GREATER VANCOUVER REGIONAL TRAVEL MODEL PHASE 3

Development and Validation Report

Greater Vancouver Regional Travel Demand Model Phase 3 Development and Validation Report

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Introduction

The report documents the development, calibration, and validation of the Greater Vancouver Regional Travel Model (RTM) Phase 3, initially released in March 2017. The RTM Phase 3 (RTM3) the range of policy options the model can evaluate with new features and improved Phase 2 model components.

Data Sources

The following section describes the major data sources used for RTM3 estimation, validation, and calibration.

Trip Diary

The 2011 Metro Vancouver Regional Trip Diary survey was the primary data source for RTM3 model estimation. This household survey contains records for over 20,000 households in the region with detailed information on the household, including income and auto-ownership, the persons residing the in the household, including age and employment status, and the trips made by all household residents, including purpose and mode. The household survey was used to estimate most demand-side models from socio-economic segmentation through mode choice/distribution. The household survey methodology report is available here: Trip Diary

Screenline Survey

Traffic count data from the 2011 Regional Screenline Survey was also used in model estimation and calibration. Two weeks of traffic count data were collected at each of 109 stations forming 32 screenlines during the fall of 2011. Vehicle occupancy and classification by vehicle type were manually collected on a single day at a subset of these stations as well. The screenline survey report is available here: Screenline Report

Population and Employment

Metro Vancouver Planning staff provided land use and socio-demographic data sets at the Traffic Analysis Zone (TAZ) level for the base year (2011) and future years (2030, 2045). The household, population, and employment totals from the 2011 data set were used to estimate models.

This data set includes population totals for the following age categories:

- 0 to 4 years
- 5 to 12 years
- 13 to 17 years
- 18 to 24 years
- 25 to 34 years

- 35 to54 years
- 55 to 64 years
- 65 years and above

Households by number of occupants:

- 1
- 2
- 3
- 4+

And employment by the following categories:

- Construction and Manufacturing
- Finance, Insurance, and Real Estate (FIRE)
- Transportation, Communication, Utilities, and Wholesale
- Retail
- Business and Other Services
- Accommodation, Food, Information (e.g. publishing), Culture
- Health, Education, and Public Administration

Digital Road Atlas

The Provincial Digital Road atlas was used to comprehensively update road networks. Documentation for the Digital Road Atlas can be found here: DRA. A methodology report for the network update can be found in Appendix A.

Parking Prices

Parking price data was collected specifically for RTM3 development. This dataset includes information on parking rates and capacity across Metro Vancouver and the Fraser Valley. The data was compiled for two types of parking, on-street and off-street. A detailed description of this dataset is available in the parking model section of this report.

Data Preparation

Extensive data preparation was required prior to submodule re-estimation.
The land use data for all analysis years had to be modeled at the new refined 1,700 TAZ level. Planning staff from Metro Vancouver provided and updated demographic data set for 2011 prior to RTM3 submodule re-estimation.

TRIP DIARY RE-WEIGHTING

The household survey data is one of the main sources of data for the development of the RTM's sub-model. The 2011 Household survey was used for developing Phases 2 and 3 models; however, the data was re-weighted for models' estimation and calibration of RTM3.

The weighting factors used in the development of Phase 2 were based on the size of the household, and the age and gender of each person. These factors did not take into consideration the household income which is an important segmentation variable within the modelling framework. In addition, the household survey data is biased towards a higher transit mode share and since the weighting factors were developed only based on socio-economic controls, Phase 2 results and the corresponding observed travel statistics were not consistent. As such, multiple re-weighting and adjustments for the estimation/calibration of some sub-models were needed. These adjustments violated the original weighting factors and created inconsistencies between the weights at different stages of the model.

Therefore, in RTM3, one consistent set of weights was developed for the estimation and calibration of all sub-models. The weights take into account socio-economic controls (household size, household income, and person age and gender) and aggregate travel statistics (total number of auto and transit trips by sub-areas). The socio-economic controls are obtained from the 2011 census data, while the aggregate travel statistics are obtained from the 2011 screenline survey data. Because of sample size considerations the data is expanded at a reasonable aggregate level (52 sub-regions).

MISSING INCOME IMPUTATION

Some households did not respond to the income level question in the household survey. In Phase 2 these records were either removed from estimation data sets or included as a separate category but not applied in the model. For RTM3 the missing records for household income were imputed. A number of different classification approaches were attempted, including logistic regression and k-means clustering. Ultimately two multinomial logistic regression models were selected: one for households that answered the number of vehicles question, and one for households that did not answer the question. Other variables included the number of household workers and students, the dwelling type, the distance to the CBD and household transit accessibility. These models were applied and allowed all household records to be used in the model estimation.

SKIM BLENDING

Skim blending methods were updated to incorporate the additional PM peak hour assignments and directionality for production/attraction level estimation. Modules that used two skims (AM and MD) now require six skims, AM, MD, and PM in both the inbound and outbound directions. These blends were estimated from the household survey.

Modeling Process

This section documents the modeling process as implemented in the RTM3

Model Years

At the time of initial release RTM3 had demographic forecasts and transportation networks to allow for travel forecasts for the following years: 2011, 2030, and 2045

Version 3.1 released in December, 2017 added demographic data and transportation networks for 2016, while further land use forecasts for years 2035 and 2050 are under preparation by Metro Vancouver planning staff.

Trip Purposes

The RTM3 estimates travel demand for nine travel sub-markets. These sub-markets include the following home-based trip purposes:

- Work (HBW)
- University (HBU)
- School (HBSCH)
- Escorting (HBESC)
- Shopping (HBSHOP)
- Personal Business (HBPB)
- Social and Recreational (HBSOC)

And the following non-home-based trip purposes:

- Work (NHBW)
- Other (NHBO)

These categories are consistent with the data reported in the 2011 Trip Diary.

Peak Periods

RTM3 generates household and freight travel demand for a typical 24 hour fall weekday. Three peak hours are extracted from the 24-hour demand and assigned to the auto and transit networks to determine travel impendences. These peak hours include:

- Morning (AM) 07:30 to 08:30
- Mid-day (MD) 12:00 to 13:00
- Afternoon (PM) 16:30 to 17:30

The AM and PM peak hours were determined through analysis of the 2011 trip diary and the AM and MD hours were set to be consistent with the Phase 2 release.

GEOGRAPHIES

Traffic Analysis Zones (TAZs) are the principal geography used in RTM3. RTM3 increased the number of TAZs to 1700 from 641 in Phase 2. Development of the new TAZ system is documented in Appendix B. Additional ensembles, or groups of TAZs, are defined at a variety of geographic scales, including the municipal level (GM) and the sub-regional superzone level (GY). The GY is the primary geographic level used for model validation. Maps of the TAZ system and the GY ensemble are available at the end of this section.

MODEL STRUCTURE

The structure and user operation of RTM3 changed substantially from Phase 2. RTM3 allows the user to create a databank and define a year for each model run. The following is a list of RTM3 sub-modules.

- <u>Create Scenarios</u>: set the modeled year and networks based on user input from the model's home screen
- <u>Data Import</u>: Import all of the required data for the model run
- <u>Data Generation</u>: Create the data required for the model run that is dependent on user's inputs. For instance, accessibility measures require the user's transportation networks and may change from run to run.
- <u>Socio-economic segmentation</u>: The model estimates the number of workers and the income category each household belongs to.
- <u>Vehicle availability</u>: This submodule extends the socio-economic segmentation submodule to add the number of vehicles available for each household. Vehicle availability is defined as the lesser of number of autos owned or driving age residents in the household.
- <u>Trip Productions</u>: This submodule estimates trip-making at the production (household) end of the trip
- <u>Trip Attractions</u>: This submodule estimates trip-making at the attraction (or non-home) end of the trip
- <u>Mode/Destination Choice</u>: Trip mode and destination is now estimated jointly in this submodule
- <u>Truck Model</u>: This module estimates the amount of truck travel in the region
- <u>Auto assignment</u>: Auto and truck trips for the three peak hours are assigned to the road network
- <u>Transit assignment</u>: Transit trips for the three peak periods are assigned to the transit networks
- <u>Data Export</u>: Commonly used model outputs are exported to the trip summaries database and comma separated value (csv) format

Major Changes for Phase 3 Release

A number of features were added or subtracted from the RTM between the Phase 2 and Phase 3 releases. The following features were added:

- TAZs. The number of traffic analysis zones (TAZs) was extended from 641 in Phase 2 to 1,700 in Phase 3 (see Figure I-01)
- Auto and transit networks. Networks were redeveloped using the GeoBC Digital Road Atlas (DRA). The new networks were required to allow for assignment of the refined TAZ system
- VDFs. The form of the volume delay functions (VDFs) was simplified and additional VDFs defined for the representation of delay at merging/weaving sections and signalized intersections
- Socio-economic segmentation. Modeule was moved from cross-classification to an econometric form
- Joint mode choice/distribution. Distribution now incorporates the mode-choice logsum and distance terms to improve response to impedances – particularly monetary impedances. Additionally, mode choice now operates at the production/attraction level (instead of origin/destination). This improves directionality in the peak hour time slices
- West Coast Express (WCE) transit sub-mode. West Coast Express was moved out of the 'rail' category to better represent it's availability, fare structure, and level-of-service attributes
- Park-and-ride: Updated to allow for optimal lot choice and integrated within the mode choice model for home-based work trips. Park-and-ride was previously run after mode choice to segment transit trips
- Econometric estimation of values of time (VOTs): unlike in previous versions of the model, the mode choice parameters produced reasonable VOT estimates, allowing direct use and negating the need to assert VOTs.
- Econometrically estimated bus/rail perception factors: the mode choice model now includes different in-vehicle travel time parameters between bus and rail. This stems from the observation that, all things being equal, people usually prefer using rail over bus.
- PM peak hour auto and transit assignments in addition to the AM and MD assignments that were available in RTM2
- A number of new components to improve the estimation of transit impedances including,
    - Congested/capacitated transit: transit riders now experience disutility from crowding and additional travel time from pass-ups. Formerly transit was assigned by demand as opposed to constrained demand. This change brings transit assignment in line with the approach for auto-assignment. The feature can be disabled by the user
    - Journey levels assignment: This tool ensures that the transit mode chosen in mode choice (West Coast Express, Bus or Rail) is respected in the transit assignment without the need for distorting impedance factors.

- Fare skimming: this feature replaces the fare matrix and allows fare to be read from the network during the assignment process. This allows for more accurate transit fare representation and increased fare scenario modeling options
- Transit Time Factors (TTFs) and dwell time functions. TTFs were updated to better represent transit delay from user activity.

- Traffic assignment by value of time (VOT) group. 12 total classes are assigned. Five classes for SOV, five classes for HOV, one class each for LGV and HGV. The Phase 2 model assigned work trips by three income classes and combined all other trips were combined by mode.
- Passenger Car Equivalent (PCEs): trucks and buses are weighted higher (x1.5 to x2.5) than private vehicles in the traffic assignment to improve the representation of their effect on delay on the auto network
- Parking price model: determines whether TAZ has paid parking and if so, estimates the 2-hour and 8-hour parking rates
- Various adjustment factors were eliminated or reduced, including the demand adjust for the AM peak hour.
- Model implementation code was re-written to reduce runtimes and improve the ability of users to read, modify, and extend the model.

Two model elements were subtracted in the move from RTM2 to RTM3 in order to reduce run times and improve reliability:

- The school bus mode was eliminated from the mode choice submodule
- The model is no longer packaged with pre-run scenarios

Iterative Estimation Process

The RTM3 model estimation was performed iteratively. Modules were first estimated using initial skims based on RTM Phase 2. The RTM3 was developed with the new module forms and coefficients and then run to produce new skims. These skims were then fed back to the module estimation process to update the estimated parameters and coefficients. This approach allowed the model estimation to move incrementally towards optimal factors.

