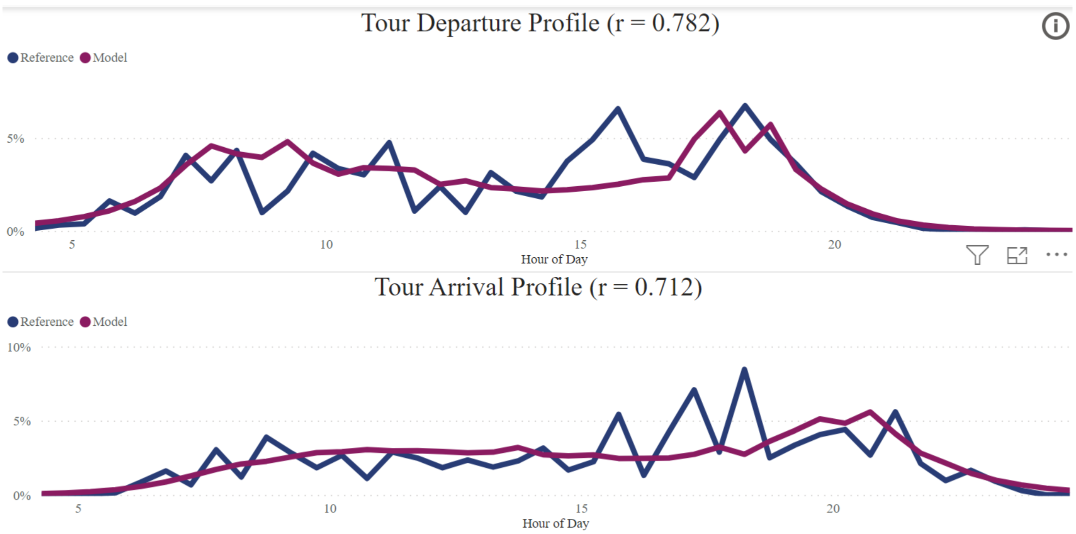


FIGURE 44: INDIVIDUAL DISCRETIONARY TOD PROFILE

At Work Tour Frequency

A series of models is used to specify tour attributes that happen while an individual is at work. The first of these models is the at work tour frequency model. This model assigns each worker a number of subtours that are made during the workday, with their origin at the work location. At work tour alternatives include no tours, one eating out tour, one business tour, one maintenance tour, two business tours and one eating out/one business tour.

At Work Destination Choice

Following the prediction of number and type of tours, the at work subtours are assigned to a destination.

Examining the performance of the model compared to the observed data (Figure 46) reveals that the model fits well to the observed data with an r of 0.957.

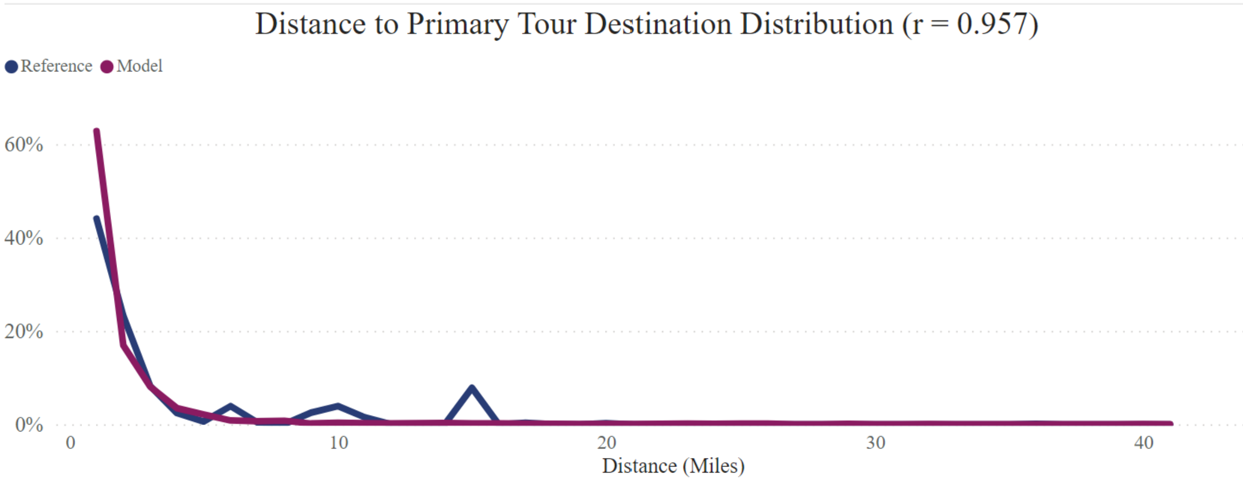


FIGURE 45: DISTANCE TO PRIMARY TOUR DESTINATION

At Work Scheduling

In similar fashion to the mandatory tour scheduling, at work subtours are assigned a tour departure and duration period. The at work subtours alternatives are constrained to the time windows in which a person is at work. Calibration constants were added to the model and are provided in Table 13.

TABLE 13: AT WORK SUBTOUR SCHEDULING CALIBRATION CONSTANTS

Coefficient	Constant
coef_Calibration_Constant_Departure_eq_18 (6pm)	-0.046
coef_Calibration_Constant_Departure_eq_19 (7pm)	-0.099
coef_Calibration_Constant_Arrival_eq_20 (8pm)	-0.0698
coef_Calibration_Constant_Arrival_eq_21 (9pm)	-0.0644

The resulting model and observed data time of day profile for at work subtours is provided in Figure 46. Results show that the departure and arrivals of at work subtours peak during the lunch hour for both the model and the observed data. There are tours in the observed data that happen before or after the lunch hour peak that are not seen in the model estimate. The model overpredicts midday tours, and underpredicts the AM and PM tour departures and arrivals (Figure 47).,.

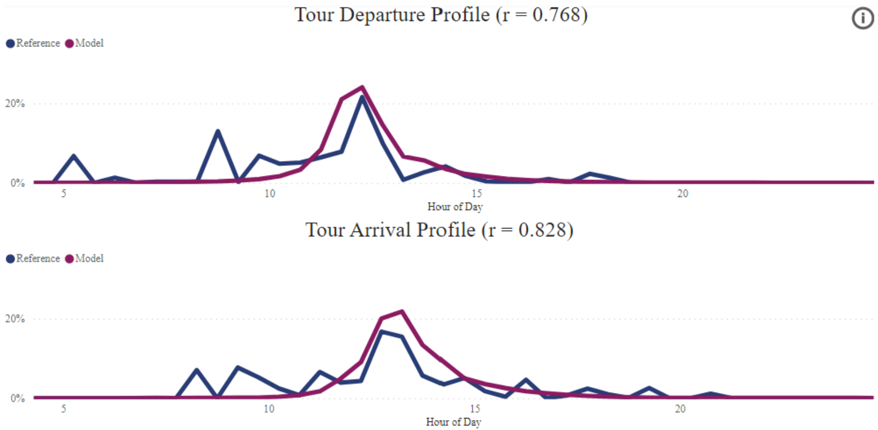


FIGURE 46: WORK BASED TOUR SCHEDULING TOD PROFILE

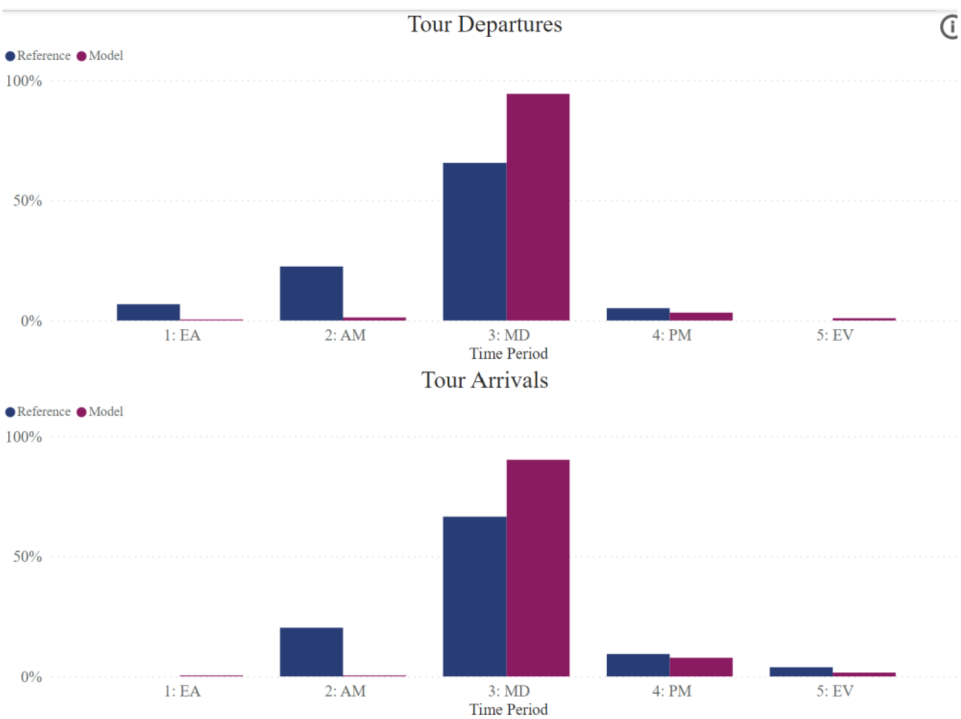


FIGURE 47: WORK BASED TOUR SCHEDULING BY TIME PERIOD

Vehicle Allocation Model

The vehicle allocation model selects the vehicle that would be used for each auto tour mode, by occupancy, prior to tour mode choice. The alternatives for the choice are the vehicles that the household owns, plus one non-household vehicle. Zero auto households are assigned non-household vehicle options since there are no vehicles owned by the household. The outcome of the vehicle allocation model is appended to the tour table to be used in tour mode choice. This model was not calibrated to observed data.[2]

Tour Mode

Following the vehicle allocation model, the tour mode model is run to select a mode for the tour. This is a nested logit mode choice model in which similar modes are grouped together (auto, active transport, transit, micromobility, and ride-hail). Note that observed data for tour mode calibration includes both household travel survey data and 2015 on-board survey data, adjusted to 2023 transit boarding estimates. Table 14 shows the adjusted transit target data used for this model calibration.

TABLE 14 ADJUSTED TRANSIT TARGET DATA USED FOR MODEL CALIBRATION

TOUR MODE	AUTO DEFICIENT HH	AUTO SUFFICIENT	ZERO AUTO HH	TOTAL
KNR-TRANSIT	7028	1781	3746	12555
PNR-TRANSIT	2248	2136	174	4557
TNC-TRANSIT	113	0	66	179
WALK-TRANSIT	24066	8873	25681	58620
Total	**33455**	**12790**	**29667**	**75912**

Calibration constants were added to the model and are provided in the appendix. Constants are segmented by mode, auto parity (0 autos, autos less than adults, autos greater than or equal to adults) and purpose. There are also distance-based constants for some modes to better match the tour length by mode and some district level constants to explain differences in mode usage by destination district.

Modeled versus observed tours by mode are provided in Figure 48 through Figure 52. Results show that the model matches tour mode very closely for most modes. Notable differences in the

[2] Note that although the model was estimated with 2017 National Household Travel Survey data using the chosen vehicle by mode, it predicts which vehicle would have been chosen, not the actual vehicle choice.

observed data versus the model mode share by auto sufficiency exist. This is the only mode and market segment in which there is no share of the tours allocated, but it is something that needs further investigation. Additionally, the model allocates a higher share of the tour mode share to walk (43.8%) than is indicated in the observed data (34.3%) for zero auto households, and a higher TNC single mode share at 14.89% compared to 8% observations in the data, which might necessitate further investigation and calibration.

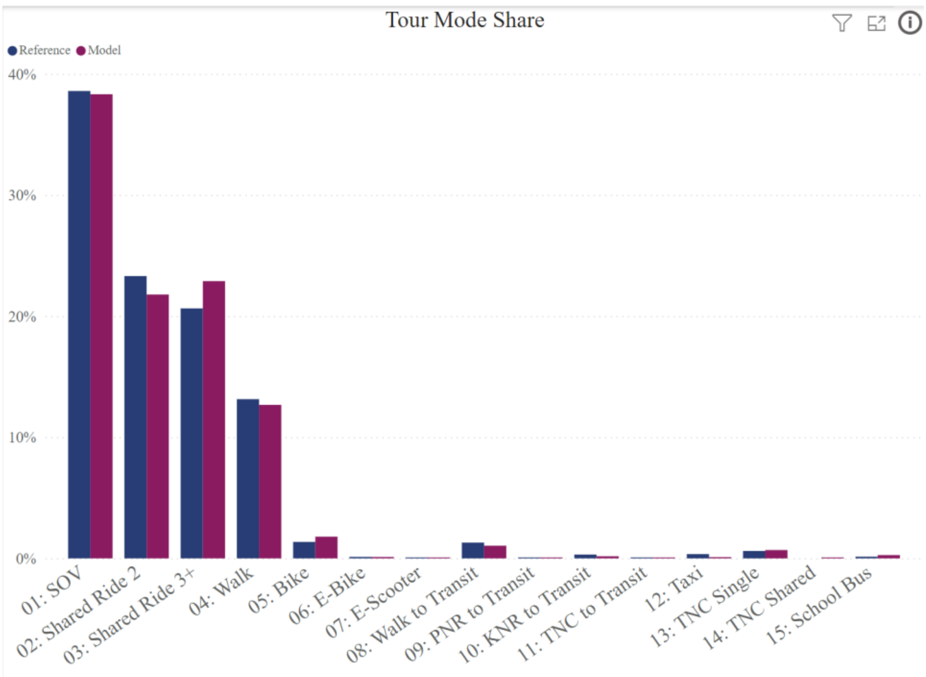
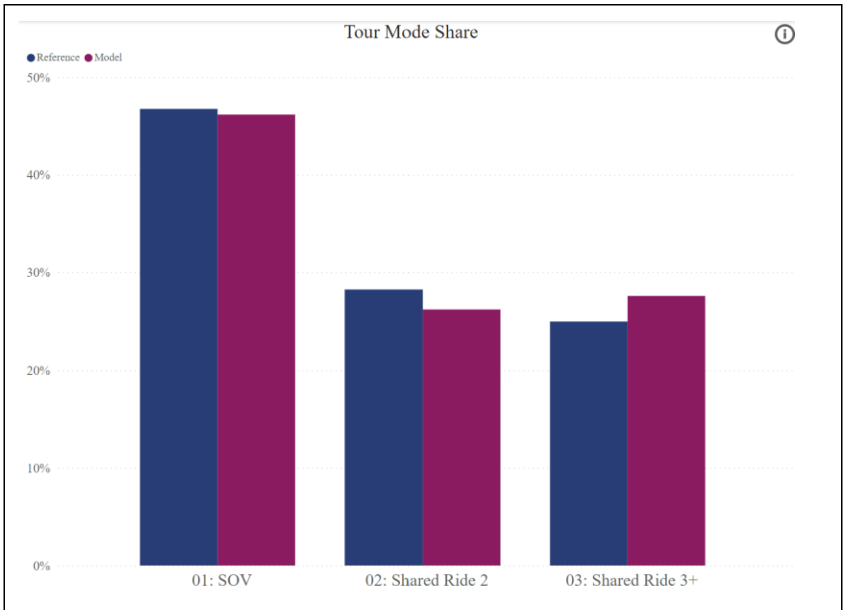
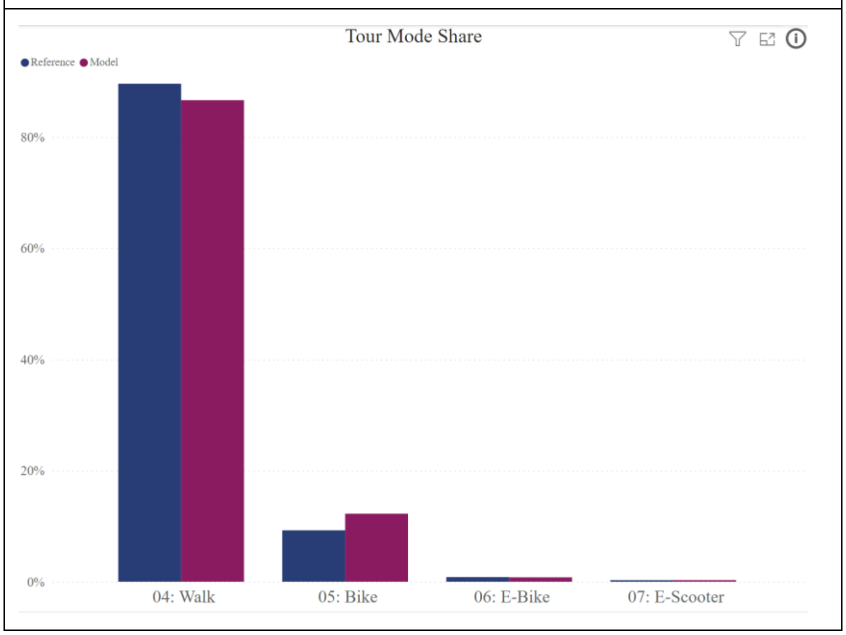