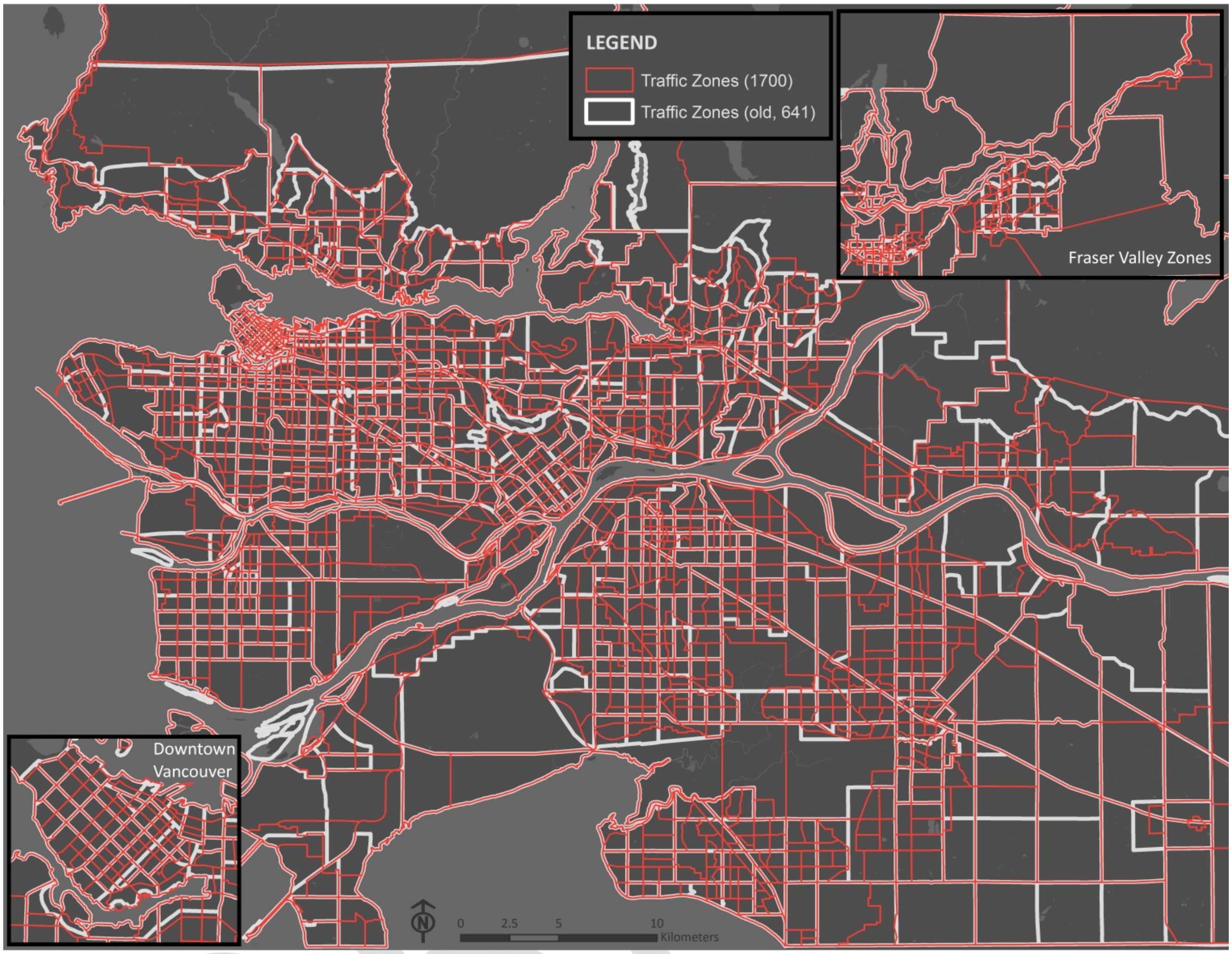

Figure I-01: Traffic Analysis Zones

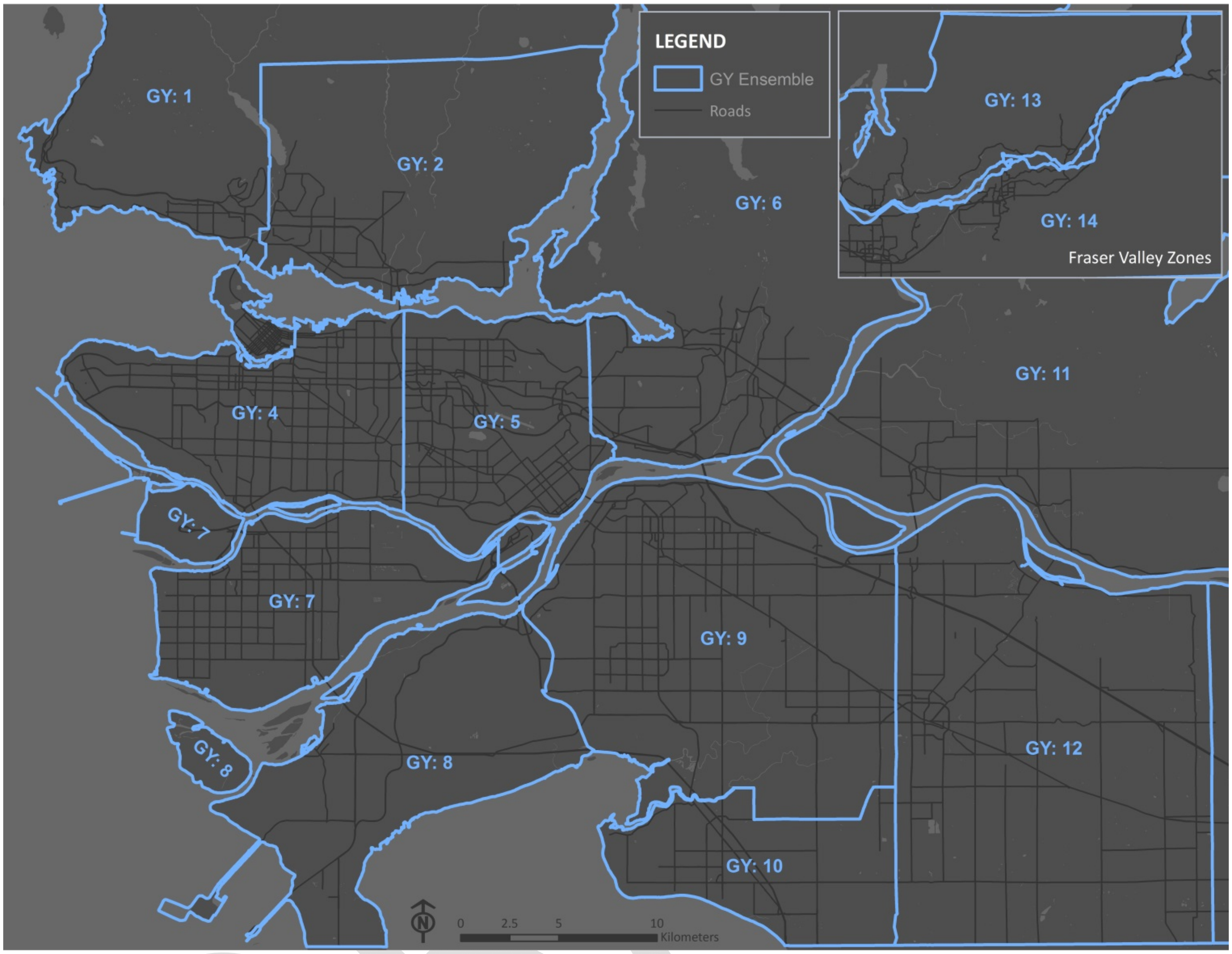

Figure I-02: GY Ensemble

1: Workers and Income

This sub-module splits households into market segments defined by the number of workers and income level. Households are classified by the number of workers present:

- Zero (0)
- One (1)
- Two (2)
- Three or more (3+)

Households are placed into one of three income categories based on total household income[1]:

- Low: $0-$50,000
- Medium: $50,000 - $100,000
- High: $100,000+

The Phase 2 model assigned households to these market segments by cross-classification. That is, the share of households for each worker and income level segment was derived from the 2011 household survey for a given geography and applied to the input model socioeconomic data for all model years. The drawback of this structure is that it does not allow the market segment shares to change on the basis of land use and demographic changes. It also limits the number of variables that can be used for segmentation due to sample size restrictions.

A more appealing approach would be to derive the number of workers in each household and then predict the income level based on the number of household workers within a single model. These models would also incorporate a number of regional transportation-related and socio-economic variables to create a linkage between the transportation system and demographic shifts. This was the approach taken for the RTM3.

The 2011 Trip Diary is the main data source used for estimating this sub-module. Other geographic-specific information, such as distance from household location to different town centres and other transportation variables, was extracted from the RTM and joined to the estimation dataset. Some of these geographic variables were aggregated at the TAZ level and others were aggregated at sub-regional levels (a higher level of aggregations than TAZs).

Model Structure

Workers and income was specified as a nested-logit model where the number of workers per household is classified at the upper level and the income level of the household is classified at the lower level. The primary reason for this structure is that the two household characteristics are almost inseparable as the number of workers largely defines household income; there are few two-worker households in the low income category and few zero-worker households in the high income category (primarily households with a retired head of household).

[1] One-person households that reported incomes in the $25,000 - $50,000 range were classified as medium income and one-person households that reported incomes in the $75,000 - $100,000 range were classified as high income.

While it was assumed that workers would be in the upper level nest, a model was estimated with income in the upper nest that failed its statistical tests (the nesting parameter or theta was not within the required range - between 0 and 1). As such, household workers in the upper level nest and income category in the lower level nest, as presented in Figure 1-01, was deemed the preferred modelling structure.

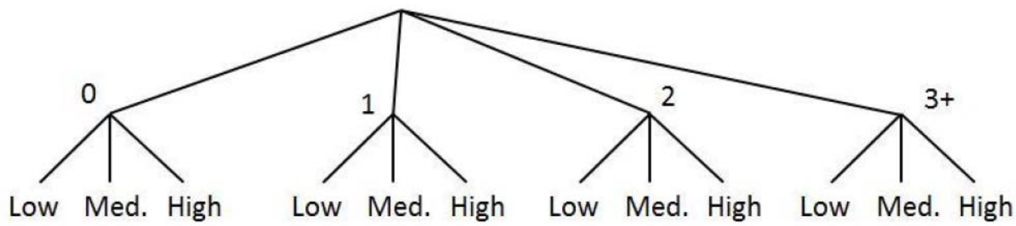

Figure 1-01: Workers and Income Model Structure.

Households of all sizes could be classified as low, medium, or high income. That is, any of the income categories could apply to any given household. However, every level of workers is not available to every household because the number of household workers cannot exceed the number of household residents. For instance, a one person household can have either zero or one worker; it cannot be in the two or three-or-more worker categories. These infeasible combinations were screened out during model estimation and implementation.

Model Form

The systematic utility of each of the lower level nest alternatives 'i' can be defined in a linear form as:

$$V_i = ASC + \sum_{j}^{m} \beta_j \cdot x_j$$

Where:

'ASC' is the alternative-specific constant,
'x_j' represents a set of 'm' explanatory variables and
'β_j' represents their corresponding estimated coefficients

These utilities are used directly for calculating the conditional choice probabilities of each alternative within each of the nests as follows:

$$P_{i|n} = \frac{e^{V_i}}{\sum_j^k e^{V_j}}$$

Where 'k' is the number of alternatives in a given nest 'n'. The utilities of each of the upper level nest alternatives (composite alternatives) or the 'logsums', are given by:

$$V_n = \theta \cdot \log(\sum_{j}^{k} e^{V_j})$$

Where ‘θ’ is the structural or tree coefficient of nest ‘n’ and the sum is taken over its elementary alternatives. The logsums are used to define the probabilities of the higher level nest alternatives ‘n’:

$$P_n = \frac{e^{V_n}}{\sum_j^c e^{V_j}}$$

Where ‘c’ is the number of nests. Finally, the probability of the lower level nest alternatives ‘i’ can be defined as follows:

$$P_i = P_{i|n} * P_n$$

Model Examination

The final model specification includes variables such as large household size (very important for 2 and 3+ worker households), proportion of seniors in a zone (generally having a negative correlation to workers), proportion of children in a zone, distance to CBD and/or town centres, and geographic binary variables.

Although the use of geographic binary variables was minimized, the Downtown Eastside (DTES) indicator had strong explanatory power for low-income and zero-worker households whereas the North Shore indicator explained the above average number of smaller households with high income (presumably due to high number of retirees).

Employment characteristics of the household’s TAZ had an impact as well, though it must be remembered that the employment mix only refers to the household location and not the typical work location of any of the working members of the household. Figure 1-02 shows the variables’ definitions and the estimated coefficients in the final model. All variables’ coefficients are statistically significant at the 95% confidence level and estimated with the expected sign and relative magnitude. The reported rho-squared (w.r.t. the null model) value is 0.12. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Utility Function	Coefficient	t-Statistics
Alternative Specific Constant	Medium Income - 0 Worker	-0.55	-10.15
Alternative Specific Constant	High Income - 0 Worker	-2.15	-23.35
Alternative Specific Constant	Low Income - 1 Worker	1.16	3.02
Alternative Specific Constant	Medium Income - 1 Worker	1.92	4.97
Alternative Specific Constant	High Income - 1 Worker	1.26	3.22
Alternative Specific Constant	Low Income - 2 Workers	3.05	4.59
Alternative Specific Constant	Medium Income - 2 Workers	3.51	5.29
Alternative Specific Constant	High Income - 2 Workers	3.93	5.88

Variable	Utility Function	Coefficient	t-Statistics
Alternative Specific Constant	Low Income - 3+ Workers	1.26	2.23
Alternative Specific Constant	Medium Income - 3+ Workers	2.16	3.90
Alternative Specific Constant	High Income - 3+ Workers	3.15	5.65
Percentage of Population 18-24	Medium Income - 0 Worker High Income - 0 Worker	3.89	2.87
Percentage of Population 18-24	Low Income - 0 Worker Low Income - 1 Worker Low Income - 2 Workers Low Income - 3+ Workers	3.18	6.34
Percentage of Population 18-24	Low Income - 2 Workers Medium Income - 2 Workers High Income - 2 Workers Low Income - 3+ Workers Medium Income - 3+ Workers High Income - 3+ Workers	-3.93	-2.91
Large Household (>2) - Dummy	Low Income - 2 Workers Medium Income - 2 Workers High Income - 2 Workers	0.86	5.87
Very Large Household (>3) - Dummy	Medium Income - 3+ Workers High Income - 3+ Workers	0.60	6.98
Very Large Household (>3) - Dummy	Low Income - 0 Worker Medium Income - 0 Worker High Income - 0 Worker	-2.93	-5.97
Log Distance to the Closest Town Centre (only for households outside the CBD)[2]	Low Income - 1 Worker Medium Income - 1 Worker High Income - 1 Worker	-0.05	-2.66
Percentage of Population >=65 (only in the North Shore)	High Income - 0 Worker High Income - 2 Workers High Income - 3+ Workers	3.16	9.43
Downtown Eastside - Dummy[3]	Low Income - 0 Worker Low Income - 1 Worker Low Income - 2 Workers Low Income - 3+ Workers	0.93	5.89
Log Employment Density	Low Income - 1 Worker Medium Income - 1 Worker High Income - 1 Worker	0.09	2.81

[2] The CBD is defined as all TAZs within GY3
[3] The Downtown Eastside is defined as the following TAZs: 22480, 22620, 25020, 25090, 25100, 25110, 25120, 25130, 25160, 25170, 25180, 25190, 25200, 25210, 25220, and 25230

Variable	Utility Function	Coefficient	t-Statistics
Log Employment Density	Low Income - 3+ Workers Medium Income - 3+ Workers High Income - 3+ Workers	-0.23	-3.54
Percentage of Population 0-17	Low Income - 2 Workers	-7.26	-8.32
Percentage of Population 0-17	Medium Income - 2 Workers	-3.25	-4.14
Percentage of Population >=65	Low Income - 1 Worker Medium Income - 1 Worker High Income - 1 Worker	-8.21	-6.10
Percentage of Population >=65	Low Income - 2 Workers Medium Income - 2 Workers High Income - 2 Workers	-11.18	-6.20
Percentage of Population >=65	Low Income - 3+ Workers Medium Income - 3+ Workers High Income - 3+ Workers	-8.48	-5.51
Log Distance to the CBD	Low Income - 1 Worker Medium Income - 1 Worker High Income - 1 Worker	-0.09	-2.61
UBC/SFU - Dummy[4]	Low Income - 0 Worker Medium Income - 0 Worker High Income - 0 Worker Low Income - 1 Worker Medium Income - 1 Worker High Income - 1 Worker	1.84	3.60
Log Population Density (only for households outside the CBD)	High Income - 0 Worker High Income - 1 Worker High Income - 2 Workers High Income - 3+ Workers	-0.08	-6.23
Log Distance to the Closest Town Centre (only for households outside the CBD)	High Income - 0 Worker High Income - 1 Worker High Income - 2 Workers High Income - 3+ Workers	0.10	8.48
North Shore - Dummy[5]	Low Income - 0 Worker Low Income - 1 Worker Low Income - 2 Workers Low Income - 3+ Workers	-0.23	-3.41
North Shore - Dummy	Low Income - 3+ Workers Medium Income - 3+ Workers High Income - 3+ Workers	-0.62	-3.23
theta	Nesting structure	0.56	6.38

Figure 1-02: Workers and Income Model Results

[4] UBC/SFU is defined as the following TAZs: 21010, 21020, 21030, 21060, 21070, 21100, 21120, 21130, and 27170
[5] The North Shore is define as all TAZs in GY1 and GY2

Model Validation

A cross-validation test was conducted to assess the estimated model's performance at the disaggregate level (household level). The model was re-estimated using a stratified random sample of the full dataset (80%) and then applied to a hold-out sample (20%). The observed shares and the resulting aggregate shares predicted by the model are shown in Figure 1-03 below. In general, the model predicts the observed household segment shares with slight variations. This result suggests that the model was reasonably specified and that the model estimation was not performed on a dataset uniquely well-suited to returning the desired results (i.e., no signs of overfitting).

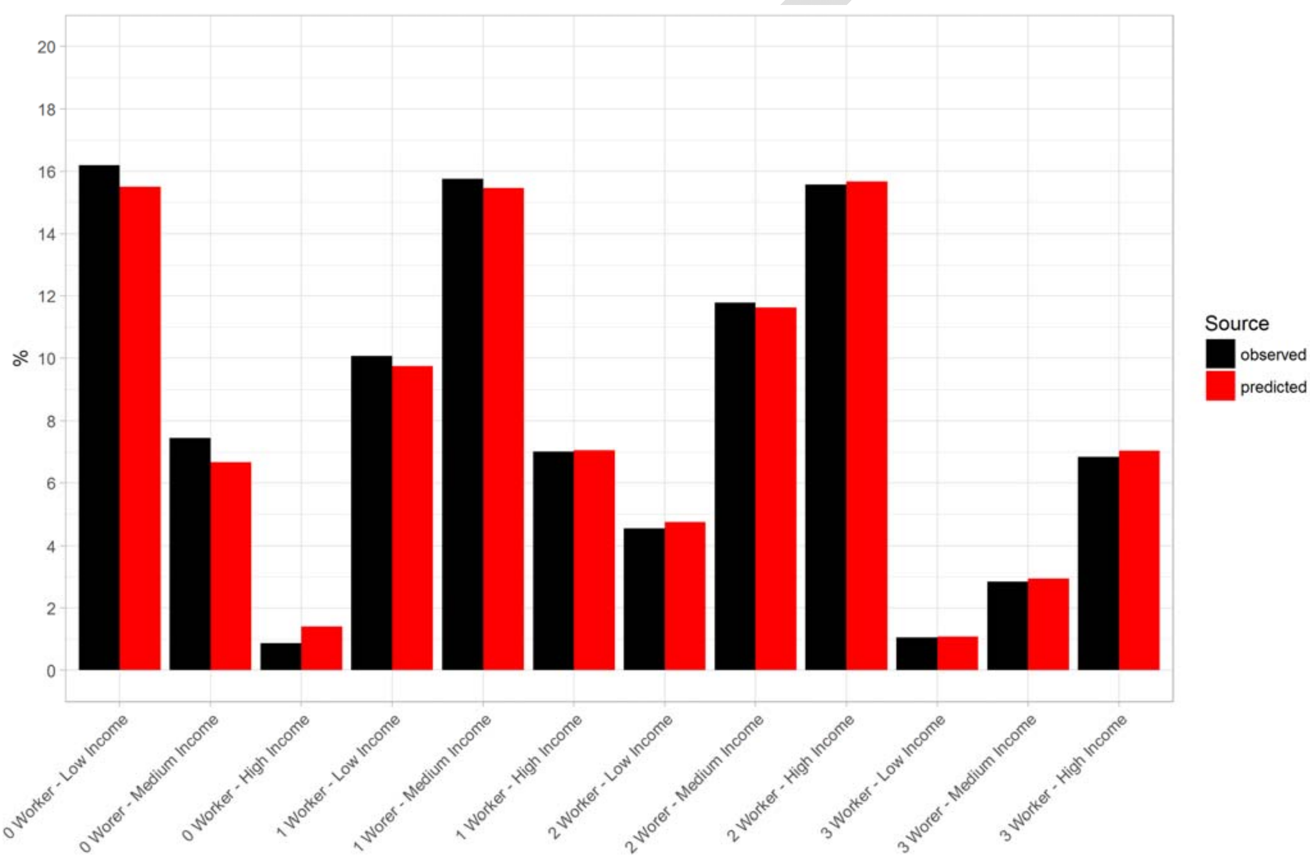

Figure 1-03: Workers and Income Cross-validation Results

Variation of the model estimated household segments from the observed data increased when the model was applied at the aggregate (TAZ) level. This result is not surprising; it is a very frequent occurrence that when a full implementation of the households using aggregate land use information takes place, the resulting distribution of households by household size is expected to be slightly different from that represented by the expanded travel survey. Nonetheless for most alternatives the variation is within 2%. Figure 1-04 shows the model predictions at the aggregate level compared to the observed shares.

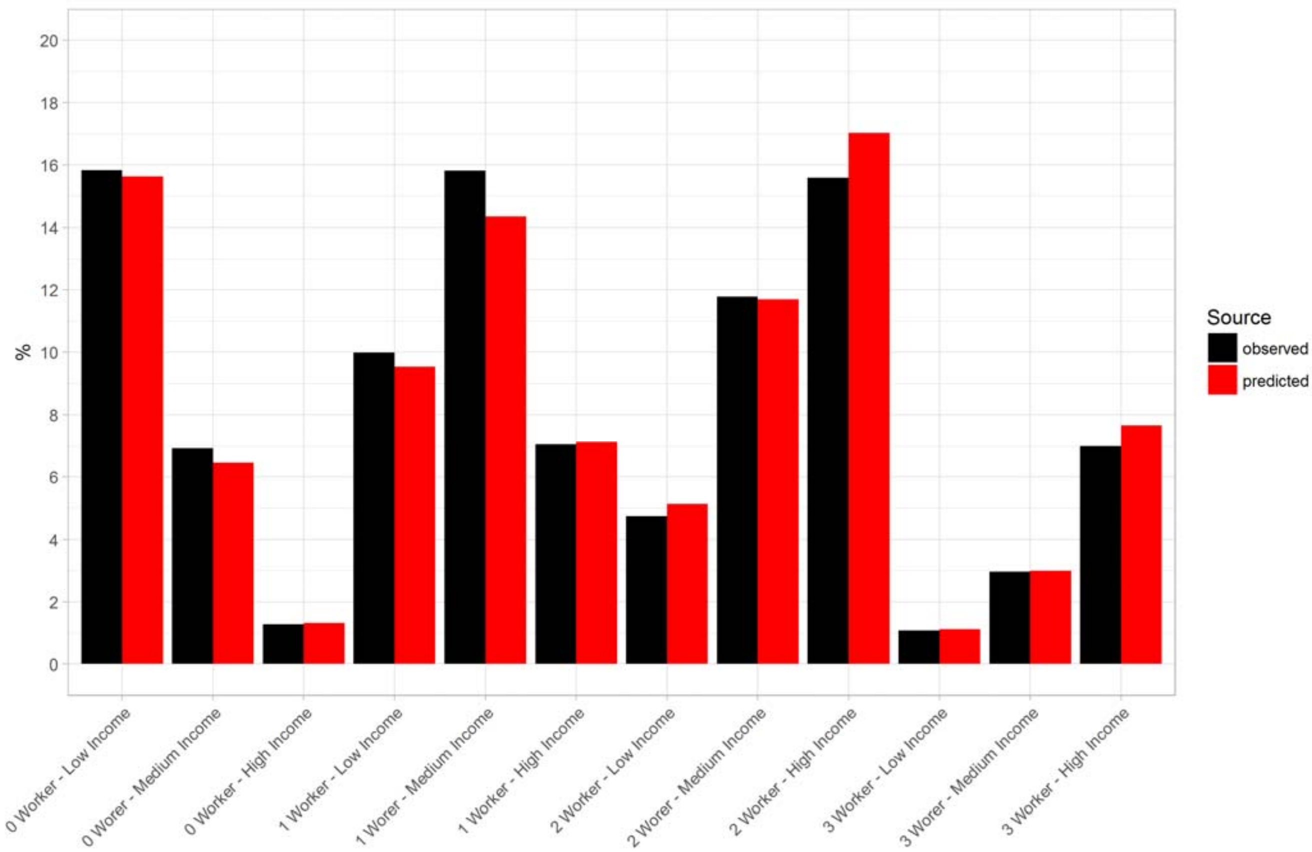

Figure 1-04: Workers and Income Aggregate Level Implementation Results

2: Vehicle Availability

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This sub-module splits households into market segments defined by the number of available household vehicles. The long-term choice to own a vehicle impacts the short-term mode choice decision and thus the ability to accurately predict the short-term mode choice of a trip requires knowledge of the trip-maker's vehicle availability.