FIGURE 48: TOUR MODE CHOICE ALL HOUSEHOLDS ALL PURPOSES


Tour Mode Share
Reference
Model
50%
40%
30%
20%
10%
0%
01: SOV
02: Shared Ride 2
03: Shared Ride 3+


Tour Mode Share
Reference
Model
80%
60%
40%
20%
0%
04: Walk
05: Bike
06: E-Bike
07: E-Scooter

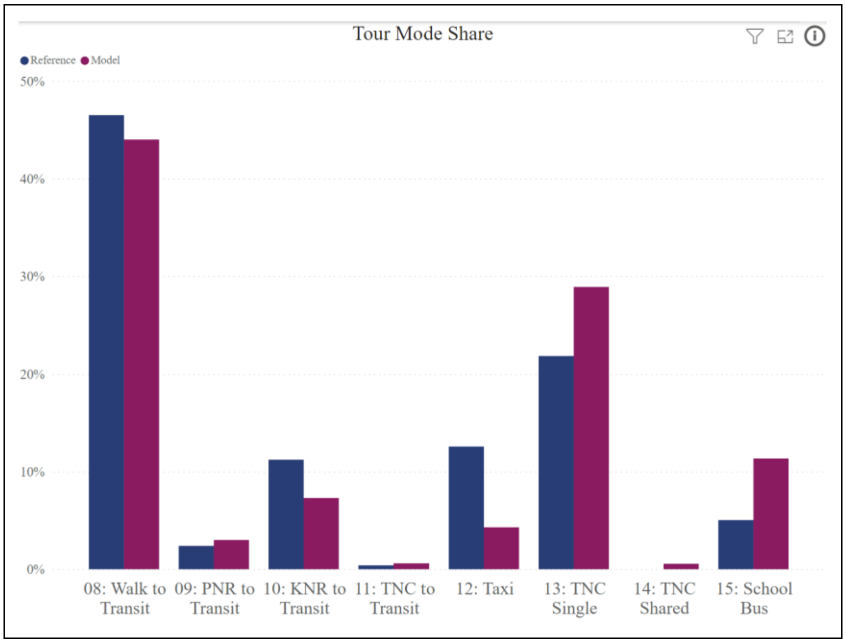


FIGURE 49: TOUR MODE CHOICE

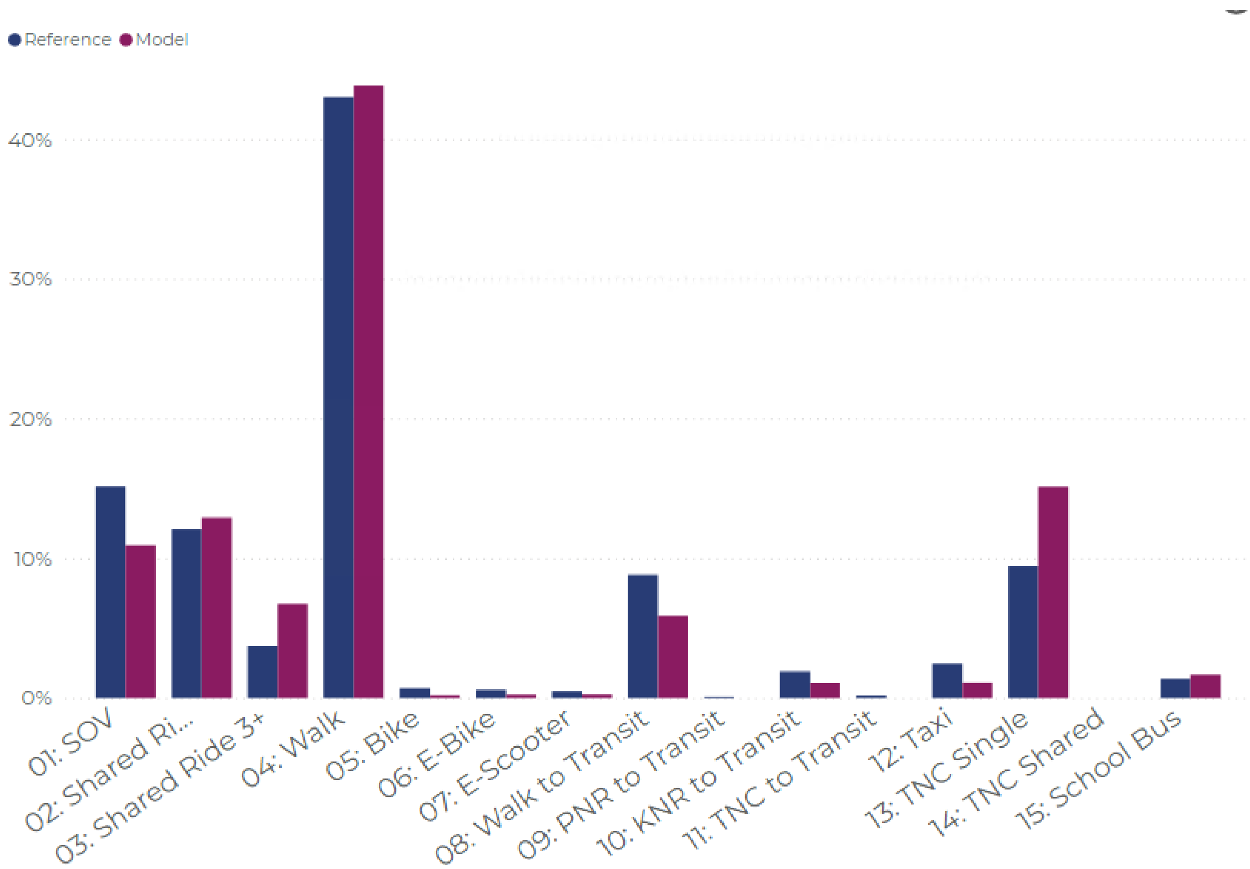


FIGURE 50: TOUR MODE CHOICE FOR ZERO AUTO HOUSEHOLDS

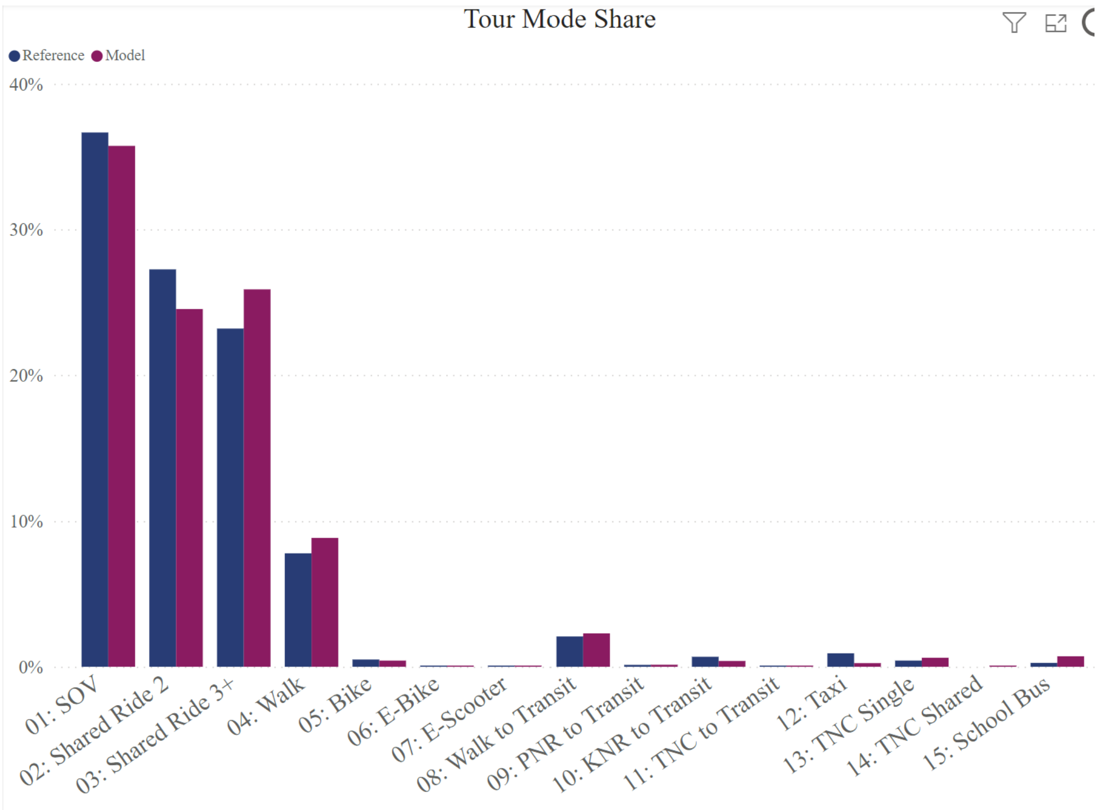


FIGURE 51: TOUR MODE CHOICE FOR AUTO INSUFFICIENT HOUSEHOLDS

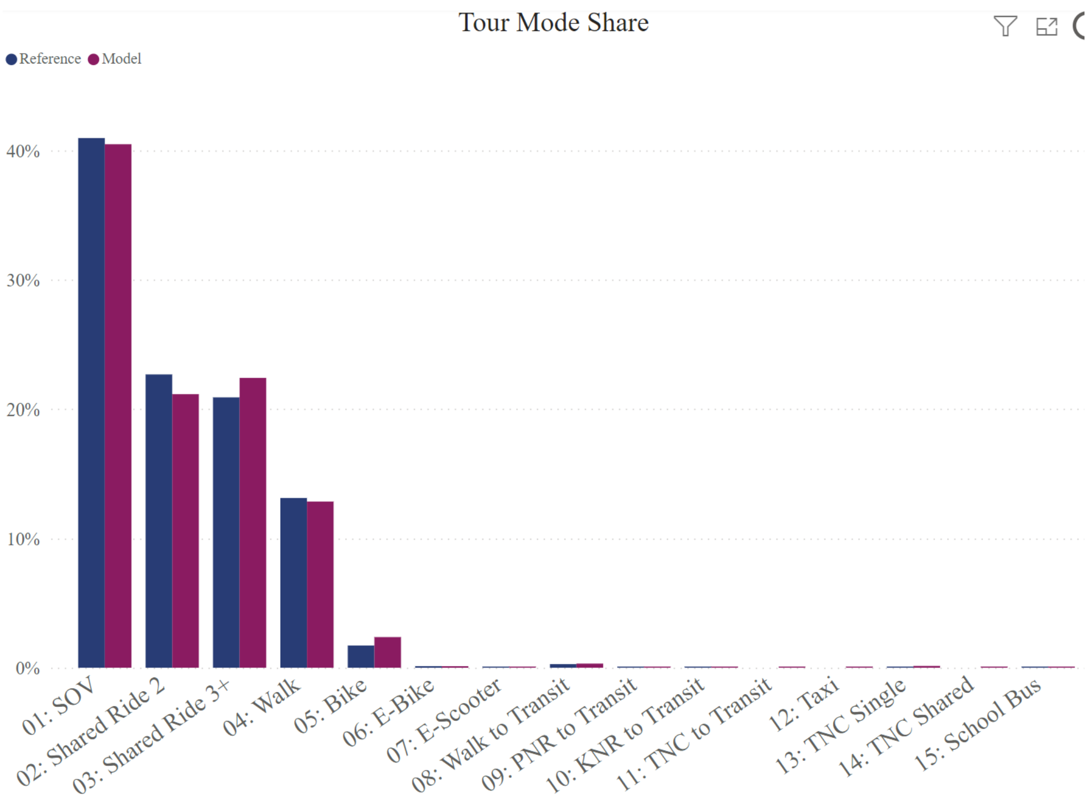


FIGURE 52: TOUR MODE CHOICE FOR AUTO SUFFICIENT HOUSEHOLDS

Stop and Trip Level Models

Stop Frequency

The stop frequency model predicts how many and what type of intermediate stops are made on a tour for each leg of the tour. The stop frequency model was reestimated for ABM3. There are separate models by tour purpose: work, school, university, escorting, shopping, other maintenance, eating out, social/visiting, other discretionary and at work tours. The model simultaneously predicts the number of stops on each tour by tour direction (outbound refers to the journey between home or work [for work-based tours] and the primary destination, and inbound refers to the journey between the primary destination and home or work).

Comparisons of the model and observed data shown in Figure 53 indicate that the model matches observed stop frequency well across all tour purposes. The model predicts 10%fewer zero stop outbound legs (Figure 54), and approximately 8% more zero inbound legs (Figure 55) than observed data.