Unlike vehicle ownership models, such as the model implemented for Phase 2, this vehicle availability model was estimated after constraining the number of household vehicles to the number of licensed drivers in the household. For example, a household with two licensed drivers and three vehicles would be classified as having two vehicles available. In the RTM3 households can have one of the following vehicle availability classifications:

- Zero available vehicles (0)
- One available vehicle (1)
- Two available vehicles (2)
- Three or more available vehicles (3+)

The 2011 Trip Diary is the main data source used for estimating this sub-module. Other geographic-specific information, such as distance from household location to different town centres and other transportation variables, was extracted from the RTM and joined to the estimation dataset. Similarly, other transportation (e.g. accessibility and car share availability) and land use (e.g. density) variables were included. Model variables were aggregated at the TAZ level. Household variables such as size, number of workers, and income level were available at the household level.

Model Structure

This sub-module was specified as a multinomial logit model with four alternatives: 0-car, 1-car, 2-cars, and 3+cars, as shown in Figure 2-01. The 0 car alternative was set as the reference alternatives.

During estimation a variety of nested-logit model structures was explored including:

- 0-car in one nest and 1+ cars in another nest
- 0-car in one nest, 1-car in another nest, and 2+ cars in a third nest

All of these nested-logit models failed statistical tests (the nesting parameter or theta was not between 0 and 1).

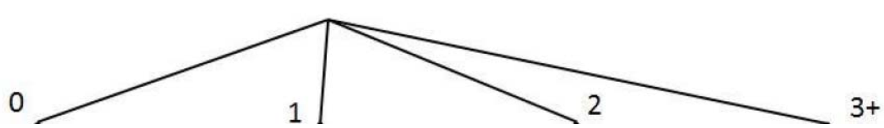

Figure 2-01: Vehicle Availability Model Structure.

Model Form

The model was estimated in alogit 4.2 using the following model formulation.
The systematic utility of each alternative can be defined in a linear form as:

$$V_i = \sum_{j}^{m} \beta_j \cdot x_j$$

Where:

‘x_j’ represents a set of ‘m’ explanatory variables and
‘β_j’ represents their corresponding estimated coefficients.

These utilities are used directly for calculating the choice probabilities of each alternative ‘i’ as follows:

$$P_i = \frac{e^{V_i}}{\sum_j^k e^{V_j}}$$

Where ‘k’ represents the number of alternatives.

Model Examination

Various model specifications were attempted. Figure 2-02 shows the variables’ definitions and the estimated coefficients. Almost all variables’ coefficients are statistically significant at the 95% confidence level and estimated with the expected sign and relative magnitude. The reported rho-squared (w.r.t. the null model) value is 0.40. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Utility Function	Coefficient	t-Statistics
Alternative Specific Constant	1 Car	1.02	2.96
Alternative Specific Constant	2 Cars	-1.95	-5.00
Alternative Specific Constant	3 Cars	-8.74	-12.12
Percentage of Population 0 -24	1 Car	1.29	3.17
Percentage of Population 0 -24	2 Cars	2.97	6.04
Percentage of Population 0 -24	3 Cars	4.23	5.93
Percentage of Population 25 - 54	1 Car	-0.75	-2.36
Percentage of Population 25 - 54	2 Cars	-2.75	-6.85
Percentage of Population 25 - 54	3 Cars	-5.44	-8.59
Household size	1 Car	1.02	17.10
Household size	2 Cars	2.39	34.75
Household size	3 Cars	3.45	20.88
Number of Workers per Household	1 Car	0.73	8.50

Variable	Utility Function	Coefficient	t-Statistics
Number of Workers per Household	2 Cars	2.15	20.38
Number of Workers per Household	3 Cars	3.64	12.84
Interaction Term Household Size and Number of Workers	1 Car	-0.40	-10.97
Interaction Term Household Size and Number of Workers	2 Cars	-0.81	-19.65
Interaction Term Household Size and Number of Workers	3 Cars	-0.87	-10.78
Low Income Level - Dummy	1 Car	-1.20	-19.94
Low Income Level - Dummy	2 Cars	-1.74	-23.79
Low Income Level - Dummy	3 Cars	-1.92	-16.19
High Income Level - Dummy	1 Car	0.52	5.66
High Income Level - Dummy	2 Cars	1.20	12.21
High Income Level - Dummy	3 Cars	1.77	15.72
Log Distance to the CBD	1 Car	0.10	2.02
Log Distance to the CBD	2 Cars	0.17	2.97
Log Distance to the CBD	3 Cars	0.16	2.19
Log Distance to the Closest Town Centre	1 Car	0.01	0.88
Log Distance to the Closest Town Centre	2 Cars	0.09	4.04
Log Distance to the Closest Town Centre	3 Cars	0.11	3.27
Log Total (Employment + Population) Density	1 Car	-0.17	-4.03
Log Total (Employment + Population) Density	2 Cars	-0.40	-8.46
Log Total (Employment + Population) Density	3 Cars	-0.49	-8.59
Log Relative Accessibility (Auto/Transit)	1 Car	0.04	2.55
Log Relative Accessibility (Auto/Transit)	2 Cars	0.07	4.30
Log Relative Accessibility (Auto/Transit)	3 Cars	0.10	5.33
Car Share Level within 500m	1 Car	-0.26	-5.89
Car Share Level within 500m	2 Cars	-0.49	-9.09
Car Share Level within 500m	3 Cars	-0.60	-7.73

Figure 2-02: Vehicle Availability Model Results

Household size and the number of workers per household are positively correlated with higher number of vehicles available. As expected, higher income households have a higher propensity to have more vehicles available compared to low income households. Households that are located closer to the CBD or town centres, in denser areas, in areas where the ratio of transit accessibility to auto accessibility is higher, or in the vicinity of car share home zones are less likely to have more vehicles available. Zones with high proportion of young people are less likely to have high vehicle availability, while the opposite is true for TAZs with a high proportion of working-age persons.

Model Validation

A cross-validation test was conducted to assess the estimated model's performance at the disaggregate level (household level). The model was re-estimated using a stratified random sample of the full dataset (80%) and then applied to a hold-out sample (20%). The observed shares and the resulting aggregate shares predicted by the model are shown in Figure 2-03 below. In general, the model predicts the observed vehicle availability segment shares with slight variations (less than 1.8% for each of the 4 alternatives). These results suggest that the model was reasonably specified and that the model estimation was not performed on a dataset that was uniquely well-suited to returning the desired results (i.e., no signs of overfitting).

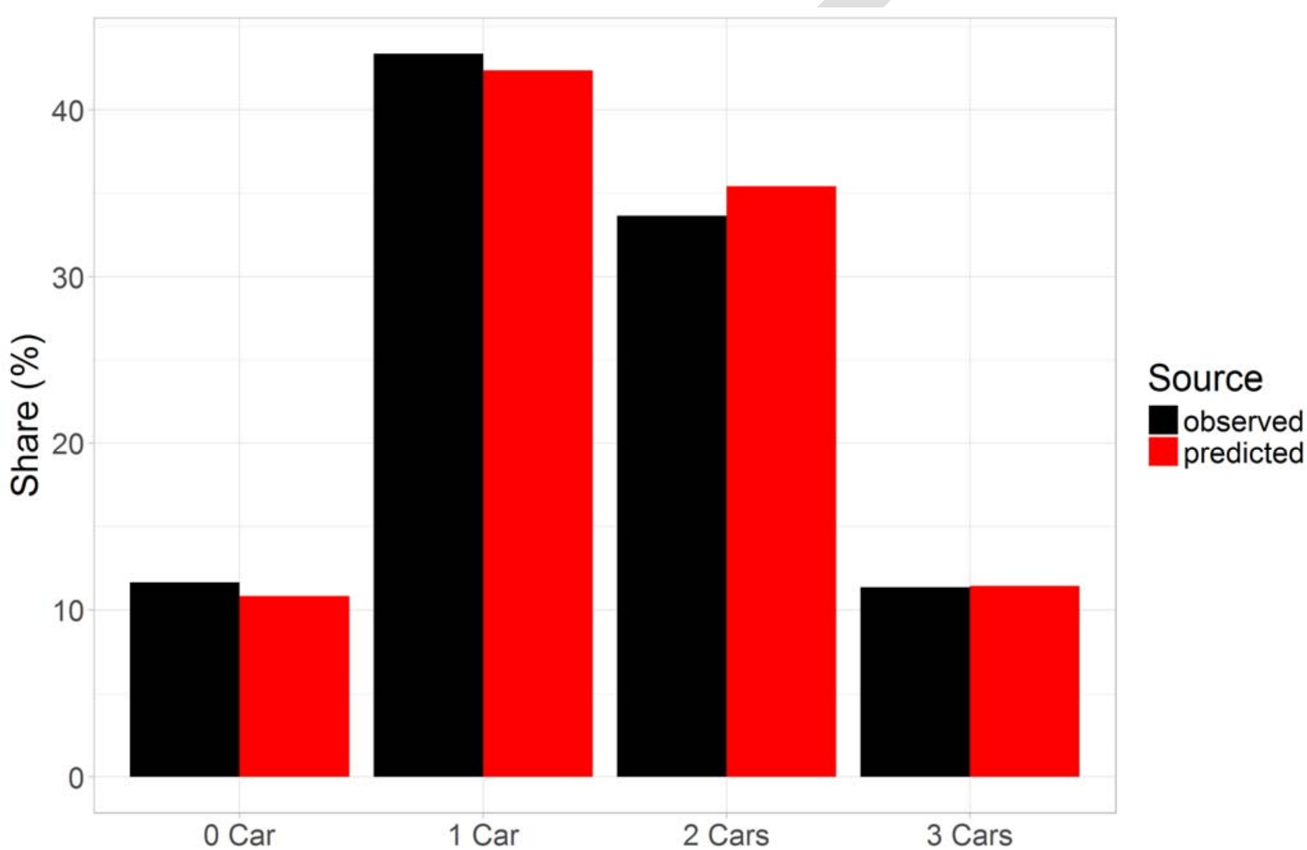

Figure 2-03: Cross-validation Results

Variation of the model estimated vehicle availability segments from the observed data increased when the model was applied at the aggregate (TAZ) level. This result was not surprising; the distribution of households by household size in the TAZ land use data set is different than the distribution from the expanded trip diary.
Nonetheless, for most alternatives, the gap is within 1%, which seems a very reasonable result. Aggregate validation at the GY level is shown in Figure 2-04.