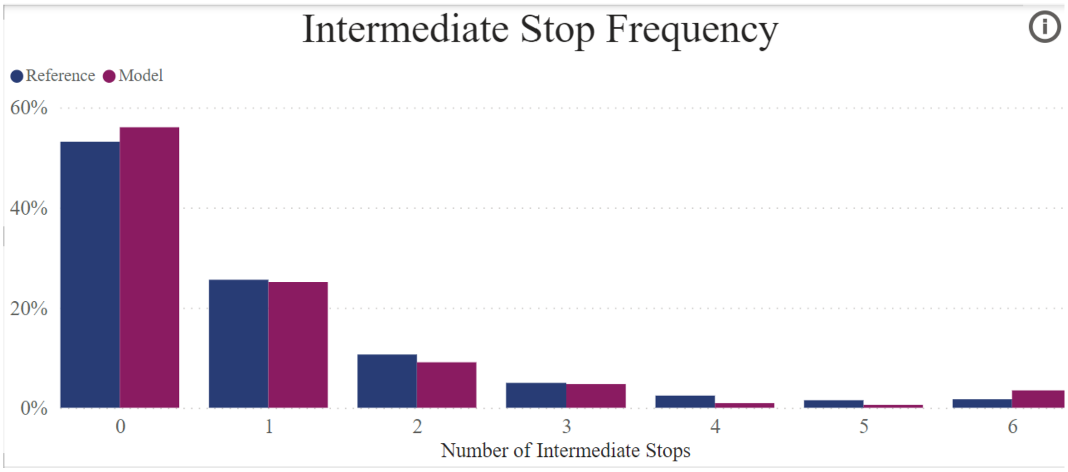


FIGURE 53: INTERMEDIATE STOP FREQUENCY ALL STOPS

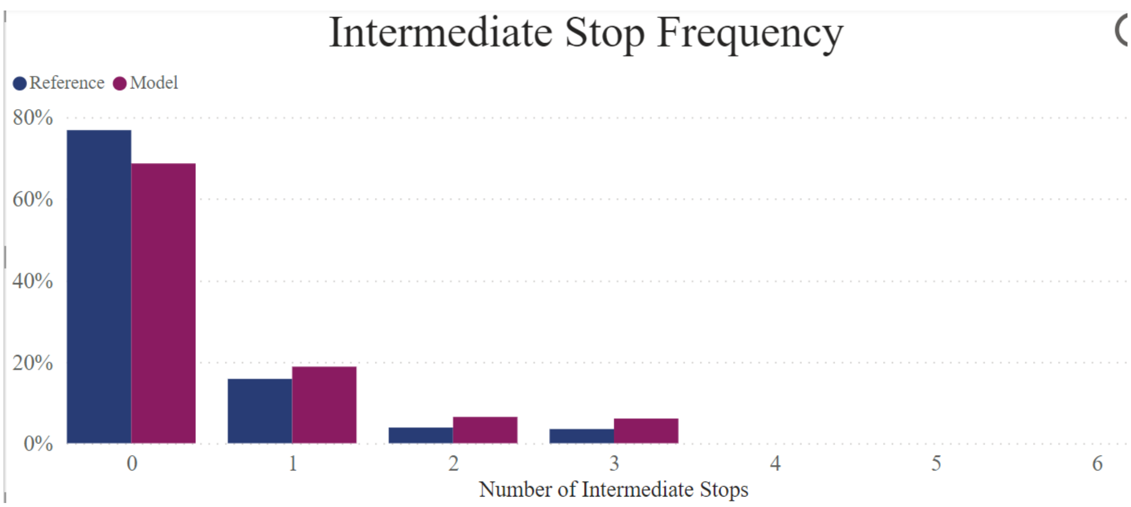


FIGURE 54: INTERMEDIATE STOP FREQUENCY OUTBOUND DIRECTION

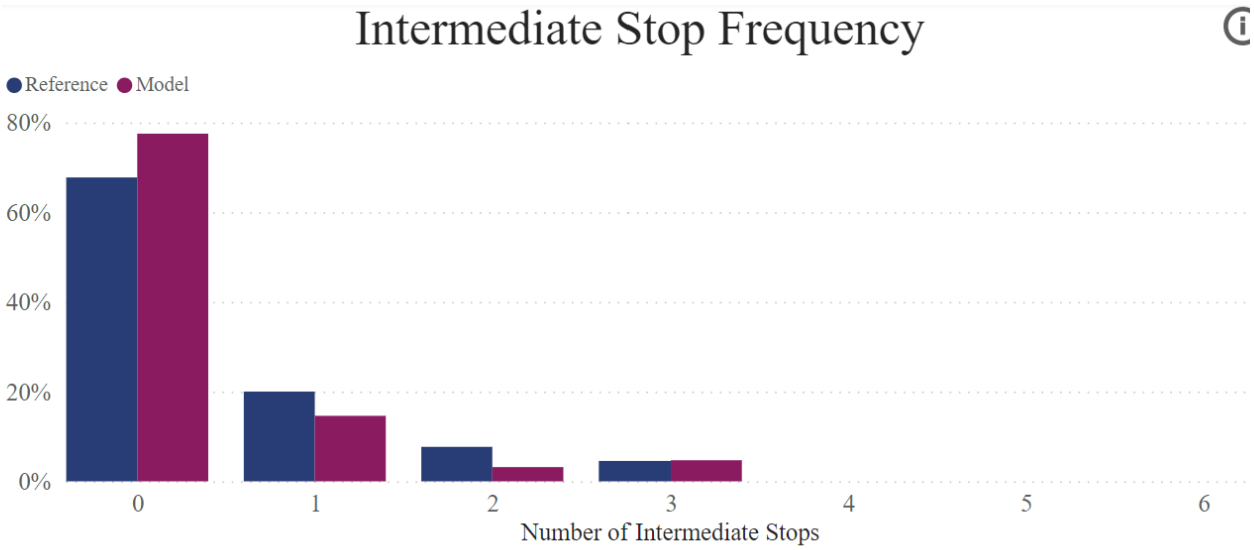


FIGURE 55: INTERMEDIATE STOP FREQUENCY INBOUND DIRECTION

The largest differences between the modeled stop frequencies by tour purpose and the observed data are in the school tours (Figure 58), individual discretionary (Figure 61), and joint discretionary (Figure 63) tours. We note previously survey bias with respect to school tour reporting so we do not expect to match the observed data well for school tours.

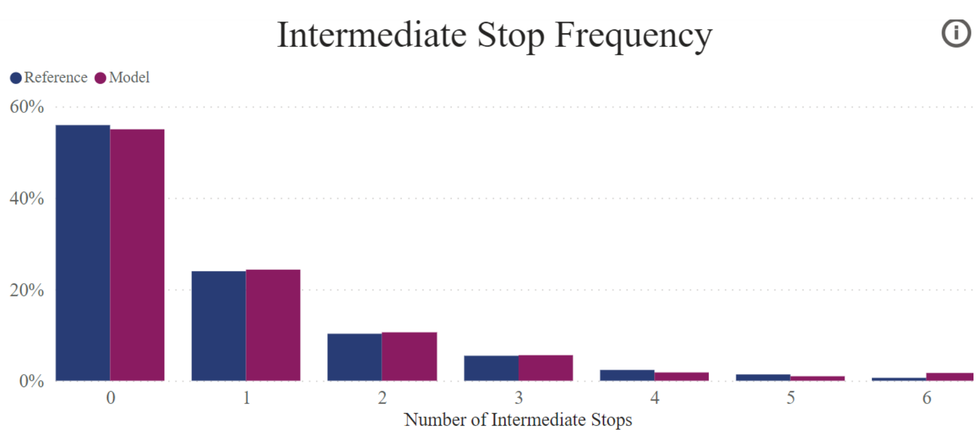


FIGURE 56: INTERMEDIATE STOP FREQUENCY FOR WORK TOURS

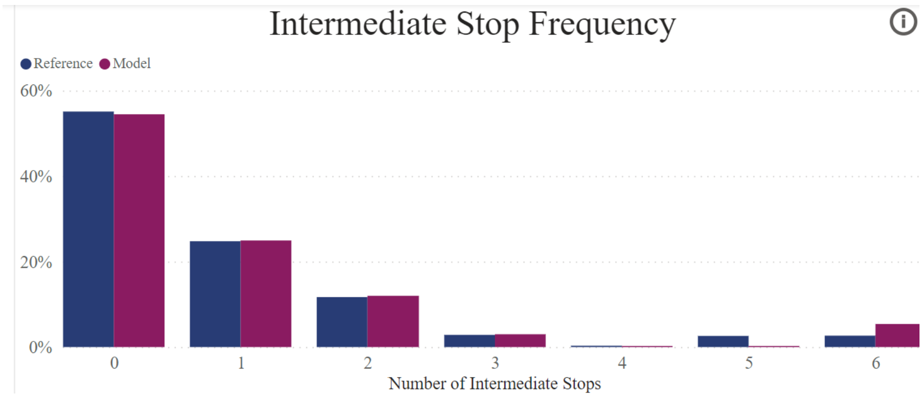


FIGURE 57: INTERMEDIATE STOP FREQUENCY FOR UNIVERSITY TOURS

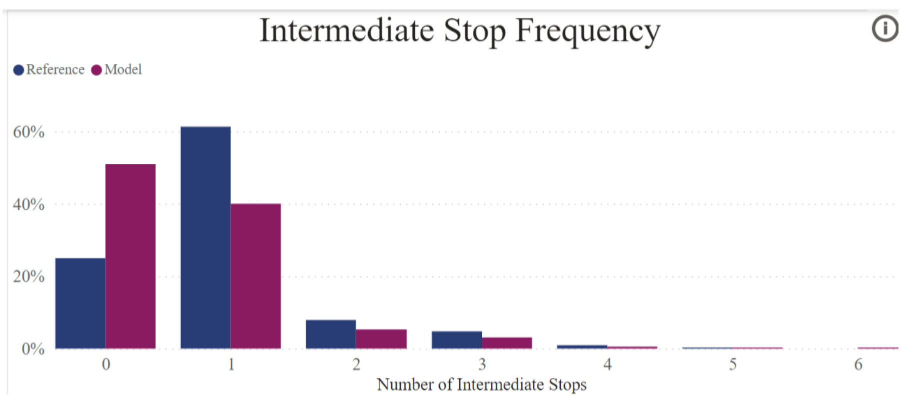


FIGURE 58: INTERMEDIATE STOP FREQUENCY SCHOOL TOURS

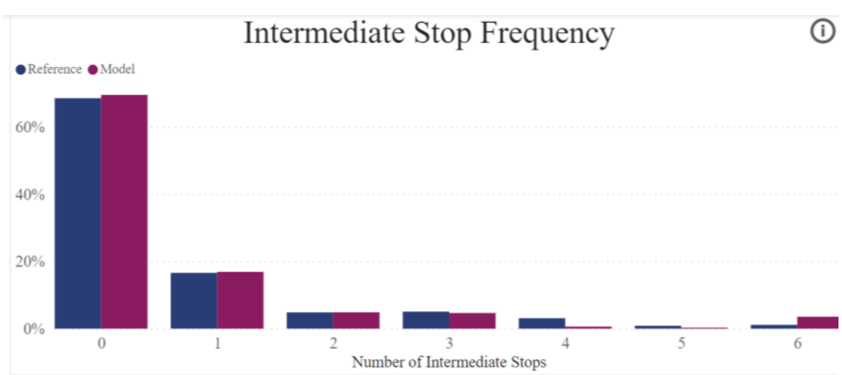


FIGURE 59: INTERMEDIATE STOP FREQUENCY ESCORT TOURS

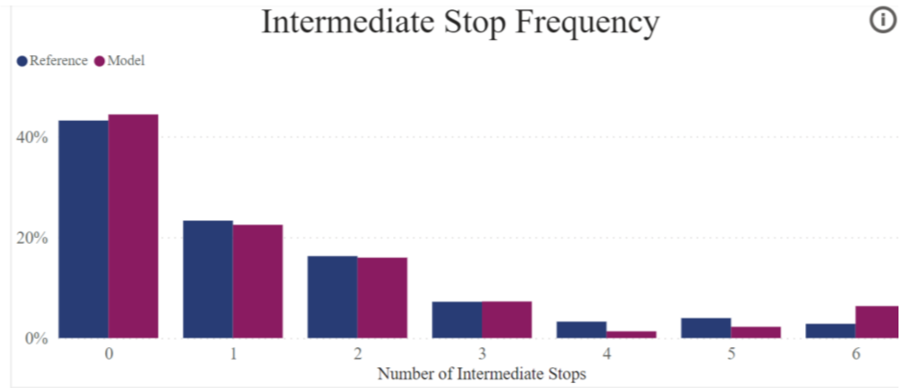


FIGURE 60: INTERMEDIATE STOP FREQUENCY INDIVIDUAL MAINTENANCE TOURS

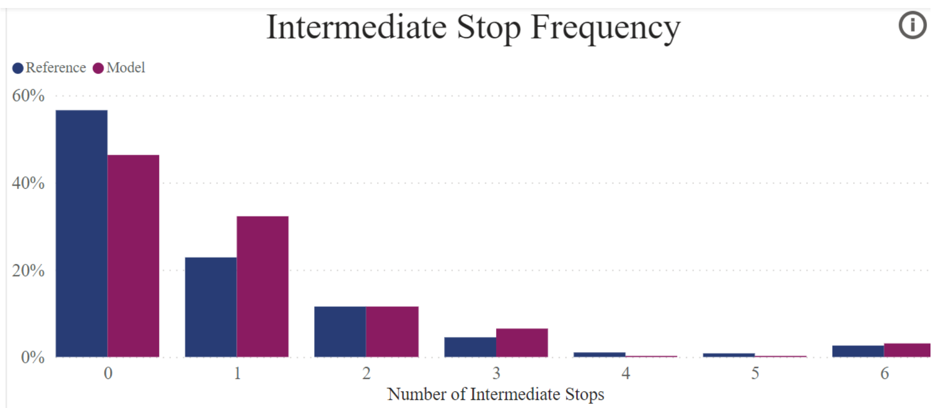


FIGURE 61: INTERMEDIATE STOP FREQUENCY INDIVIDUAL DISCRETIONARY TOURS

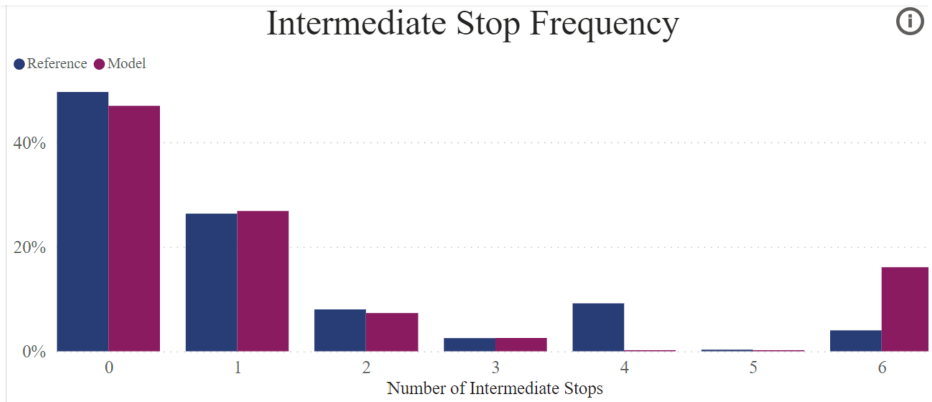


FIGURE 62: INTERMEDIATE STOP FREQUENCY JOINT MAINTENANCE TOURS

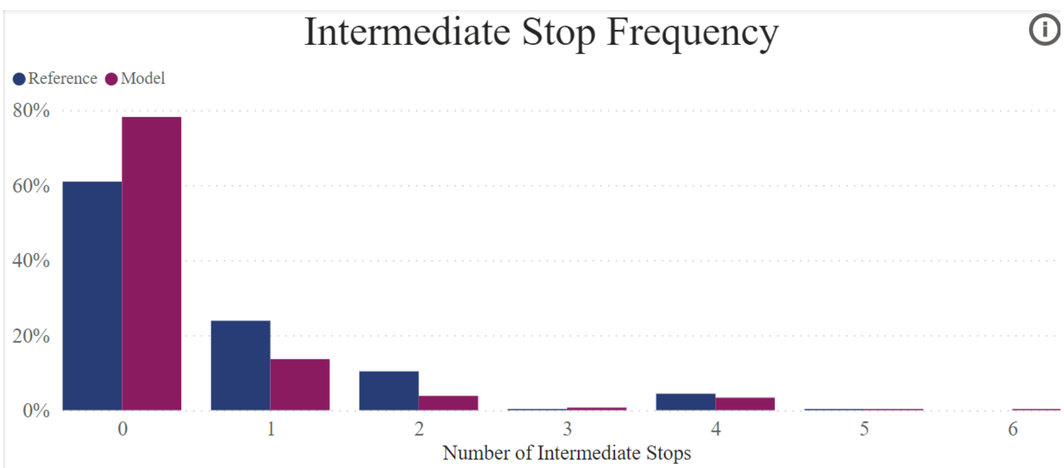


FIGURE 63: INTERMEDIATE STOP FREQUENCY JOINT DISCRETIONARY TOURS

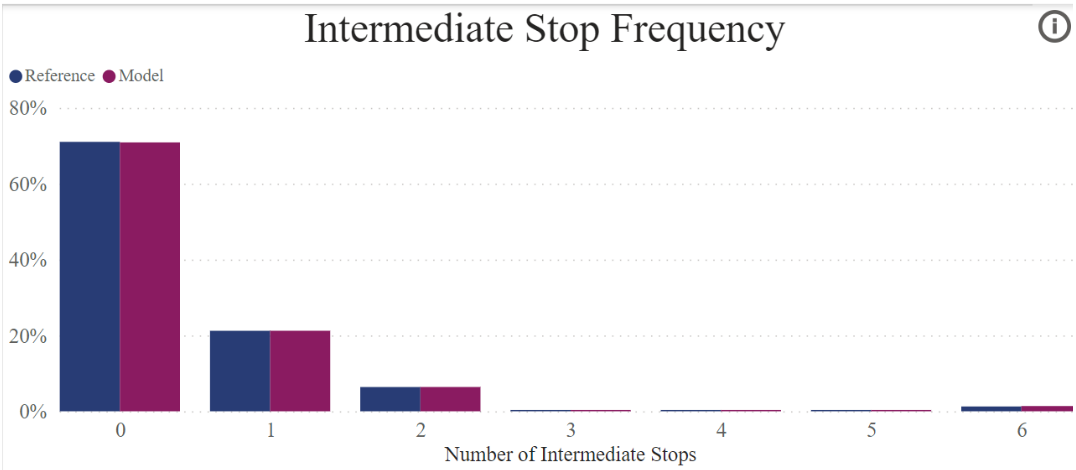


FIGURE 64: INTERMEDIATE STOP FREQUENCY AT WORK TOURS

Trip Purpose

The trip purpose model assigns a purpose to each intermediate stop generated by the stop frequency model. The trip purpose is assigned based on a Monte Carlo simulation from probabilities that vary by tour purpose, direction and person type. The probabilities were generated by combining household travel survey data from SANDAG, SEMCOG, and Chicago Metropolitan Agency for Planning (CMAP), in order to maximize data coverage.