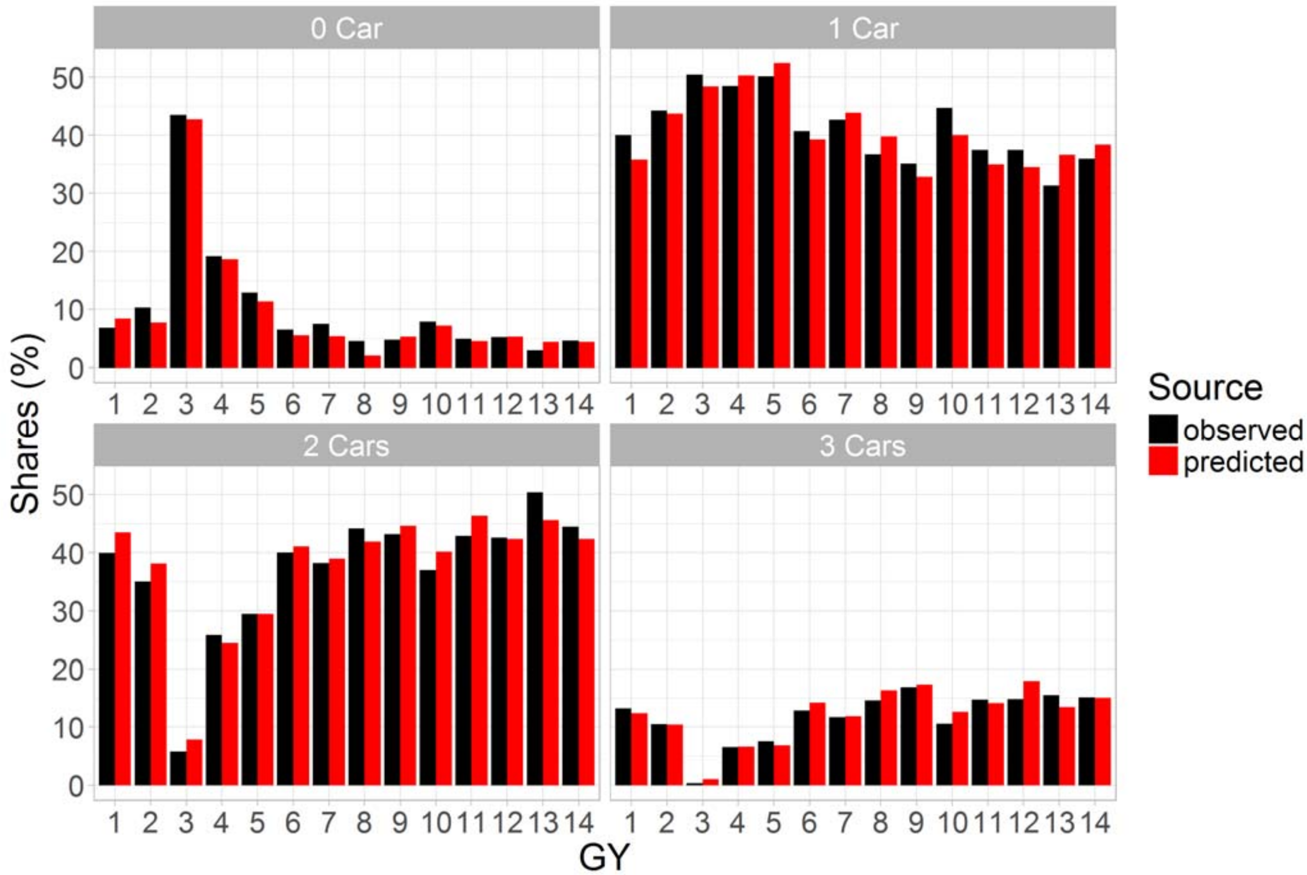

Figure 2-04: Aggregate Validation Results at the GY Level

3: Trip Productions

Trip generation is the demand portion of travel demand modeling and trip productions are the home-end of trip-making. Trip productions have the richest data source from the trip diary and are thus the foundation of the trip generation process in the RTM Phase 3.

This sub-module estimates the daily number of trips generated at the home end for each TAZ by household segment for all households in the region. One trip production model is estimated for each of the nine trip purposes.

Three trip purposes require additional consideration; home-based university, non-home-based work, and non-home-based other. Typical household variables such as household size and income have not reliably predicted home-based university productions in past model implementations. This is likely because many post-secondary students do not live in traditional household arrangements. As such, a TAZ level model based on the presence of university aged population and proximity to universities was estimated for the home-based university purpose.

Non-home-based trip models have two facets; the quantity of these trips is a function of the regional population and these trips occur, by definition, away from the home location. Regional population data is held at the home location. As such, household level models were estimated for the non-home-based trip purposes to estimate regional trip control totals. These models allow non-home-based trip-making to respond to population change.
A second model was estimated for each non-home-based purpose that is used to locate the trips away from home using TAZ attributes such as population and employment characteristics. The number of trips estimated from the TAZ level model is scaled to equal the number of trips estimated from the household level model.
This submodule was estimated using the trips reported in the 2011 Trip Diary.

Model Structure

The trip production models were estimated as linear regression models with categorical variables predicting person trip rates by household segment. Trip rates are estimated by categories of household – Workers/Size/Income. Note that all three of these variables are categorical, in that household workers and household size are capped, and households are binned into income categories.

Not all household segment variables are used in each model. For instance, home-based work trip production rates are based on the number of workers in the household and the household income level. Other trip production models are based on household size (residents) and income level. Household size was found to be highly correlated with the number of household workers so only one of these two variables was used for a given model.

Vehicle availability was found to be highly correlated with income and the addition of that variable did not improve any of the models. All combinations of these household variables were tested in estimation but additional variables were not found to be statistically significant and did not improve test model accuracy. See the household variables used for each trip purpose in Figure 3-01.

The estimated trip rates are applied to all households that match that category. For instance all households with one worker and medium income have the same home-based work trip rate regardless of the number of people in the household or the number of autos available to them.

As mentioned, non-home-based trip purposes have two trip production models each. The first model is estimated and applied at the household level based on household attributes, and used to provide control totals. These models make the non-home-based trip-making responsive to changes in population levels. The second model is at the TAZ level, estimated based on population and employment characteristics, and used to locate the trips away from the home.

Trip Purpose	Included Variables
Home-based Work	Workers, income
Home-based Escorting	Size, income
Home-based Personal Business	Size
Home-based School	Size, income
Home-based Shopping	Size, income
Home-based Social/Recreational	Size, income
Home-based University	18-34 year old population interacted with university accessibility
Non-home-based Work (control total)	Workers, income
Non-home-based Other (control total)	Size, income

Figure 3-01: Variables Used in Each Trip Production Model

Model Form

A linear regression model for each of the nine trip purposes was estimated to forecast trip productions from all TAZs. The model takes the form:

$$y = intercept + \sum_{j}^{m} \beta_j * x_j$$

Where:

‘y’ represents the continuous dependent variable, in this case: $trip\ productions$

‘x_j’ represents a set of explanatory variables and

‘β_j’ represents their corresponding estimated coefficients

Model Examination and Validation

The following section presents the estimated variables and coefficients for the trip production models. Additionally, cross-validation test were conducted to assess the each model’s performance at the disaggregate level (household level)[6]. Each model was re-estimated using a stratified random sample of the full dataset (80%) and then applied to a hold-out sample (20%). The observed trips in the trip diary are compared to the estimated trips at the GY level in the following figures.

[6] Cross-validation for the home-based university, non-home-based work, and non-home-based other trip purposes was performed at the TAZ level. The non-home-based trip purposes tested used the location models as opposed to the control total models.

HOME-BASED WORK

Size	Workers	Income	Productions
*	1	1	1.14
*	2	1	2.04
*	3	1	3.49
*	1	2	1.28
*	2	2	2.43
*	3	2	3.81
*	1	3	1.39
*	2	3	2.39
*	3	3	4.16

Figure 3-02: Home-based Work Trip Production Rates

As noted, household size and number of workers are highly correlated. The inclusion of both variables led to counterintuitive results.

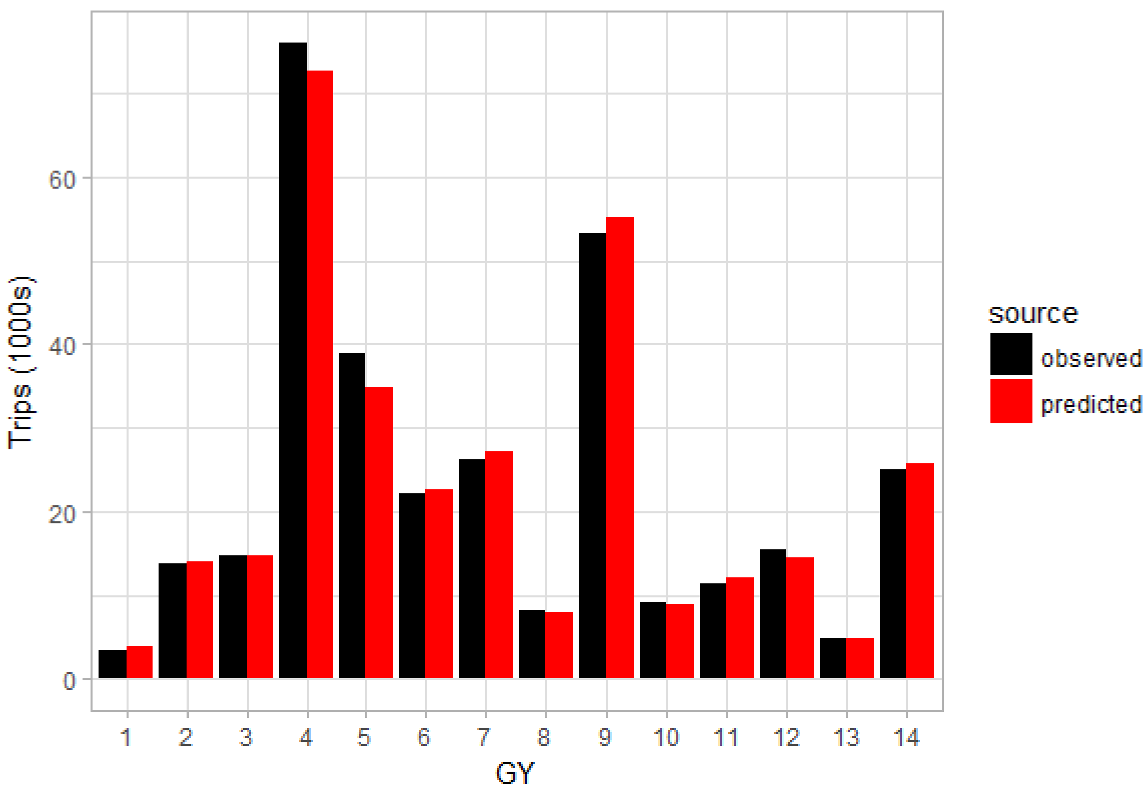

Figure 3-03: Home-based Work Cross-validation Results

HOME-BASED ESCORTING

Size	Workers	Income	Productions
1	*	1	0.06
2	*	1	0.30
3	*	1	0.68
4	*	1	1.55
1	*	2	0.10
2	*	2	0.27
3	*	2	0.72
4	*	2	1.71
1	*	3	0.06
2	*	3	0.23
3	*	3	0.73
4	*	3	1.54

Figure 3-04: Home-based Escorting Trip Production Rates

There is a significant jump in escorting trips between 3 and 4+ person households.

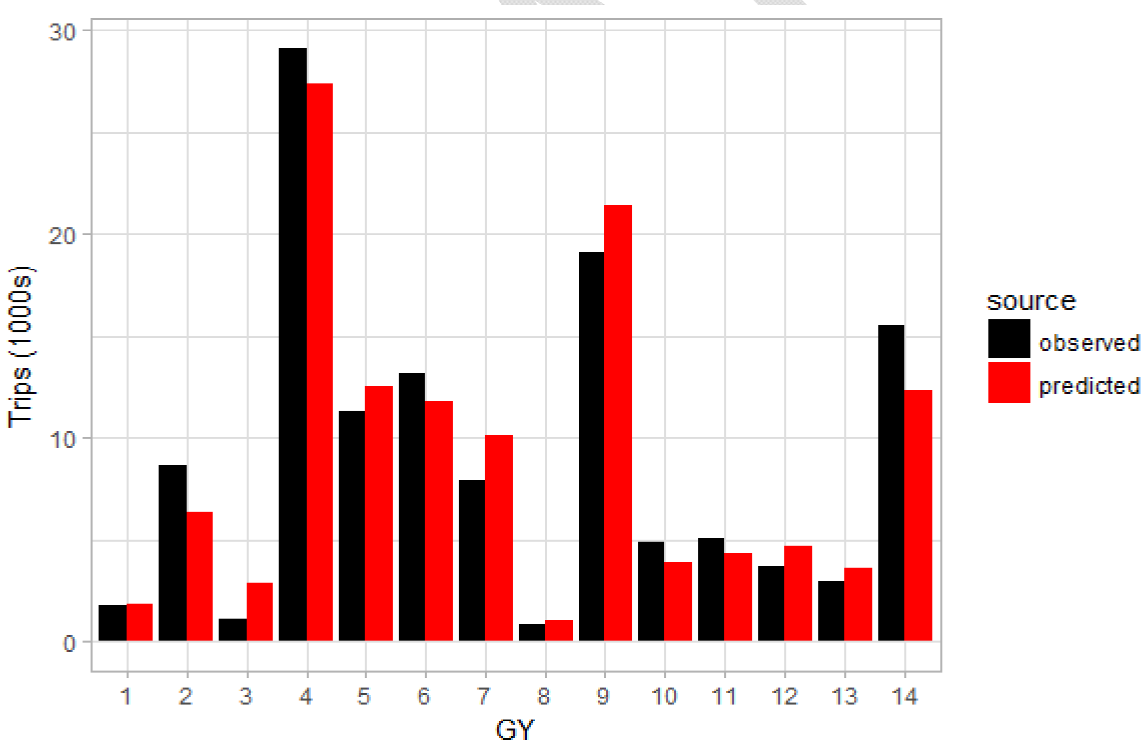

Figure 3-05: Home-based Escorting Cross-validation Results

Home-based Personal Business

Size	Workers	Income	Productions
1	*	*	0.33
2	*	*	0.52
3	*	*	0.52
4	*	*	0.50

Figure 3-06: Home-based Personal Business Trip Production Rates

This trip purpose showed significant variation between the modeled and observed results, possibly because the reported classification of these trips varied considerably between individuals.