This model was not calibrated in ABM3. Aggregate results of the trip purpose model are provided in Figure 65. The model results show slightly fewer work trips compared to the observed data, and no university or school trips despite these trips existing in the observed data because their share is so low that they were eliminated from the stop purpose distributions. On an aggregate level, the distribution of trip purposes aligns within less than 5% differences to the observed data with the exception of escort, visiting and other discretionary.

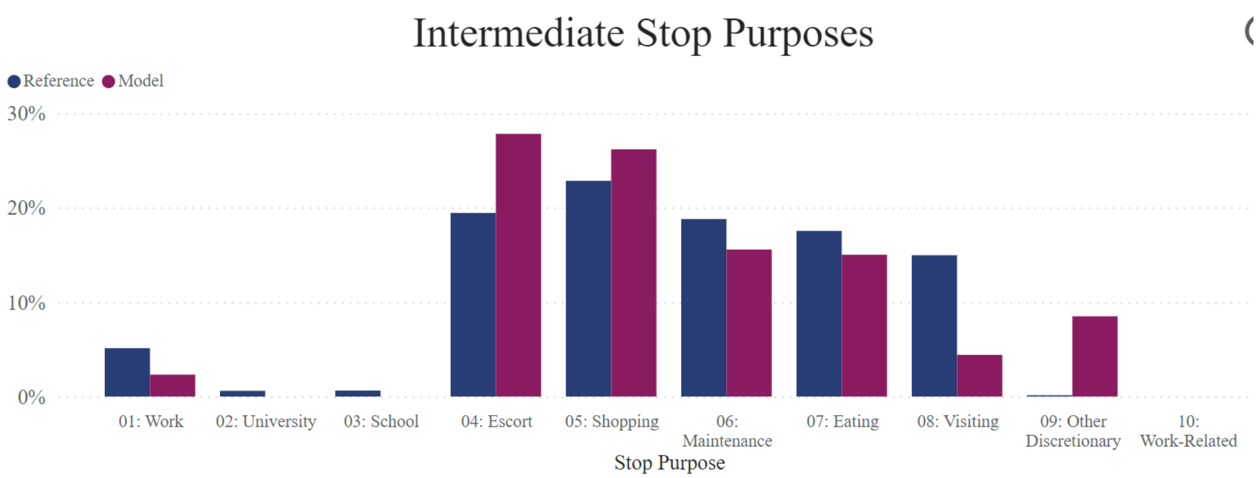


FIGURE 65: TRIP PURPOSE FOR ALL TOURS

Trip Destination

The trip destination choice model assigns the location of trips or stops that are made on a tour other than the primary destination. This model uses tour deviation impedance coefficients, sociodemographic attributes that increase sensitivity to deviations, destination choice logsums, and tour mode choice logsums to estimate the destination zone from a selection of alternatives.

Average “out of direction” stop distance (the difference between the origin to stop plus the stop to destination distance minus the origin to destination distance) is provided in Figure 66. At work stop distance shows the largest differences between the model (at 8.7 miles) and the observed data (at 0.8 miles) out of the tour direction. This large difference should be further investigated, as the observed data average is much lower than the average out of direction stops for any other tour purpose, and the modeled is much higher than any other average distance. Joint tours and school tours also had larger differences of 1.5 miles on average higher for modeled joint maintenance tours, 2 miles on average higher for school tour stops, and 2.4 miles higher average for joint discretionary.

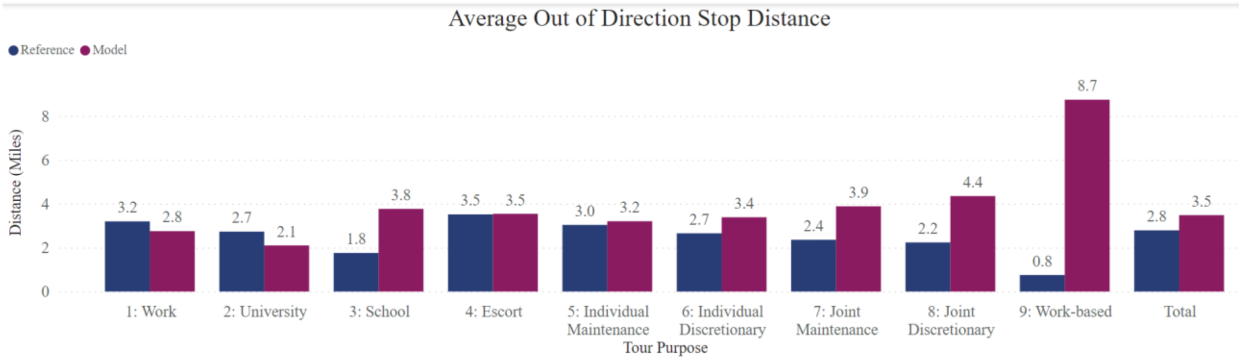


FIGURE 66: AVERAGE OUT OF DIRECTION STOP DISTANCE FOR ALL TOURS

Trip Scheduling

The trip scheduling model is a probabilistic model that involves assigning a trip to a window of time during the outbound or inbound leg of a tour for the trip to take place.

Trip departures by time of day (Figure 67) and by time period (Figure 68) indicate that the model produces aggregate trip results are very close to the observed data with an r of 0.96.

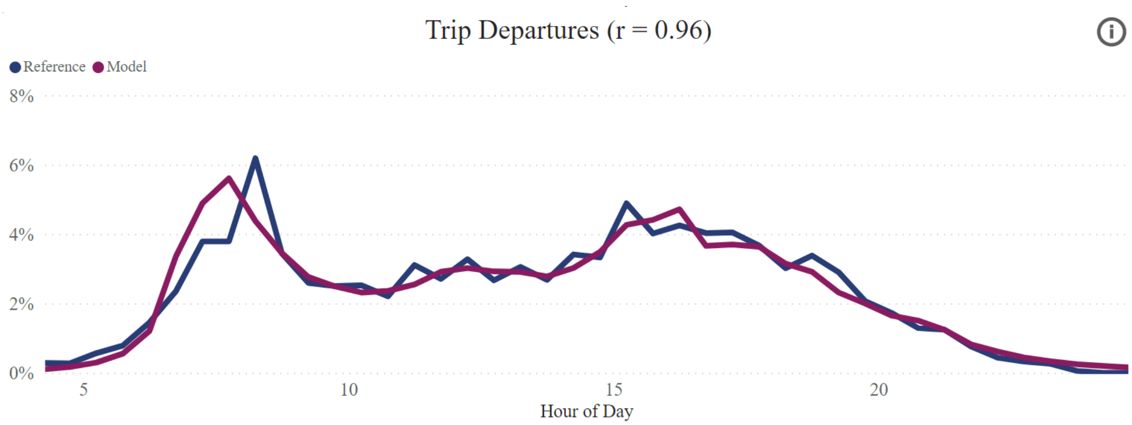


FIGURE 67: TRIP DEPARTURES BY TIME OF DAY

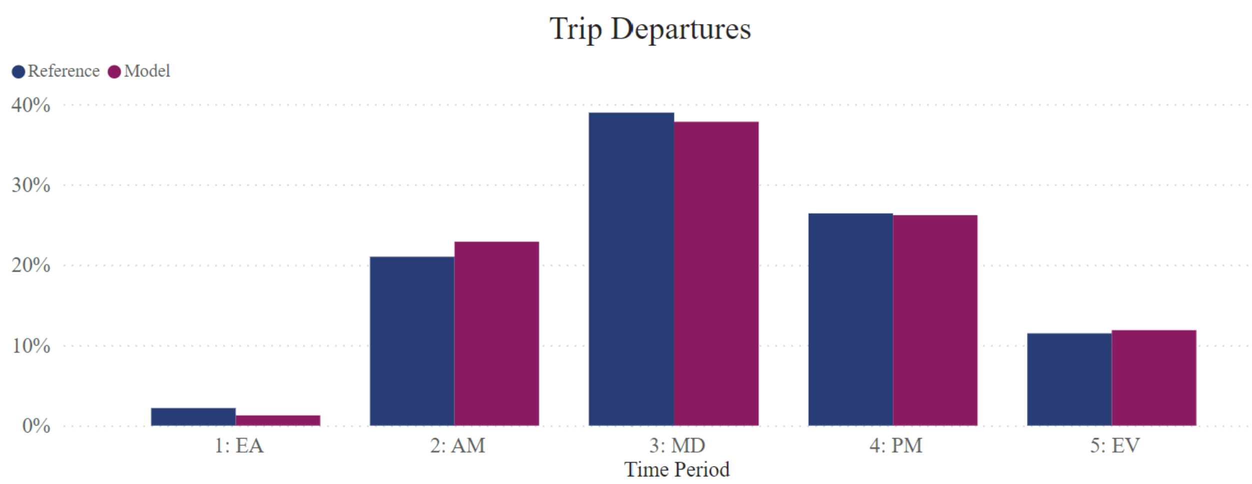


FIGURE 68: TRIP DEPARTURES BY TIME PERIOD

Segmented into tour purpose, trip departure times from the model are not as closely matched to the observed data. University tour related trip departure times have a particularly low fit to the observed data at r = 0.487, due to low sample size. Joint maintenance tours also have a lower fit to the observed data with an r = 0.686. Work tour and individual maintenance tour related trip departure times have the best fit to the observed data above an r = .9. The low fit for trip departure time profiles for some tour types should be investigated to determine whether the model should be adjusted further or whether a small sample size may be causing the poor fit.