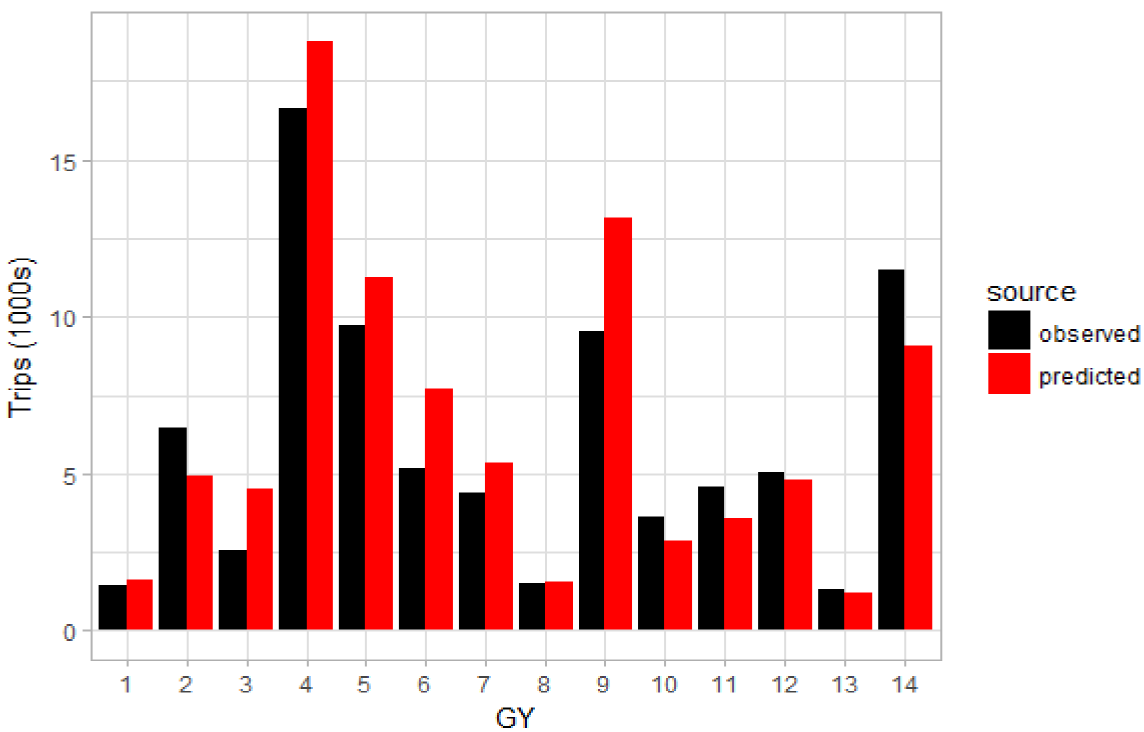

Figure 3-07: Home-based Personal Business Cross-validation Results

HOME-BASED SCHOOL

Size	Workers	Income	Productions
1	*	1	0.00
2	*	1	0.07
3	*	1	0.68
4	*	1	1.78
1	*	2	0.00
2	*	2	0.02
3	*	2	0.43
4	*	2	1.72
1	*	3	0.00
2	*	3	0.01
3	*	3	0.36
4	*	3	1.49

Figure 3-08: Home-based School Trip Production Rates

School trips in RTM3 are for primary and secondary school students, the vast of whom are under 18 years old. It is assumed that these minors would need to live with an adult. Therefore, households of with only one occupant are assumed to be adults and not generate primary and secondary school trips.

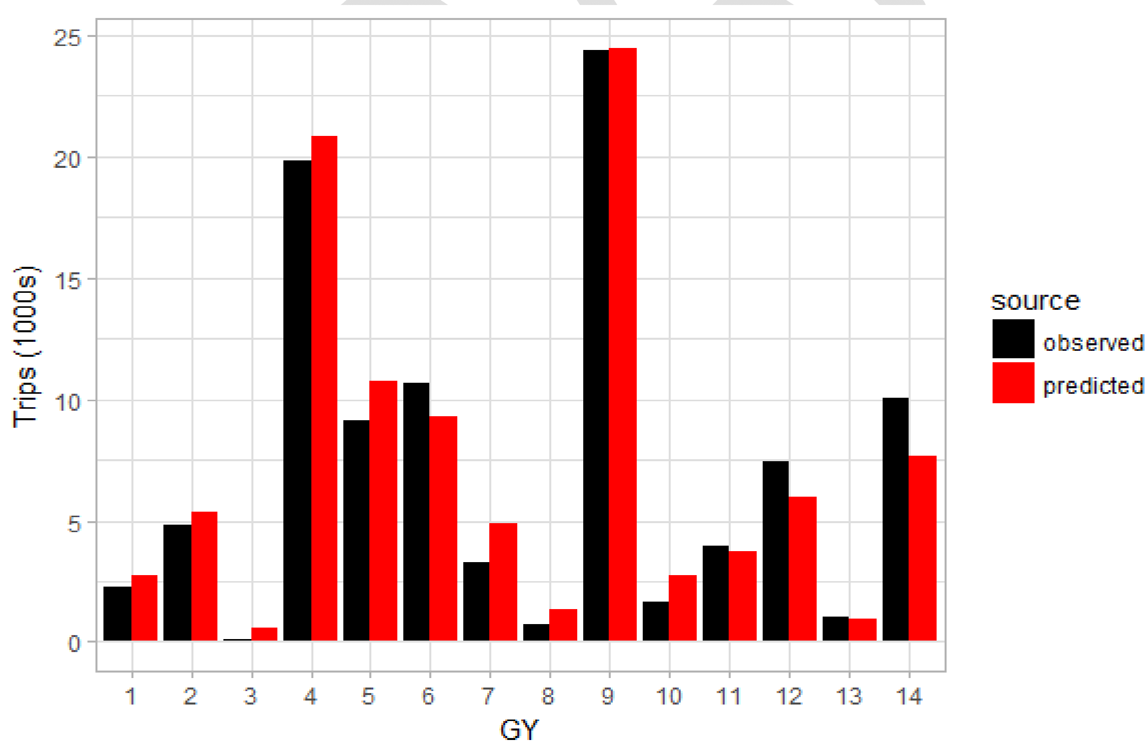

Figure 3-09: Home-based School Cross-validation Results

HOME-BASED SHOPPING

Size	Workers	Income	Productions
1	*	1	0.53
2	*	1	0.89
3	*	1	0.74
4	*	1	0.78
1	*	2	0.47
2	*	2	0.69
3	*	2	0.72
4	*	2	0.71
1	*	3	0.27
2	*	3	0.54
3	*	3	0.60
4	*	3	0.63

Figure 3-10: Home-based Shopping Trip Production Rates

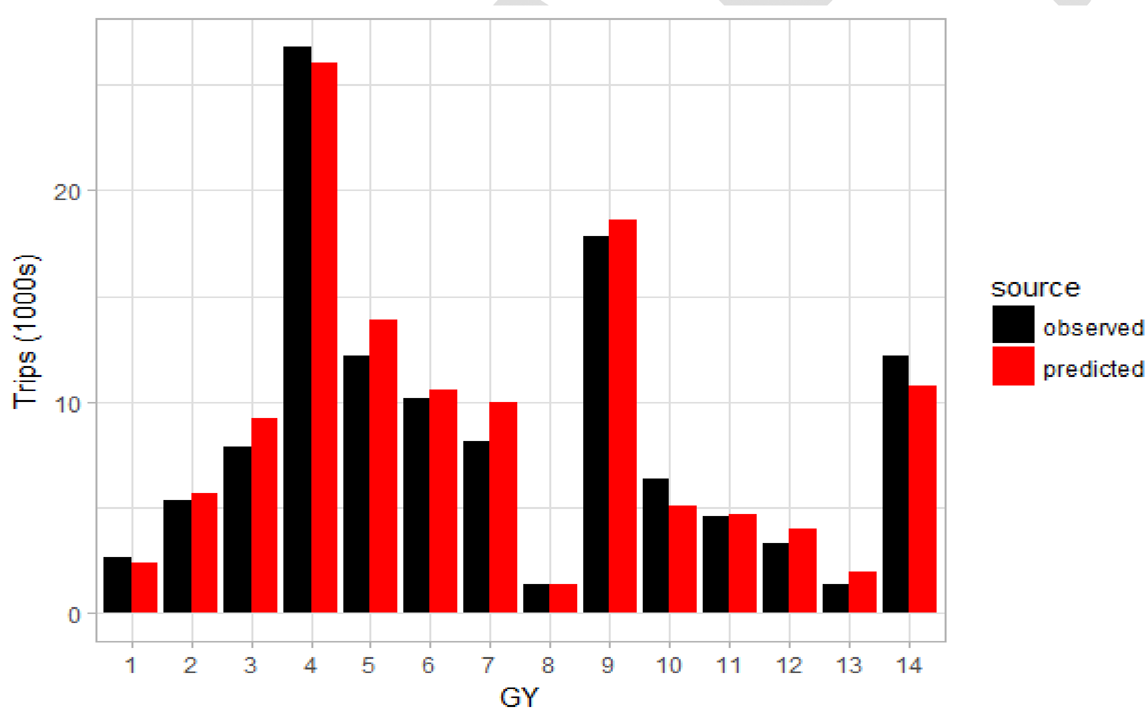

Figure 3-11: Home-based Shopping Cross-validation Results

HOME-BASED SOCIAL/RECREATIONAL

Size	Workers	Income	Productions
1	*	1	0.48
2	*	1	0.87
3	*	1	1.00
4	*	1	1.07
1	*	2	0.58
2	*	2	0.96
3	*	2	0.97
4	*	2	1.45
1	*	3	0.50
2	*	3	0.86
3	*	3	1.07
4	*	3	1.57