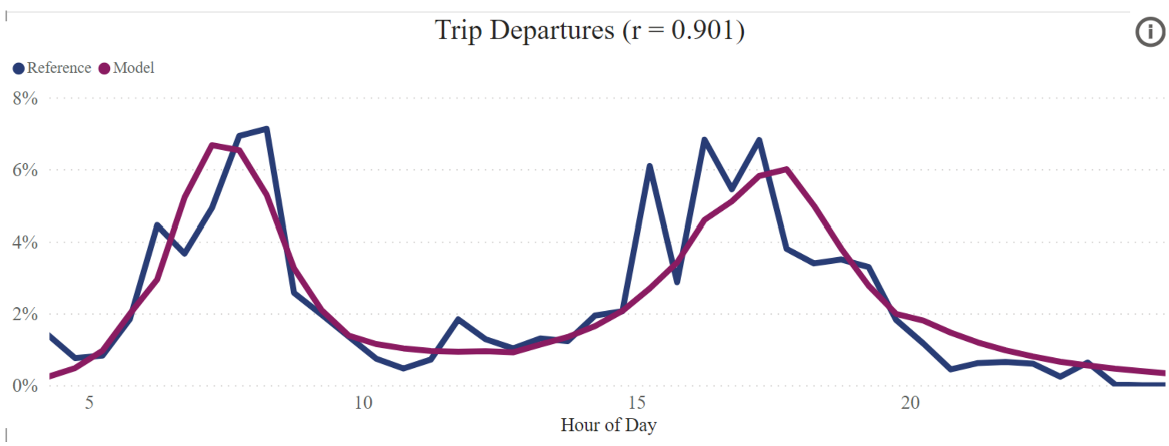


FIGURE 69: TRIP DEPARTURES BY TIME OF DAY FOR WORK TOURS

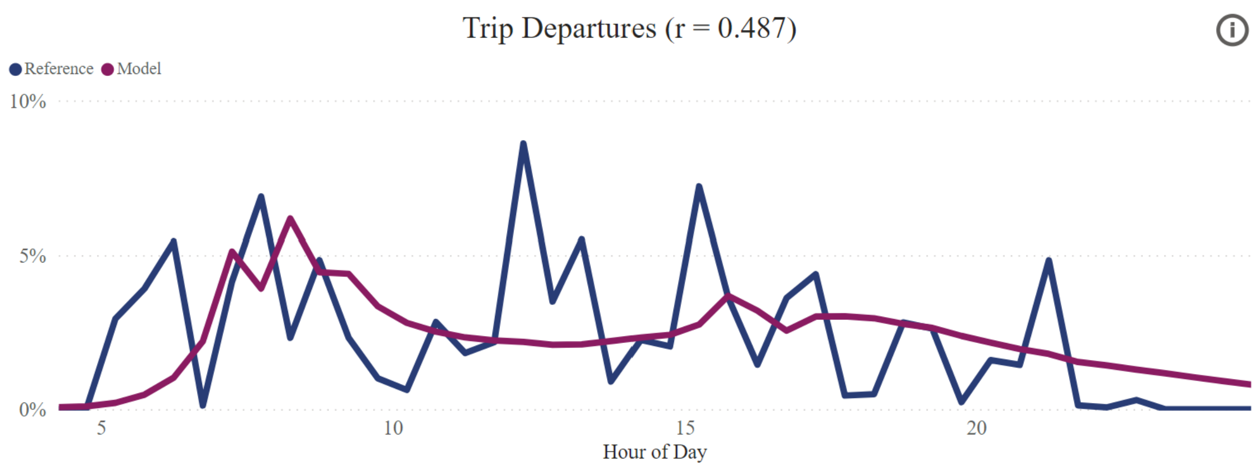


FIGURE 70: TRIP DEPARTURES BY TIME OF DAY FOR UNIVERSITY TOURS

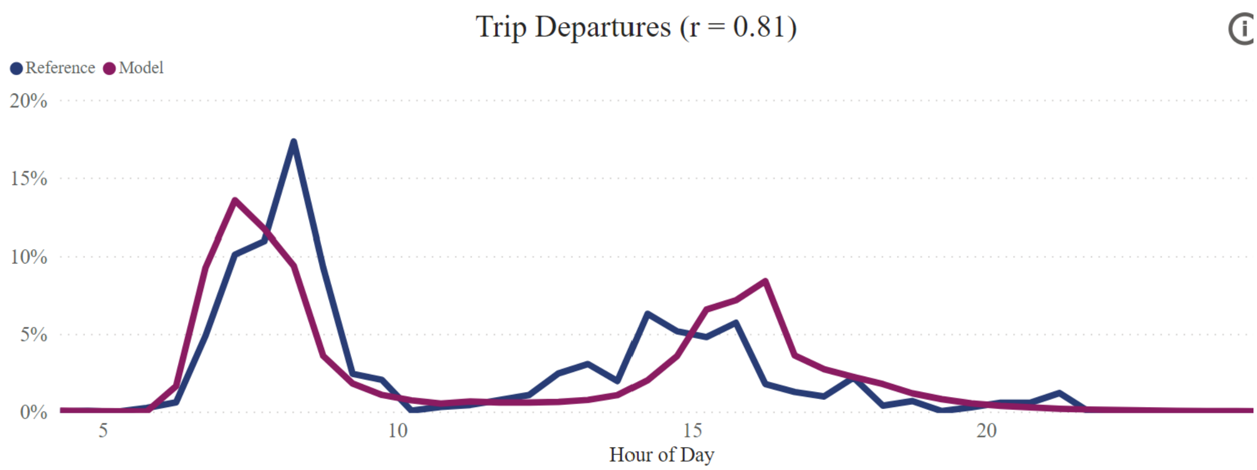


FIGURE 71: TRIP DEPARTURES BY TIME OF DAY FOR SCHOOL TOURS

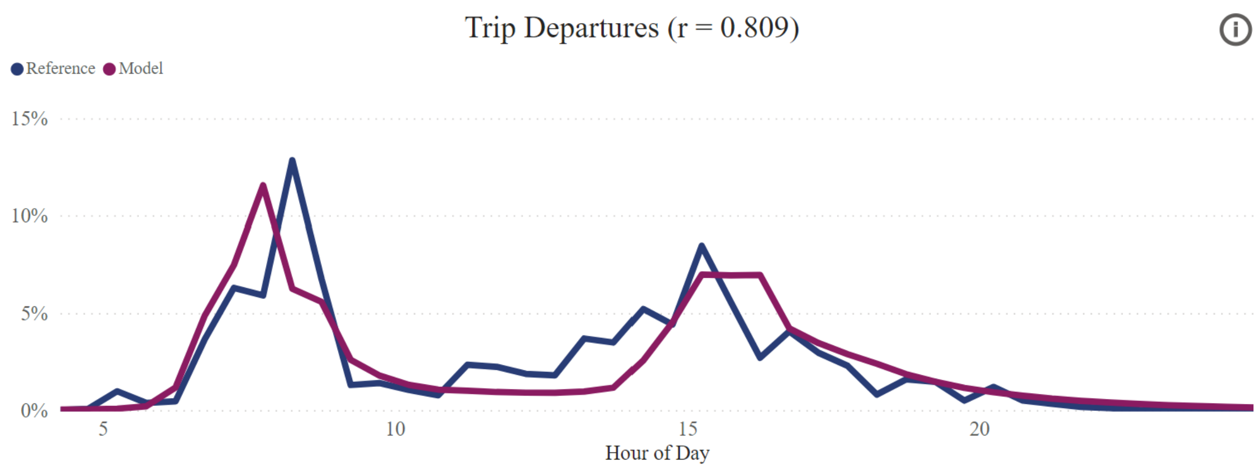


FIGURE 72: TRIP DEPARTURE BY TIME OF DAY FOR ESCORT TOURS

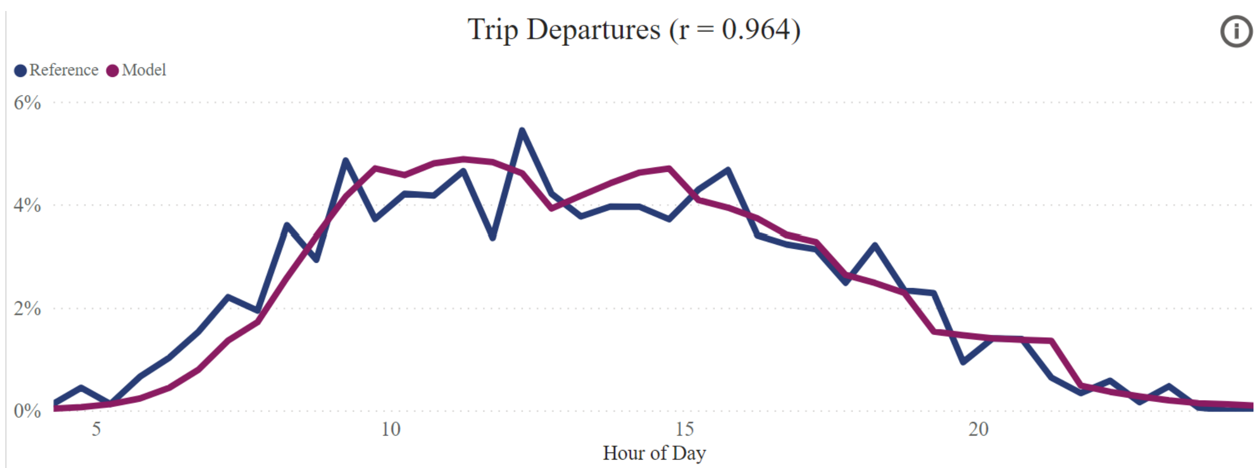


FIGURE 73: TRIP DEPARTURE BY TIME OF DAY FOR INDIVIDUAL MAINTENANCE TOURS

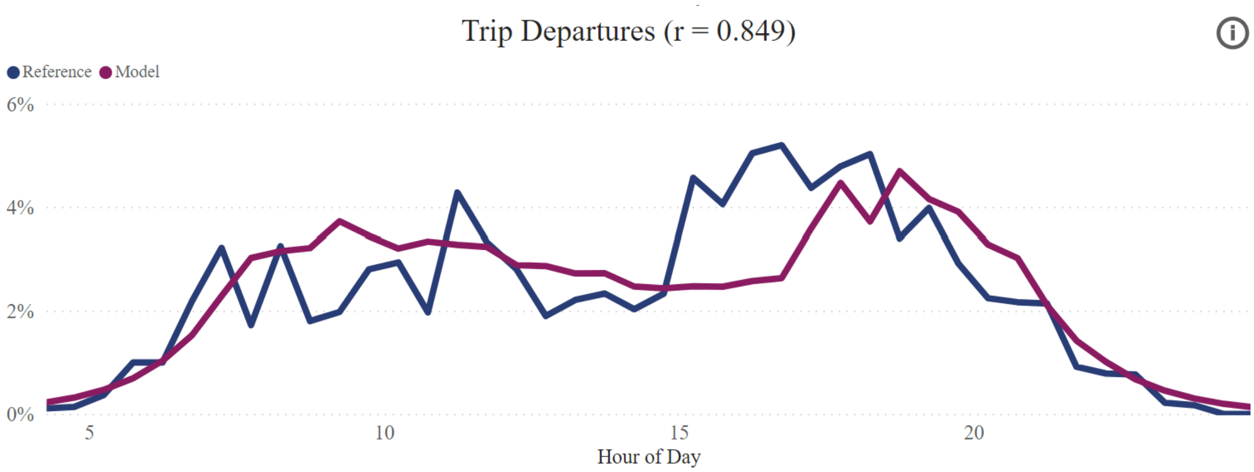


FIGURE 74: TRIP DEPARTURE BY TIME OF DAY FOR INDIVIDUAL DISCRETIONARY TOURS

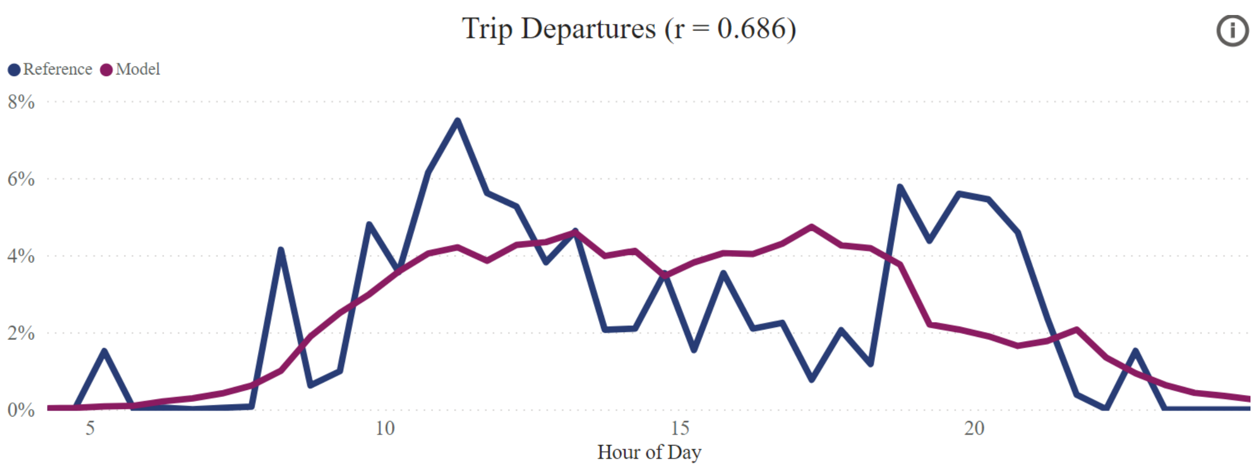


FIGURE 75: TRIP DEPARTURE BY TIME OF DAY FOR JOINT MAINTENANCE TOURS

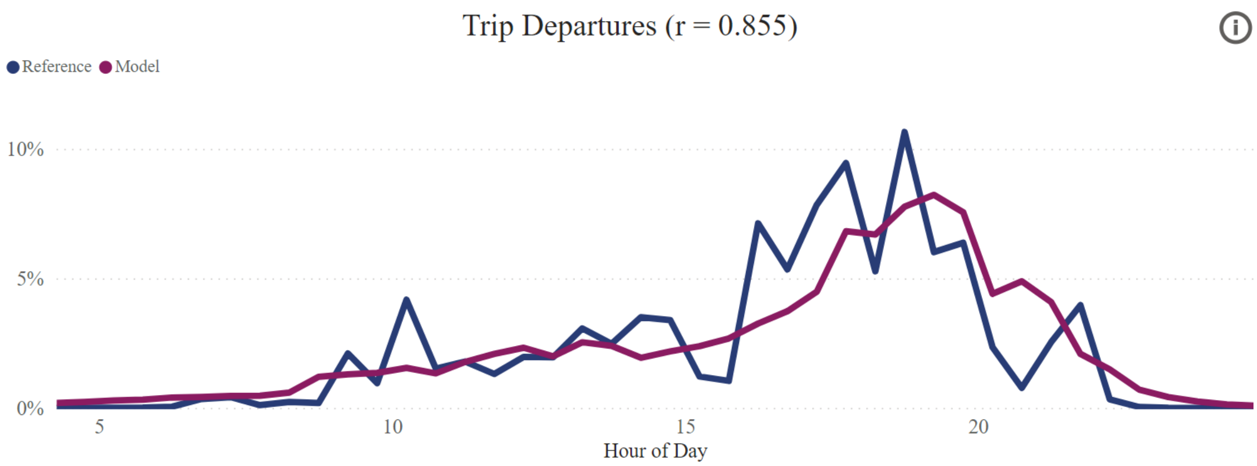


FIGURE 76: TRIP DEPARTURE BY TIME OF DAY FOR JOINT DISCRETIONARY TOURS

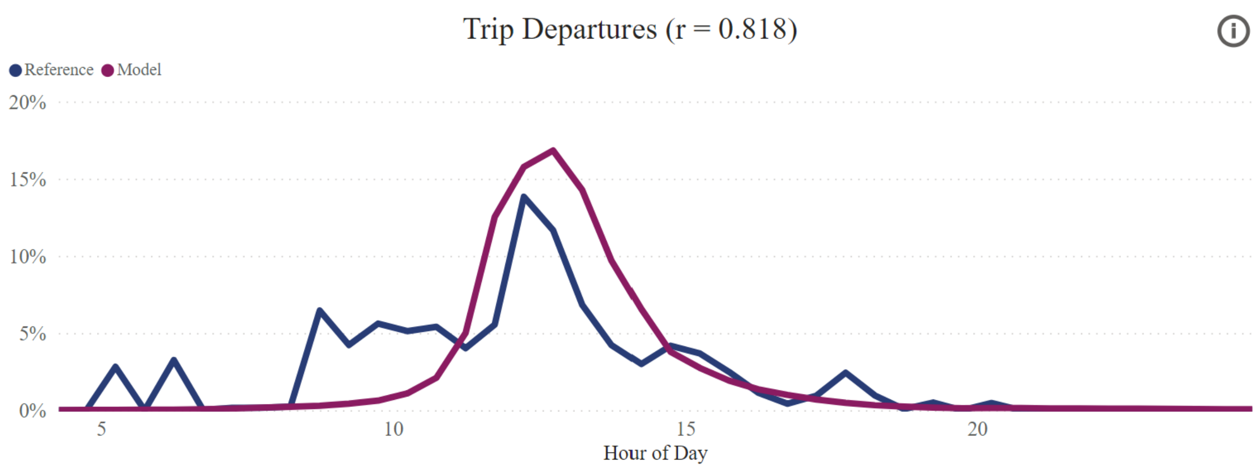


FIGURE 77: TRIP DEPARTURE BY TIME OF DAY FOR WORK RELATED TOURS

Trip Mode

Trip mode is assigned after the scheduling of a trip. The trip mode choice model assigns a mode for each trip on a tour. This model is similar to the tour mode choice model, but the trip mode choice alternatives are restricted depending on the tour mode that has been assigned.

As mentioned in the tour mode choice section, the transit portion of the trip mode choice data was adjusted using the 2015 OBS data and 2023 total ridership data. Table 15 shows the adjusted transit target data used for this model calibration.

TABLE 15 ADJUSTED TRANSIT TARGET DATA USED FOR MODEL CALIBRATION

TRIP MODE	TOTAL
KNR-TRANSIT	25558
PNR-TRANSIT	9798
TNC-TRANSIT	0
WALK-TRANSIT	136453
Total	**171809**

Calibration coefficients were added to the trip mode choice model for tour type and mode combinations. A total of 1,239 calibration constants were added to the mode choice model, and for sake of brevity have not been included in this report.

Results of the trip mode choice model are provided in Figure 78. Results show a slightly higher SOV trips and slightly lower HOV3+ and walk trips compared with the observed data, but the overall share of mode is very similar to the observed data.

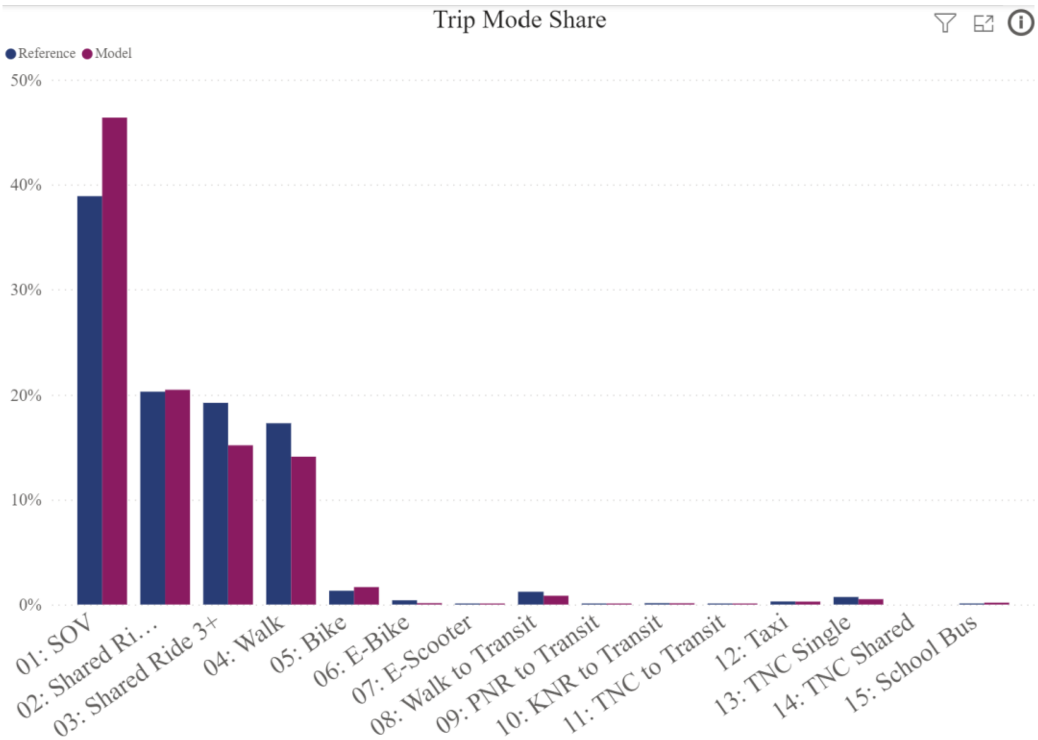


FIGURE 78: TRIP MODE CHOICE

Parking Location Choice

The parking location choice model selects a parking location for trips that require parking. For the specific trips that are selected as needing parking, a parking location zone is selected. Updates to the parking calculations used in the parking location choice model are discussed in the ABM3 Model Development Report.

4.0 VALIDATION RESULTS

This section presents the results of ABM3 model validation against observed count and ridership data as collected and maintained by SANDAG. A model validation tests the model's predictive capabilities before it is used to produce forecasts. There are two types of model validation; static validation, which compares model outputs against independent data that was not used to build the travel model, and dynamic validation, in which model inputs are systematically varied to assess the reasonableness of model responses. The static validation process compares outputs from model assignment with observed data. Model parameters are adjusted until the model outputs fall within an acceptable range of error.

In the assignment step, model demand (e.g. trips by time period, mode, and vehicle class/value-of-time) are loaded on to network. In highway assignment, the output includes vehicle flows on every link (road) in the highway network and for transit assignment, the output includes the number of boardings on each route. These are compared to observed traffic counts and observed transit ridership respectively. The two observed datasets (traffic counts and transit boardings) used in the present model validation are described below.

In the following, we first discuss the highway validation of the model, specifically using observed count data as the on-the-ground target. The transit validation section, then, compares the model's predicted transit ridership against observed ridership for each transit market.

Observed traffic counts for highway validation were collected though the Caltrans Performance Measurement System (PeMS) and local jurisdictions. SANDAG staff developed analyses to cross-reference the counts with ABM3 model network. Observed transit boardings were derived from local transit agencies. The boardings was preprocessed to match ABM3 mode and time of day periods.

4.1 HIGHWAY VALIDATION

Vehicle Miles of Travel

This section discusses the highway validation metrics by vehicle miles of travel (VMT) and volume. We compare predicted model VMT against observed VMT calculated based on count data, in addition to comparing the total predicted regional model VMT against the Caltrans Highway Performance Monitoring System (HPMS) estimate. We further investigate VMT distribution by jurisdiction and link type and compare the predicted model values against observed count data.

Table 16 shows the predicted daily vehicle miles traveled (VMT) against observed daily VMT obtained based on count data. Model is predicting 1.56 million less VMT compared to the counts'. These statistics are only for links with observed counts, and do not represent the total VMT at the regional level.

TABLE 16 DAILY VMT COMPARISON BETWEEN MODEL AND COUNT DATA

	DAILY VMT (MILLIONS)
Model	19.92
Observed count	21.48

Table 17 shows the predicted regional model VMT against HPMS VMT in the San Diego County. Unlike the comparison between model and observed count, the precited regional VMT is higher than the HPMS estimate by 6.13 million.

TABLE 17 REGIONAL VMT COMPARISON BETWEEN MODEL AND HPMS

	REGIONAL VMT (MILLIONS)
Model	78.08
HPMS	71.95

The disagreeing statistics above do not provide a clear direction for model calibration. Increasing predicted model VMT to better match observed count's VMT will inevitably result in higher predicted regional VMT, further increasing the gap between model and HPMS. RSG investigated whether such differences in VMT can be tracked to certain geographies or link type; in other words, if the model were overpredicting VMT in some sub-regions or over certain link types, while underpredicting for others.

Figure 79 shows the comparison between model and observed counts' VMT for jurisdiction within the San Diego County. With the exception of the San Diego jurisdiction (and to a lesser degree Chula Vista), the model VMT matches the observed VMT, with model predicting within 5% of the observed VMT. Overall, we do not observe any patterns of overpredicting in some geographies while underpredicting in some, with most jurisdictions showing a close match between model and observed VMTs.

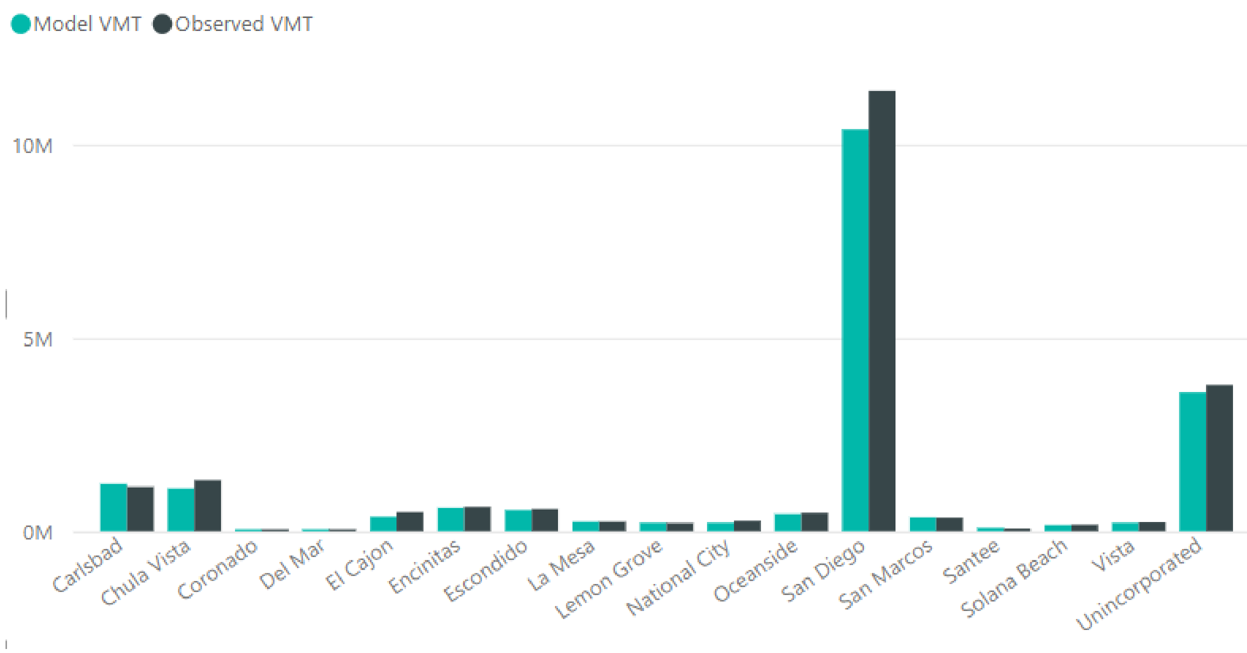


FIGURE 79 DAILY VMT BY JURISDICTION (BASED ON OBSERVED COUNT DATA)

Figure 80 shows a similar comparison of model's vs observed VMT based on links' volume category. Model VMT is underpredicted in all categories, although this difference is within 10% of the target in most cases.

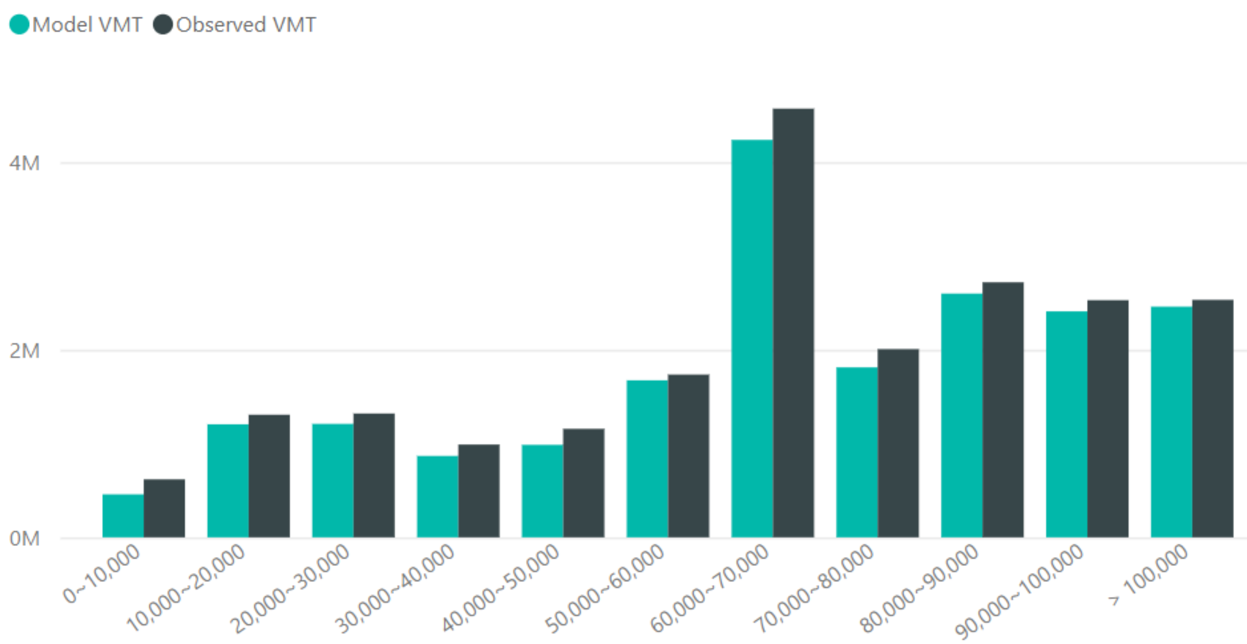


FIGURE 80 DAILY VMT BY VOLUME CATEGORY (BASED ON OBSERVED COUNT DATA)

Link volumes

Figure 81 shows the predicted regional traffic flows against the observed traffic counts. Points in the scatterplot are links where traffic counts are available. A point represents observed traffic count on the X-axis and the corresponding estimated flow on the Y-axis. The scatter plot includes the R^2 and overall PRMSE (Percent root-mean squared error) which help in assessing accuracy of the model flows with respect to the observed traffic counts. R^2 is a is a statistical measure of how close the data are to the fitted regression line. R^2 is always between 0 and 1; a value of 0 indicates that the model explains none of the variability of the response data around its mean and a value of 1 indicates that the model explains all the variability of the response data around its mean. PRMSE is the square root of the estimated flow minus the observed traffic count squared divided by the number of traffic counts. It measures the accuracy of the entire model, representing the average error between observed and estimated traffic flow on a link.

The plot also includes a 45-degree line representing a virtual scenario of perfect match between traffic counts and estimated flows. The 45-degree line is useful in quickly identifying overestimation (flow>count) or underestimation (flow<count) of a flow. Highway validation aims to make most points as close to this line as possible. An ideal validation would have all count locations on the 45-degree line. However, a perfect match for all count locations is almost impossible to achieve due to various reasons such as error in traffic counts, simulation errors in the model etc. As Figure 81 shows, there tends to be an underestimation of volumes, which is in

line with the lower predicted VMT, against the observed volume. The R^2 goodness-of-fit is 0.93 which is higher than the 0.88 value recommended by the FHWA. In addition, the overall PRMSE is %30.53, which is lower than the 40% recommended by the FHWA.

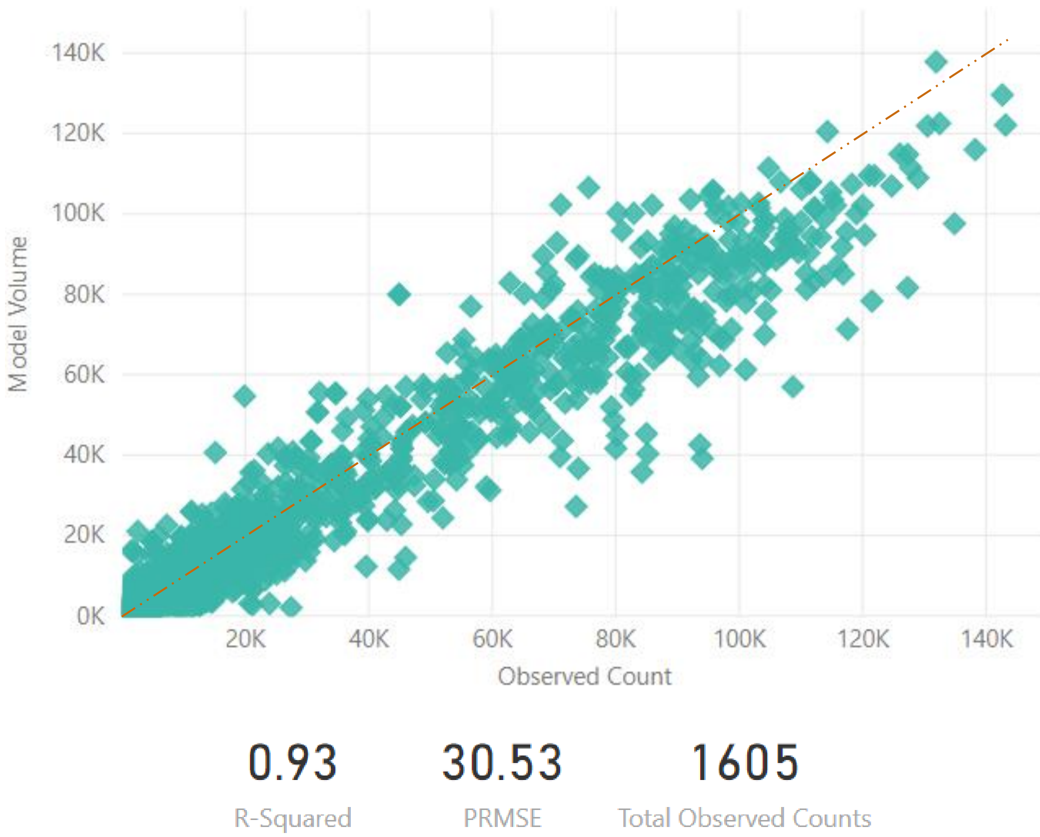
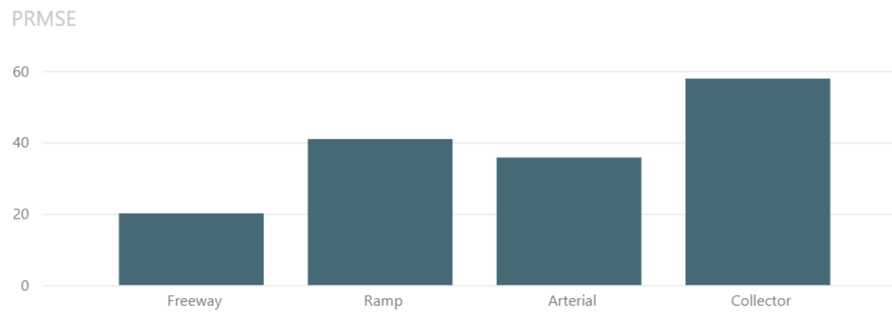
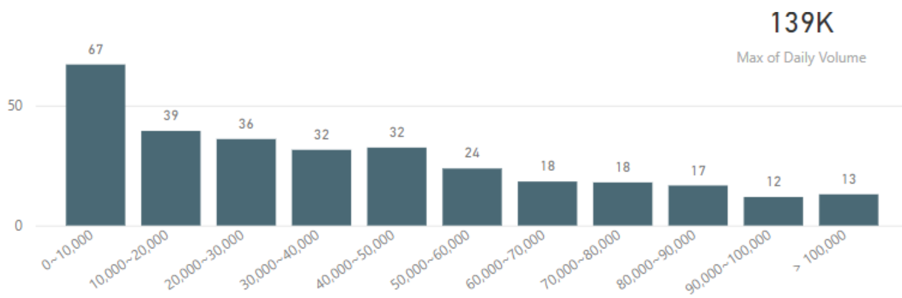


FIGURE 81 MODEL VOLUME VS. OBSERVED COUNT DATA

We further investigate the PRMSE by link category and volume. Figure 82 shows PRMSE of predicted vs. observed count volumes by link category and volume. Overall, the PRMSEs show to be within a good range, with a majority of links having a value under 40% (as recommended by FHWA). Low-volume links and collectors tend to have worse PRMSE, which is generally as expected since assignment tends to load demand onto collectors.