Figure 3-12: Home-based Social/Recreational Trip Production Rates

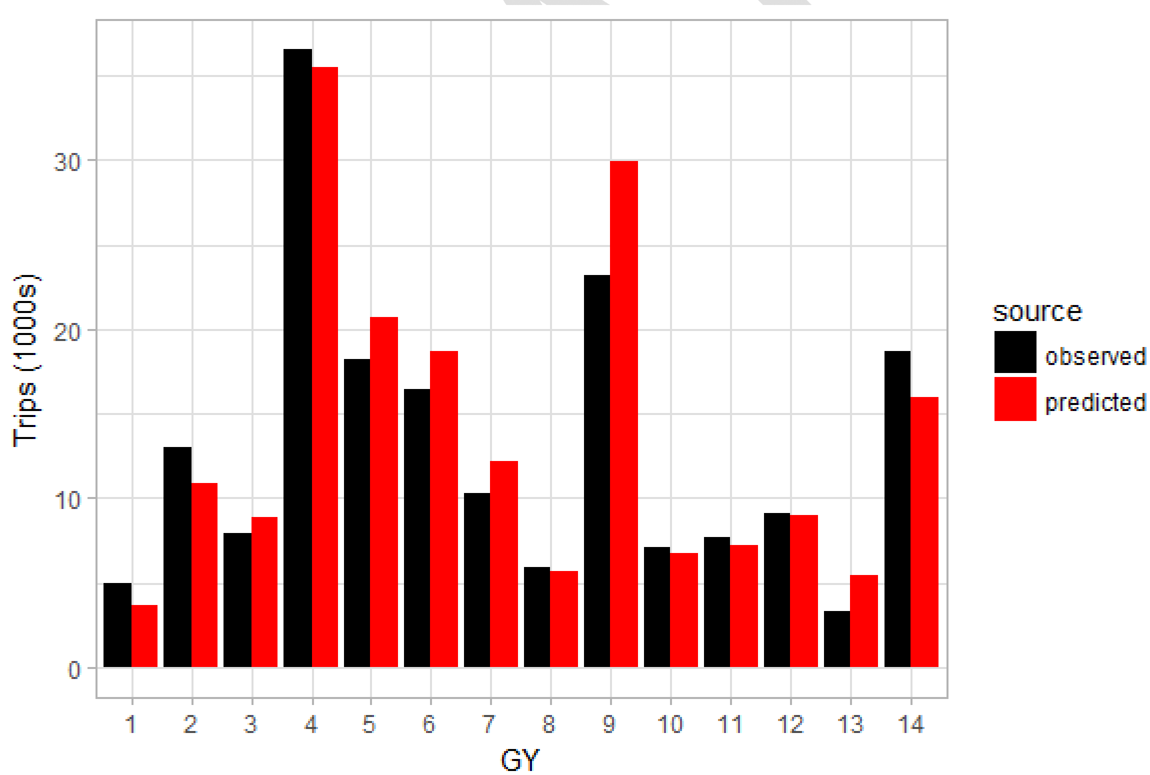

Figure 3-13: Home-based Social/Recreational Cross-validation Results

HOME-BASED UNIVERSITY

Variable	Coefficient
Intercept	20.618
I(Pop 18 to 24, TAZ in Vancouver*, University Transit Accessibility)	0.086
I(Pop 18 to 24, TAZ in Surrey*, University Transit Accessibility)	0.070
I(Pop 18 to2 4, TAZ in Other Areas*, University Transit Accessibility)	0.079
I(Pop 25 to 35, University Transit Accessibility)	0.010

* Dichotomous variable

Figure 3-14: Home-based University Trip Production Model

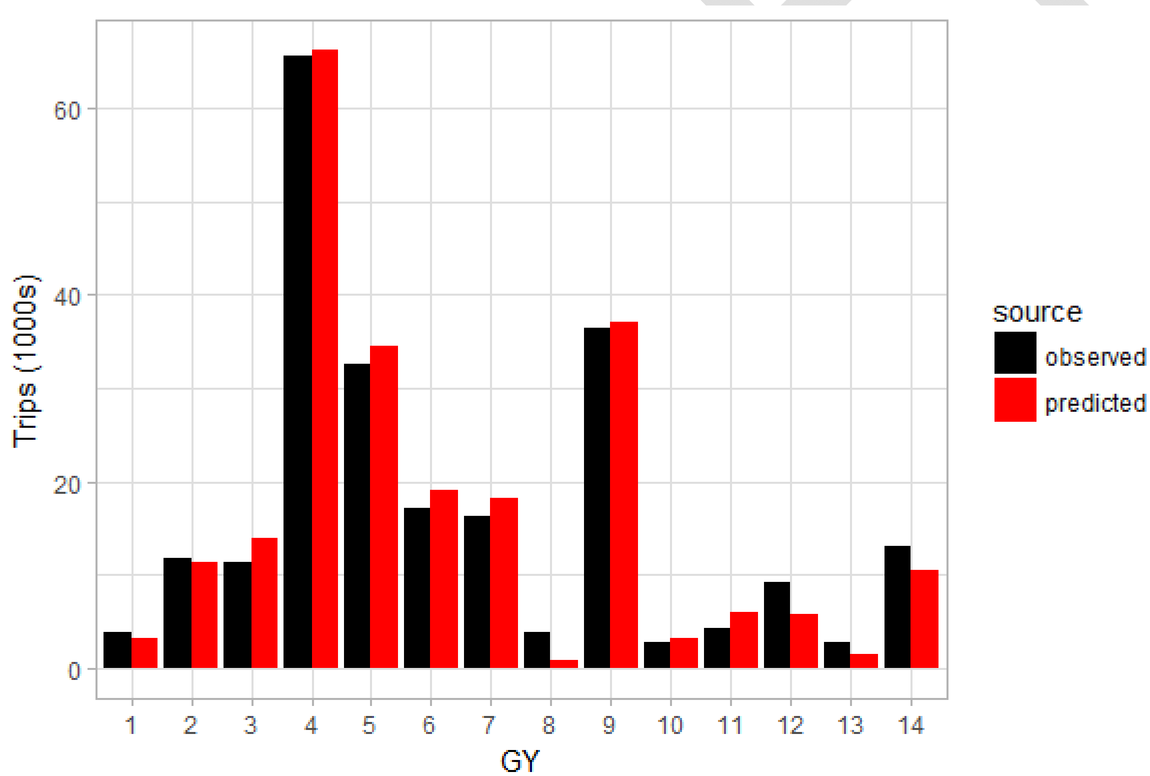

Figure 3-15: Home-based University Cross-validation Results

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Non-home-based Work

Size	Workers	Income	Productions
*	1	1	0.38
*	2	1	0.73
*	3	1	0.71
*	1	2	0.55
*	2	2	0.85
*	3	2	0.90
*	1	3	0.71
*	2	3	1.16
*	3	3	1.11

Figure 3-16: Non-home-based Work Control Total Trip Production Rates

Variable	Coefficient
Intercept	11.09
Construction and Manufacturing Employment	0.31
TCU and Wholesale Employment	0.18
FIRE Employment	0.30
Business and Other Service Employment	0.41
Accommodation, Food, Information & Culture Employment	0.25
Retail Employment	0.68
Health, Education, and Public Administration Employment	0.42
Elementary School Enrollment	0.06
Secondary School Enrollment	0.09
Number of households	0.06

Figure 3-17: Non-home-based Work Origin Model (used to locate trips)

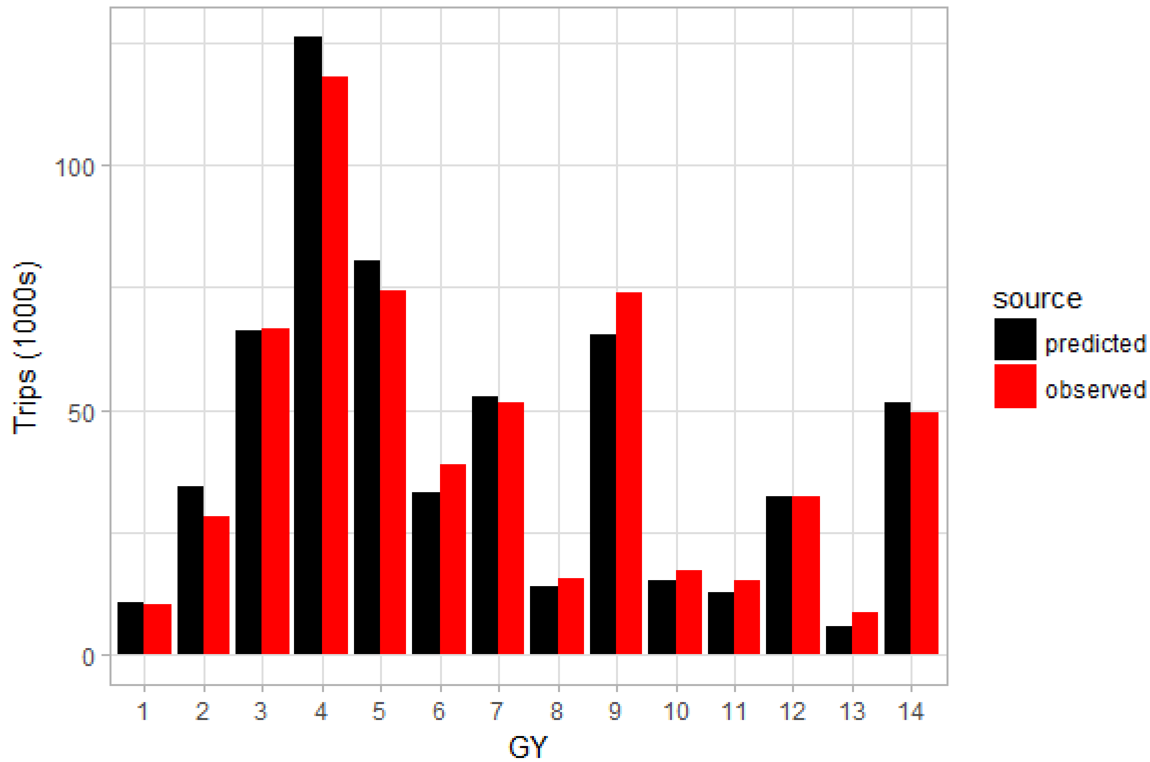

Figure 3-18: Non-home-based Work Cross-validation Results

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NON-HOME-BASED OTHER

Size	Workers	Income	Productions
1	*	1	0.52
2	*	1	0.92
3	*	1	0.87
4	*	1	1.32
1	*	2	0.58
2	*	2	0.74
3	*	2	0.92
4	*	2	1.29
1	*	3	0.38
2	*	3	0.60
3	*	3	0.75
4	*	3	1.18

Figure 3-19: Non-home-based Other Control Total Trip Production Rates

Variable	Coefficient
Intercept	12.88
Accommodation, Food, Information & Culture Employment	0.51
Retail Employment	1.83
Health, Education, and Public Administration Employment	0.36
Elementary School Enrollment	0.39
Secondary School Enrollment	0.23
Post-secondary Fulltime Equivalent Enrollment	0.04
Number of households	0.18

Figure 3-20: Non-home-based Other Origin Model (used to locate trips)

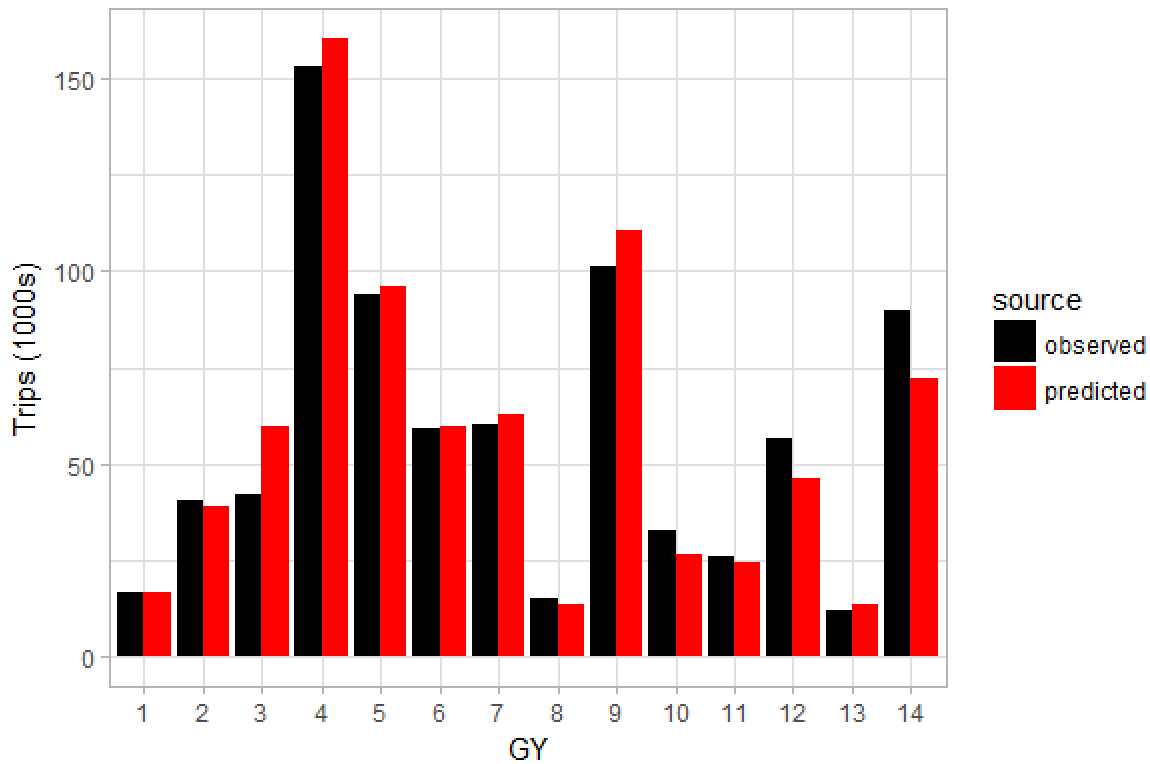

Figure 3-21: Non-home-based Other Cross-validation Results

AGGREGATE VALIDATION RESULTS

Validation tests were also run at the TAZ level on the aggregate data set. The following figures summarize the results of these tests.