(9) ***PRMSE by link category***



(b) PRMSE by volume category

FIGURE 82 PERCENT ROOT MEAN SQUARE ERROR (PRMSE) BY LINK TYPE AND VOLUME

Transit validation

This section compares the predicted transit ridership against the observed ridership obtained from the Passenger Count Program. The ridership (boarding) is compared by transit line-haul mode and time of day ridership. The recommended FHWA guidelines for transit validation are predicted ridership values by route group (local bus, express bus, etc.) within 20% of the target values.

Prior to discussing the model validation results, we refer the reader to the Introduction section of this report, where we discuss in detail the derivation and scaling of the 2022 HTS transit data using the 2015 on-board survey (OBS). Due to the timeline of the ABM3 development, RSG did not have access to the latest OBS data for model calibration purposes. Our goal, therefore, was to use the previous round of available OBS data to inform and improve our calibration efforts. This work, as expected, is not perfect, and some model boardings, as discussed in the following, may need further attention, but RSG and SANDAG decided to postpone further calibration and finetuning efforts until after the latest OBS data is available.

The scatter plot in Figure 83 shows the relationship between the predicted transit boardings and the observed boarding by transit line. The X-axis in the plot represent the observed boardings and the estimated boardings from the model are presented on the Y-axis. A high R-squared value of 0.97 indicates that the linear regression line is a very good fit for all data points or in other words the model matches route level boardings very well.

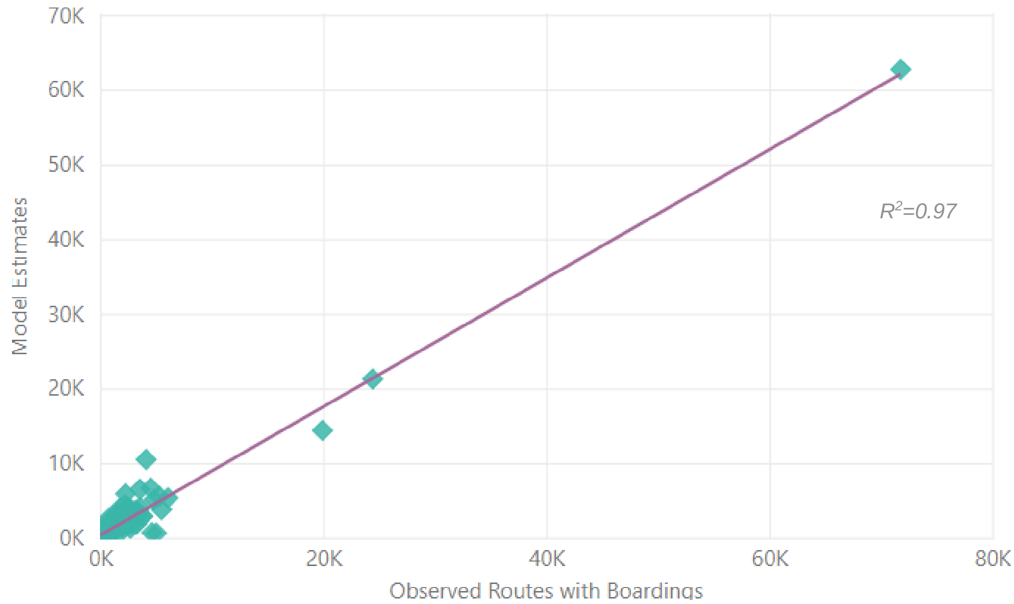


FIGURE 83 OBSERVED VS PREDICTED TRANSIT BOARDINGS

Table 18 shows predicted transit boardings against observed boarding. The total boardings predicted by the model, at 269,150, is within 2.3% of the observed boarding in the region. Local bus ridership shows an almost perfect match with the target ridership, while LRT is about 14% lower in the model than target. As discussed above, RSG, in conjunction with SANDAG, decided to revisit these boardings after the new round of OBS data is available to ensure optimal model sensitivity and accuracy.

TABLE 18 OBSERVED VS. PREDICTED DAILY BOARDINGS

MODE	DAILY BOARDINGS		DIFFERENCE	
	Observed	Model	Difference	% difference
Commuter Rail	2,456	1,530	-926	-37.70%
Express	8,094	10,218	2,124	26.24%
Local	120,615	120,335	-280	-0.23%
LRT	121,016	103,517	-17,499	-14.46%
Rapid	23,333	33,517	10,184	43.65%
Total	**275,514**	**269,150**	**-6,364**	**-2.31%**

Table 19 shows the boarding distribution by time-of-day. The predicted boardings for AM peak, midday and PM peak are close to target, but we are observing a noticeable difference between the late evening and early morning numbers. RSG considered adding an EV period constant to the model, but decided to postpone this decision until the availability and further analysis of the OBS data.

TABLE 19 OBSERVED VS. PREDICTED BOARDINGS BY TIME-OF-DAY

MODE	EA		AM		MD		PM		EV		DAY	
	Model	Observed	Model	Observed	Model	Observed	Model	Observed	Model	Observed	Model	Observed
Commuter Rail	59	128	404	599	318	476	521	1,023	749	230	1,530	2,456
Express	207	324	1,804	1,697	4,122	3,156	2,626	2,218	1,960	698	10,218	8,094
Local	1,671	2,845	19,712	23,421	51,996	52,379	31,361	31,895	19,790	10,074	120,335	120,615
LRT	1,675	5,357	18,051	21,282	45,508	46,170	23,784	32,073	15,231	16,134	103,517	121,016
Rapid	718	532	6,784	3,923	11,921	9,399	8,729	6,562	4,950	2,922	33,551	23,333
Total	**4,330**	**9,186**	**46,755**	**50,922**	**113,865**	**111,580**	**67,021**	**73,771**	**42,680**	**30,058**	**269,151**	**275,514**

5.0 CONVERGENCE TEST

This section of the report investigates the global iteration convergence to evaluate its impact on model outputs and performance metrics. Each standard ABM3 run contains three global iterations with household sample rates of 20%, 50%, and 100% applied to each iteration, respectively. In the first two iterations, trip demand is expanded to full size using a scale factor before traffic assignment. ABM3 implements traffic and transit assignment using EMME modeling software. It additionally uses a specified relative gap as the assignment convergence criterion. The relative gap is set to 0.0005 in a standard ABM3 run.

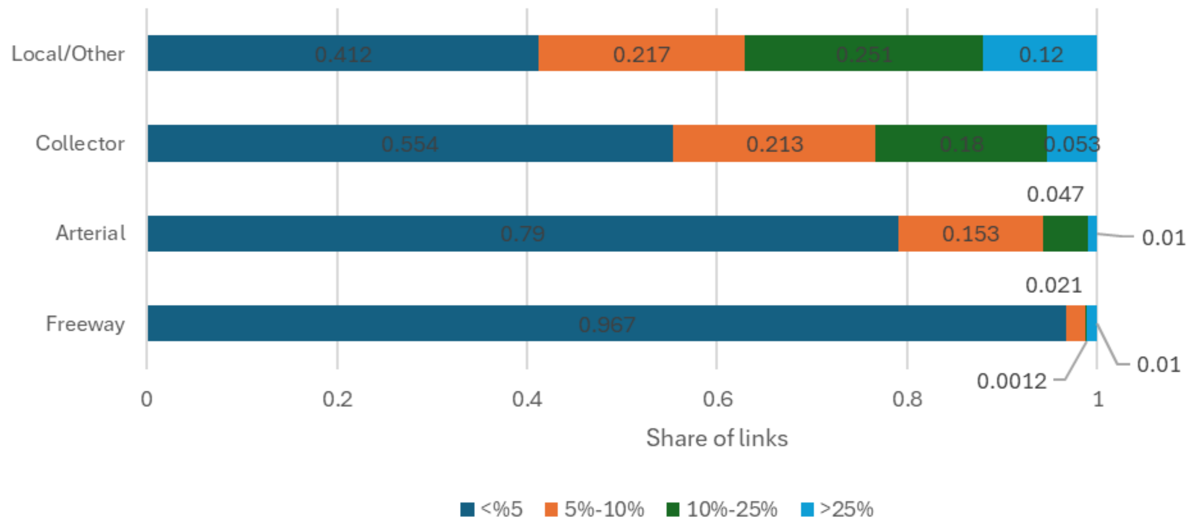
This section uses three metrics to investigate convergence: link volumes, skims, and trip tables. For each metric, we compare the value changes per iteration for the congested periods of peak morning (AM) and peak afternoon (PM).

5.1 LINK VOLUMES

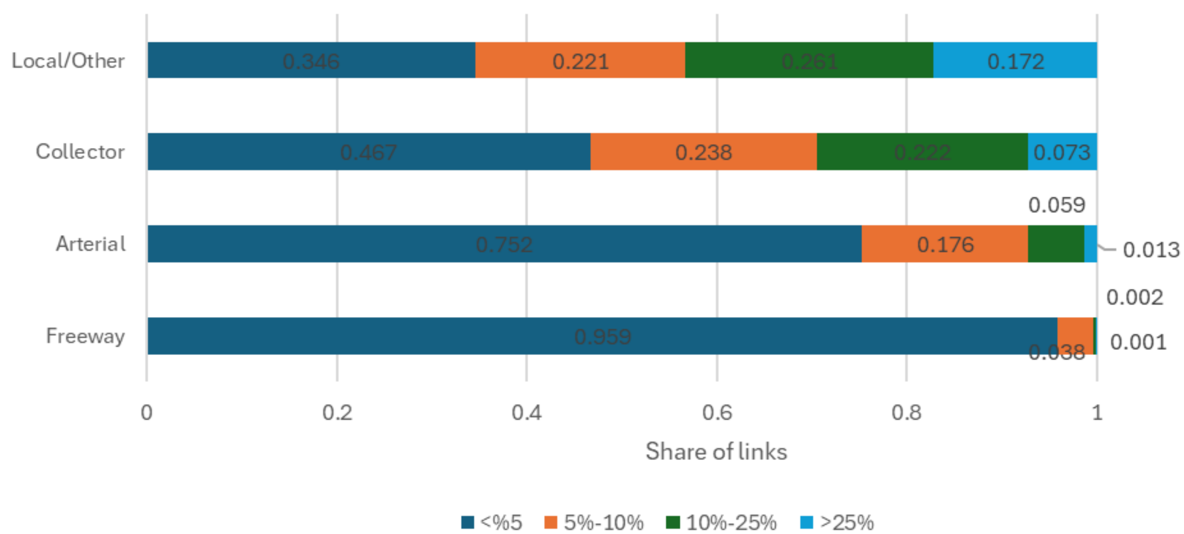
The skimming step uses the method of successive averages (MSA) in the intermediate iterations to average the flows between the result of the previous and current iterations. Skimming in the final iteration (4th), however, uses the results of the demand assigned directly to the network, without any averaging. To investigate the link volume convergence between iterations, we saved the link volumes for each link as a new attribute, and then compared the value changes between iterations.

Figure 84 visualizes the distribution of volume changes for links in the AM period. Link volume convergence was summarized into four categories by road type: Freeways, arterials, Collectors, and local/other roads. Each horizontal stacked bar shows the share of links whose value change between iterations falls within a respective range. Comparing Figure 84 (a) and Figure 84 (b) shows an improvement in volume differences, with more links having a smaller volume change between iterations.

We also see that approximately 97% of freeway links have a volume change of less than 5% between the 3rd and final iterations, pointing to a fairly stable convergence. This share steadily drops for arterial, collectors, and local roads, with only 41% of local roads showing a volume change of less than 5% between the 3rd and final iterations.

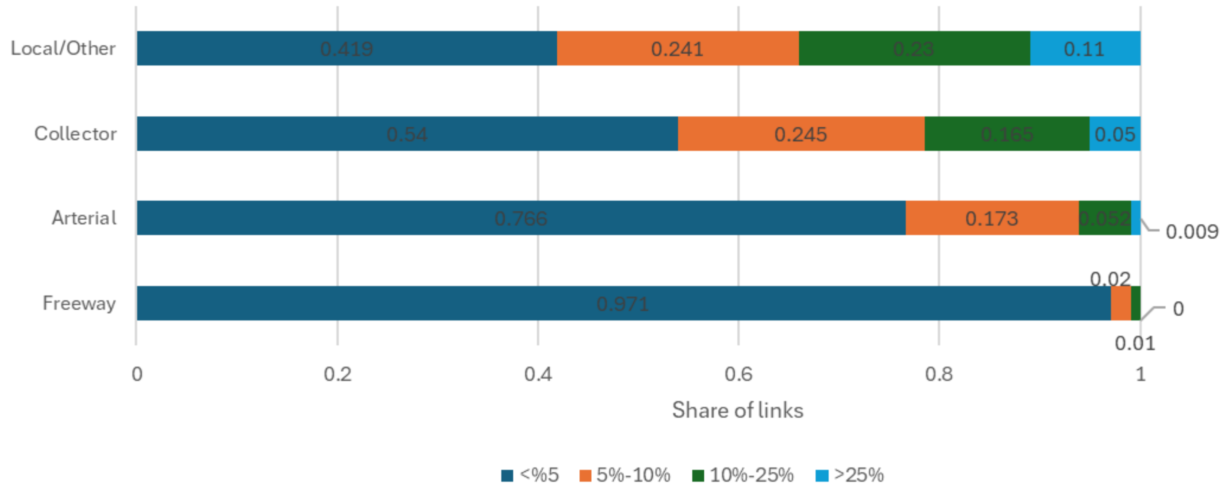


(a) Iterations 3 and 4

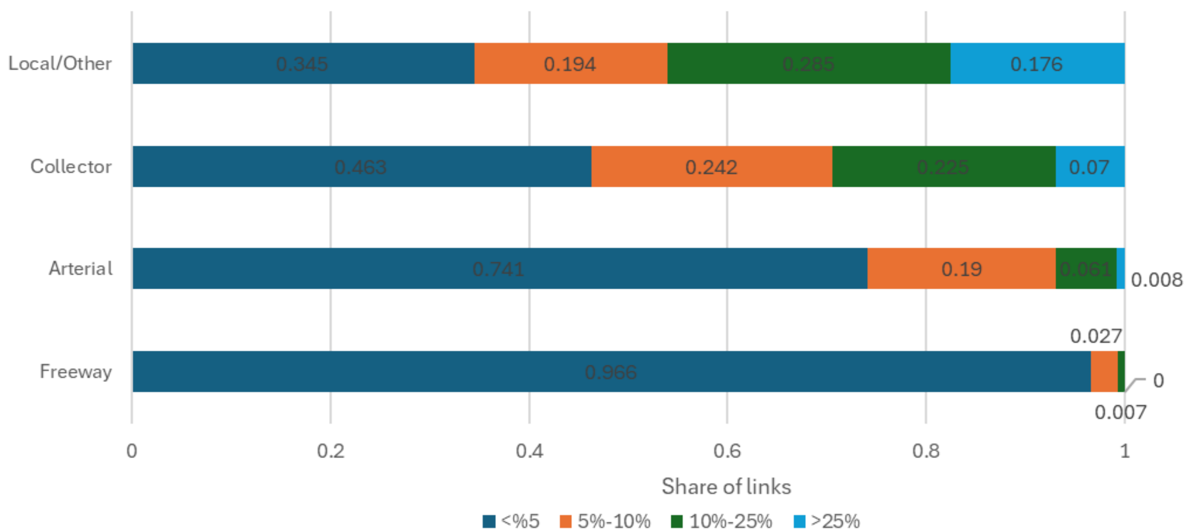


(b) Iterations 2 and 3

FIGURE 84 LINK VOLUME DIFFERENCES FOR PERIOD AM



(a) Iterations 3 and 4



(b) Iterations 2 and 3

FIGURE 85 LINK VOLUME DIFFERENCES FOR PERIOD PM

5.2 SKIM TRAVEL TIMES

This section investigates the changes in skims between iterations 2 and 3. We, specifically, focus on highway travel times and investigate the average changes in SOV, HOV2, and HOV3 travel times between zones for AM and PM periods. We use the medium value of travel time as a representative of all the trips.

As Table 20, shows the RMSE of travel time skims between iterations 2 and 3 is less than 0.5 across all highway modes, pointing to a very small change in skims between the two iterations.

TABLE 20 ROOT MEAN SQUARED ERROR OF TRAVEL TIMES ACROSS ALL ZONES BETWEEN ITERATIONS 2 AND 3

PERIOD	RMSE		
	SOV_NT_M_TIME	HOV2_M_TIME	HOV3_M_TIME
AM	0.324	0.296	0.296
PM	0.226	0.178	0.178

5.3 DEMAND TRIP TABLES

This section describes the comparison of travel demand by TOD and mode between second and third iterations. We combined the highway demand by mode, value of time (VOT), and period across all markets, and computed the RMSEs between the two iterations.

Table 21 shows the RMSE values of the demands between the two iterations. The RMSEs are all small considering the scale of demand values, showing the good level convergence between iterations 2 and 3.

TABLE 21 RMSE OF ITERATIONS2 AND 3 DEMAND TABLES

MODE	VOT	RMSE	
		AM	PM
SOV	Low	0.1944	0.2244
	Med	0.1985	0.2284
	High	0.1757	0.2078
SR2	Low	0.0728	0.0876
	Med	0.0822	0.0875
	High	0.1014	0.1163

	Low	0.029	0.0439
SR3	**Med**	0.0365	0.0416
	High	0.0641	0.0788

6.0 CONCLUSIONS

This document presented the state of calibration of validation of the SANDAG ABM3, showing how the model matches the 2022 HTS and observed count and ridership data. Some of the challenges in calibrating the model system included the target survey data with a smaller sample (2800 households) than other surveys. This lower survey observation counts resulted in sparse data for some modelsmaking the calibration efforts more challenging. For example, certain geographies had few samples making it difficult to draw conclusions on the behavior of residents of those areas. Furthermore, the proxy reporting issue, as discussed in the Introduction section of this report, required us to assert rates of daily activity pattern types for students and shares of kids being picked-up and dropped-off at school, even after applying the joint trip imputation procedure. This may effect downstream models in ways that are difficult to determine. Another issue, which especially impacts the mode choice model calibration, was the lack of recent OBS data. Although special care was taken in the survey weighting stage to weight the mode choice target data to better match the ridership, we nonetheless had to refer to the 2015 OBS and use it to further adjust the targets. Considering that SANDAG will have the latest OBS data soon (Spring 2024) we suggest revisiting the mode choice models and calibrate them further and as needed.

In the validation stage, the main challenges involved the inconsistent VMT estimates based on observed counts and HPMS data. As discussed, the model is currently overpredicting regional VMT as compared with HPMS estimate, and underpredicting VMT on links with observed VMT. We suggest further investigating the count data for any discrepancies to make sure the data is reliable. With respect to the regional VMT, SANDAG found another estimate based on fuel sales at approximately 80 million. This estimate appears to be closer to what the model is predicting; we, however, suggest further investigation of reliable regional VMTs, and revisiting this issue following that.

Following the calibration phase of the model, we saw that most model components show a good match with the survey data despite the caveats mentioned above, although a number of model components can benefit from further attention. The results specifically show a need for further calibrating the non-mandatory tour frequency for non-workers, where the share of 3+ tours is noticeably higher than the target. We also recommend a further calibration of mode choice models, as discussed above, following the availability and analysis of the latest OBS data.

7.0 APPENDIX

APPENDIX TABLE 1: TOUR MODE CHOICE CALIBRATION CONSTANTS

Coefficient	Work	School	University	Maint	Disc	At work
coef_calib_autodeficienthhind_BIKE	-6.642	-0.9982	-5.239	-4.196	-2.536	-14.79
coef_calib_autodeficienthhind_EBIKE	-6.000	-2.000	-4.000	-7.717	-2.166	-8.000
coef_calib_autodeficienthhind_ESCOOTER	-4.000			-4.000	-0.009140	-4.000
coef_calib_autodeficienthhind_KNR_TRANSIT	-5.494	-2.956	-3.095	-1.410	-3.286	-999.0
coef_calib_autodeficienthhind_PNR_TRANSIT	-6.447	-5.920	-4.208	-2.320	-4.014	-999.0
coef_calib_autodeficienthhind_SCH_BUS		-1.285				
coef_calib_autodeficienthhind_SHARED2	-2.797	-5.636	-2.305	-0.4277	-0.3096	-0.04507
coef_calib_autodeficienthhind_SHARED3	-2.569	-0.9364	-2.608	-0.07779	0.1186	-2.624
coef_calib_autodeficienthhind_TAXI	-9.667	-1079	-11.67	-4.399	-3.964	-10.88
coef_calib_autodeficienthhind_TNC_SHARED	-9.667	-1001	-11.67	-8.084	-6.658	-10.88
coef_calib_autodeficienthhind_TNC_SINGLE	-8.884	-1077	-2.596	-4.519	-4.170	-10.88
coef_calib_autodeficienthhind_TNC_TRANSIT	-9.399	-999.0	-999.0	-5.982	-999.0	-999.0
coef_calib_autodeficienthhind_WALK	-0.7049	0.4566	1.870	-0.7802	-1.699	-3.443
coef_calib_autodeficienthhind_WALK_TRANSIT	-4.946	-105.8	-1.203	-2.500	-0.8854	-9.537
coef_calib_autodeficienthhjoi_BIKE				-917.0	-917.0	
coef_calib_autodeficienthhjoi_EBIKE				-44.43	-44.43	
coef_calib_autodeficienthhjoi_ESCOOTER				-40.00	-40.00	
coef_calib_autodeficienthhjoi_KNR_TRANSIT				-46.88	-43.13	
coef_calib_autodeficienthhjoi_PNR_TRANSIT				-47.90	-45.17	
coef_calib_autodeficienthhjoi_SHARED3				-40.67	-40.67	
coef_calib_autodeficienthhjoi_TAXI				-46.97	-44.72	
coef_calib_autodeficienthhjoi_TNC_SHARED				-48.97	-46.72	
coef_calib_autodeficienthhjoi_TNC_SINGLE				-48.97	-46.72	
coef_calib_autodeficienthhjoi_TNC_TRANSIT				-999.0	-999.0	
coef_calib_autodeficienthhjoi_WALK				-41.17	-41.17	
coef_calib_autodeficienthhjoi_WALK_TRANSIT				-48.68	-45.58	
coef_calib_autosufficienthhin_BIKE	-3.605	4.601	-7.144	-1.574	-2.362	-6.793
coef_calib_autosufficienthhin_EBIKE	-4.322	-0.4524	-4.000	-3.421	-3.742	-4.438
coef_calib_autosufficienthhin_ESCOOTER	-4.000			-4.000	-3.066	-4.000
coef_calib_autosufficienthhin_KNR_TRANSIT	-6.276	-4.730	-6.049	-6.942	-4.327	-999.0

coef_calib_autosufficienthhin_PNR_TRANSIT	-7.272	-10.52	-4.671	-6.304	-3.795	-999.0
coef_calib_autosufficienthhin_SCH_BUS		-6.079				
coef_calib_autosufficienthhin_SHARED3	-2.273	-2.890	-2.654	-0.1683	0.3129	-1.872
coef_calib_autosufficienthhin_TAXI	-9.901	-999.0	-4.651	-7.780	-7.985	-9.131
coef_calib_autosufficienthhin_TNC_SHARED	-11.90	-1001	-6.651	-9.780	-9.985	-13.13
coef_calib_autosufficienthhin_TNC_SINGLE	-10.96	-1081	-6.651	-6.369	-7.651	-13.13
coef_calib_autosufficienthhin_TNC_TRANSIT	-10.70	-1029	-8.233	-8.810	-8.897	-999.0
coef_calib_autosufficienthhin_WALK	-3.498	0.5861	2.214	-0.904	-0.04984	0.5919
coef_calib_autosufficienthhin_WALK_TRANSIT	-7.437	-3.455	-5.960	-5.696	-2.762	-9.968
coef_calib_autosufficienthhjo_BIKE				-17.43	-17.23	
coef_calib_autosufficienthhjo_EBIKE				-11.14	-11.14	
coef_calib_autosufficienthhjo_ESCOOTER				-14.00	-14.00	
coef_calib_autosufficienthhjo_KNR_TRANSIT				-16.58	-22.31	
coef_calib_autosufficienthhjo_PNR_TRANSIT				-18.77	-15.46	
coef_calib_autosufficienthhjo_SHARED3				-8.296	-6.296	
coef_calib_autosufficienthhjo_TAXI				-21.31	-18.03	
coef_calib_autosufficienthhjo_TNC_SHARED				-23.31	-20.03	
coef_calib_autosufficienthhjo_TNC_SINGLE				-23.31	-20.03	
coef_calib_autosufficienthhjo_TNC_TRANSIT				-1003	-19.31	
coef_calib_autosufficienthhjo_WALK				-7.181	-5.181	
coef_calib_autosufficienthhjo_WALK_TRANSIT				-20.27	-18.92	
coef_calib_zeroautohhindivtou_BIKE	-7.602	12.22	-0.8009	-6.018	-3.318	-81.00
coef_calib_zeroautohhindivtou_EBIKE	-6.000		-6.000	0.0259	-6.278	-67.00
coef_calib_zeroautohhindivtou_ESCOOTER	-2.000		-2.000	4.924	0.5167	-25.00
coef_calib_zeroautohhindivtou_KNR_TRANSIT	-1.325	2.945	-16.47	1.333	-0.4781	-999.0
coef_calib_zeroautohhindivtou_PNR_TRANSIT	-999.0	-999.0	-2.743	-999.0	-999.0	-999.0
coef_calib_zeroautohhindivtou_SCH_BUS		29.13				
coef_calib_zeroautohhindivtou_SHARED2	-0.8061	-87.00	1.437	-0.06989	-0.3012	-81.00
coef_calib_zeroautohhindivtou_SHARED3	-4.175	28.67	0.2543	-0.6339	-1.836	-81.00
coef_calib_zeroautohhindivtou_TAXI	-1.963	-1079	-999.0	1.253	-2.637	-999.0
coef_calib_zeroautohhindivtou_TNC_SHARED	-3.963	-1001	-999.0	-3.817	-4.637	-999.0
coef_calib_zeroautohhindivtou_TNC_SINGLE	2.035	-1079	-999.0	1.976	-1.389	-999.0
coef_calib_zeroautohhindivtou_TNC_TRANSIT	-959.0	-999.0	-999.0	-959.0	-999.0	-999.0
coef_calib_zeroautohhindivtou_WALK	2.690	0.6666	-2.298	2.971	0.9465	3.581
coef_calib_zeroautohhindivtou_WALK_TRANSIT	-0.9747	1.109	0.7037	-0.8724	-0.5500	-72.76
coef_calib_zeroautohhjointtou_BIKE				-999.0	-999.0	
coef_calib_zeroautohhjointtou_EBIKE				-35.00	-35.00	
coef_calib_zeroautohhjointtou_ESCOOTER				-33.00	-33.00	
coef_calib_zeroautohhjointtou_KNR_TRANSIT				-59.00	-63.85	
coef_calib_zeroautohhjointtou_PNR_TRANSIT				-999.0	-999.0	
coef_calib_zeroautohhjointtou_SHARED3				-63.00	-68.25	

coef_calib_zeroautohhjointtou_TAXI				-999.1	-999.0	
coef_calib_zeroautohhjointtou_TNC_SHARED				-999.1	-999.0	
coef_calib_zeroautohhjointtou_TNC_SINGLE				-999.1	-999.0	
coef_calib_zeroautohhjointtou_TNC_TRANSIT				-999.0	-999.0	
coef_calib_zeroautohhjointtou_WALK				-34.78	-48.78	
coef_calib_zeroautohhjointtou_WALK_TRANSIT				-62.00	-74.88	
coef_calib_distance_KNR_TRANSIT	-0.08000	-0.05000	-0.08000	-0.085	-0.07500	-0.1600
coef_calib_distance_PNR_TRANSIT	-0.0160	-0.01000	-0.01600	-0.017	-0.01500	-0.0320
coef_calib_distance_TNC_TRANSIT	-0.0160	-0.01000	-0.01600	-0.017	-0.01500	-0.0320
coef_calib_distance_WALK_TRANSIT	-0.0160	-0.01000	-0.01600	-0.017	-0.1500	-0.0320
coef_calib_escorttour_BIKE				-1.258		
coef_calib_escorttour_KNR_TRANSIT				-5.839		
coef_calib_escorttour_PNR_TRANSIT				-5.839		
coef_calib_escorttour_TNC_TRANSIT				-5.839		
coef_calib_escorttour_WALK				-1.258		
coef_calib_escorttour_WALK_TRANSIT				-5.839		
coef_calib_parkingconst_DRV_TRANSIT	1.280	0.8000	1.280	1.360	1.200	1.920
coef_calib_parkingconst_WLK_TRANSIT	0.6400	0.4000	0.6400	0.7650	0.9000	0.9600
coef_calib_probikedistrict_BIKE	1.552	1.552	1.552	1.552	1.552	1.552
coef_calib_civtebikeownership_BIKE	1.000	1.000	1.000	1.000	1.000	1.000