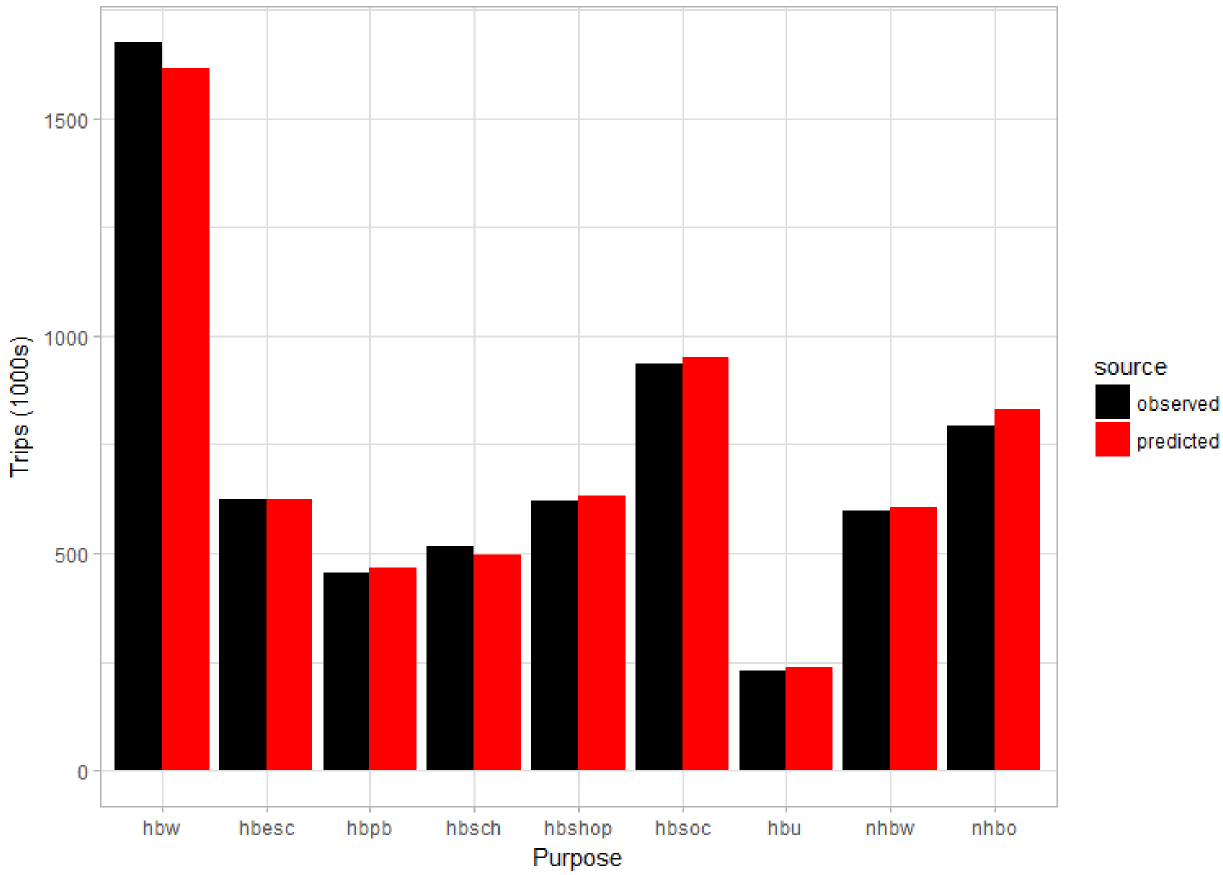

Figure 3-22: Aggregate Trip Production Validation by Purpose

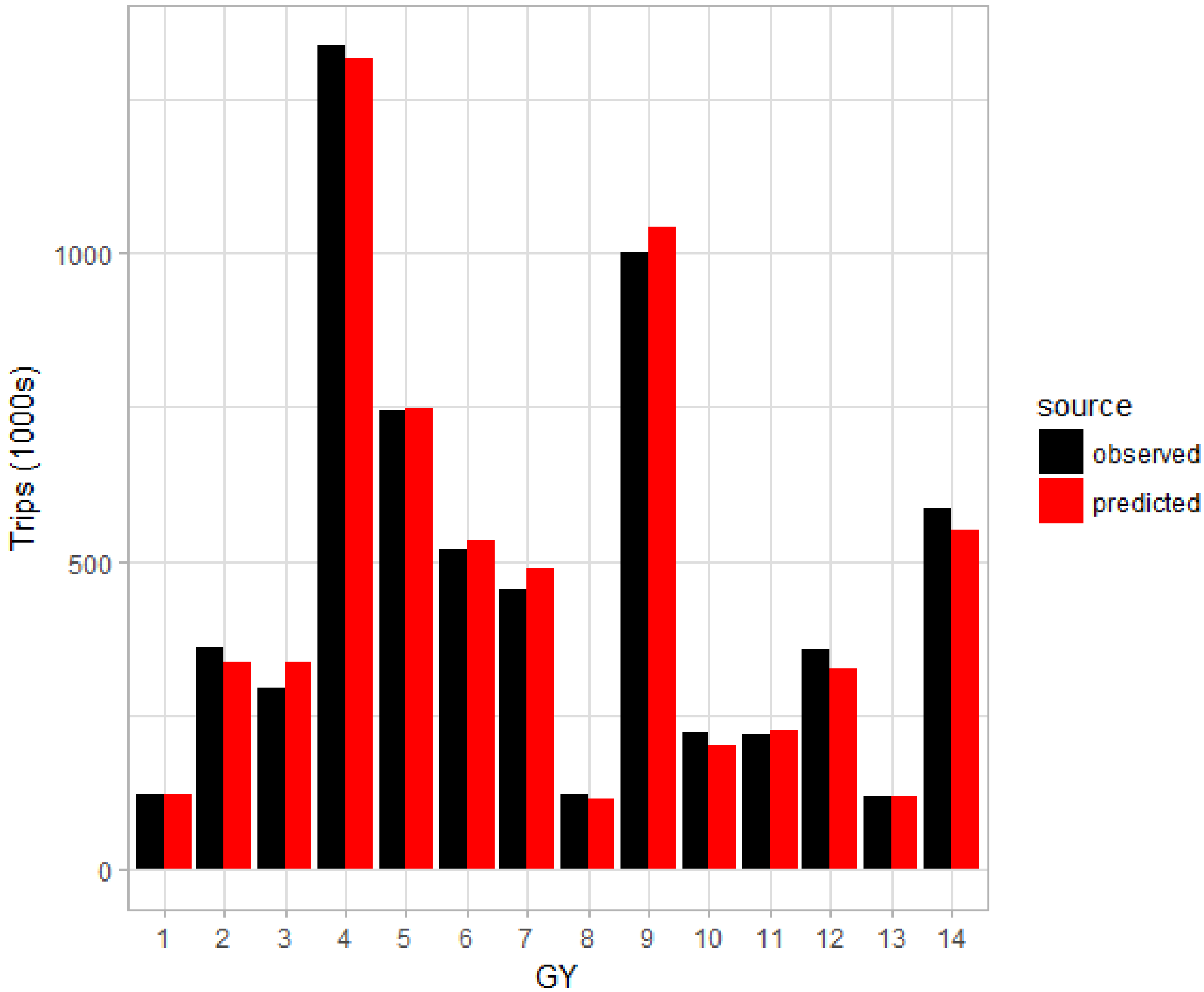

Figure 3-23: Aggregate Trip Production validation by GY

4: Trip Attractions

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While the trip production models estimate the number of trips starting and ending at the home-end, the trip attraction models estimate the daily number of trips starting and ending at the non-home-end. Trip productions and attractions are estimated based on markedly different data and therefore are developed separately. However, prior to trip distribution and mode choice the total attractions are balanced to the total productions. That is the total number of attractions will be set equal to the total number of productions. As such, trip attractions are as much a part of trip distribution as they are trip generation.

This sub-module estimates the number of trips attracted to each TAZ based on employment and demographic characteristics. One trip attraction model is estimated for each of the nine trip purposes at the TAZ level.

This module was estimated using a combination of TAZ level demographic data from Metro Vancouver and trips by purpose from the 2011 household travel survey.

Model Structure

The trip attraction models were estimated by linear regression predicting person trips resulting from a variety of different employment and household variables. These models were estimated at the TAZ level and numerous model forms were tested for significance, ability to reproduce observed results, and conformity with expectations.

Trip Purpose	Included Variables
Home-based Work	Employment by category
Home-based Escorting	Subset of employment categories, primary & secondary school enrollment, population under 18, and population over 65
Home-based Personal Business	Subset of employment categories, total population
Home-based School	Primary & secondary school enrollment
Home-based Shopping	Retail employment
Home-based Social/Recreational	Subset of employment categories, total population
Home-based University	Post-secondary fulltime equivalent enrollment
Non-home-based Work	Employment by category
Non-home-based Other	Subset of employment categories, primary & secondary school enrollment

Figure 4-01: Trip Attraction Model Variables

Model Form

A linear regression model for each of the nine trip purposes was estimated to forecast trip attractions to all TAZs. The model takes the form:

$$y = intercept\ + \sum_{j}^{m} \beta_j * x_j$$

Where:

'y' represents the continuous dependent variable, in this case: $trip\ attractions$
'x_j' represents a set of explanatory variables and
'β_j' represents their corresponding estimated coefficients.

Figure 4-02 shows the variables' definitions and the estimated coefficients for each model. All variables' coefficients are statistically significant at the 95% confidence level and estimated with the expected sign

As shown in Figure 4-02, some of the models include an intercept. The intercept was included when found to be highly significant for a trip purpose balanced to productions. In these cases it was believed that factors not accounted for in RTM3 contributed to this type of trip making. For instance, RTM3 contains no information for parks and little information for other recreational opportunities (such as community centres) that attract trips. Given the level of other variables in most zones the intercept has little effect on total trip-making and distribution, but does distribute trips more broadly in zones with lower values of the recorded variables.

Variable	HBW	HBESC	HBPB	HBSCH	HBSHOP	HBSOC	HBU	NHBW	NHBO
Intercept	x	176.89	x	x	x	89.83	x	62.22	x
Construction & Manufacturing	1.46	-	-	-	-	-	-	0.15	-
FIRE	1.62	-	-	-	-	-	-	0.10	-
Transportation, Communication, Utilities, and Wholesale	1.18	-	-	-	-	-	-	0.12	-
Retail	0.59	0.38	1.10	-	4.60	1.18	-	1.13	2.58
Business & Other Services	1.56	-	-	-	-	-	-	0.29	-
Accommodation, Food, Information, Culture	1.29	0.28	0.22	-	-	1.08	-	0.45	0.37
Health, Education, and Public Administration	1.30	0.23	0.50	-	-	0.27	-	0.39	0.30
Elementary Enrolment	-	0.54	-	1.32	-	-	-	-	0.21
Secondary Enrolment	-	0.37	-	1.24	-	-	-	-	0.18
Population Under 18	-	0.20	-	-	-	-	-	-	-
Population Over 65	-	0.11	-	-	-	-	-	-	-
Total Population	-	-	0.04	-	-	0.13	-	-	0.08
I(TCU_Wholesale, Airport)		0.84	-	-	-	-	-	-	-
Post-Secondary Full Time Equivalent Enrolment in the CBD	-	-	-	-	-	-	0.29	-	-
Post-Secondary Full Time Equivalent Enrolment outside the CBD	-	-	-	-	-	-	1.41	-	-

x: Intercept not statistically significant
* Dichotomous variable

Figure 4-02: Trip Attraction Model Variables and Coefficients

Model Validation

Cross-validation test were conducted to assess the each model's performance at the disaggregate level. .Each model was re-estimated using a stratified random sample of the full dataset (80%) and then applied to a hold-out sample (20%). The observed trips in the trip diary are compared to the estimated trips at the GY level in the following figures[7].

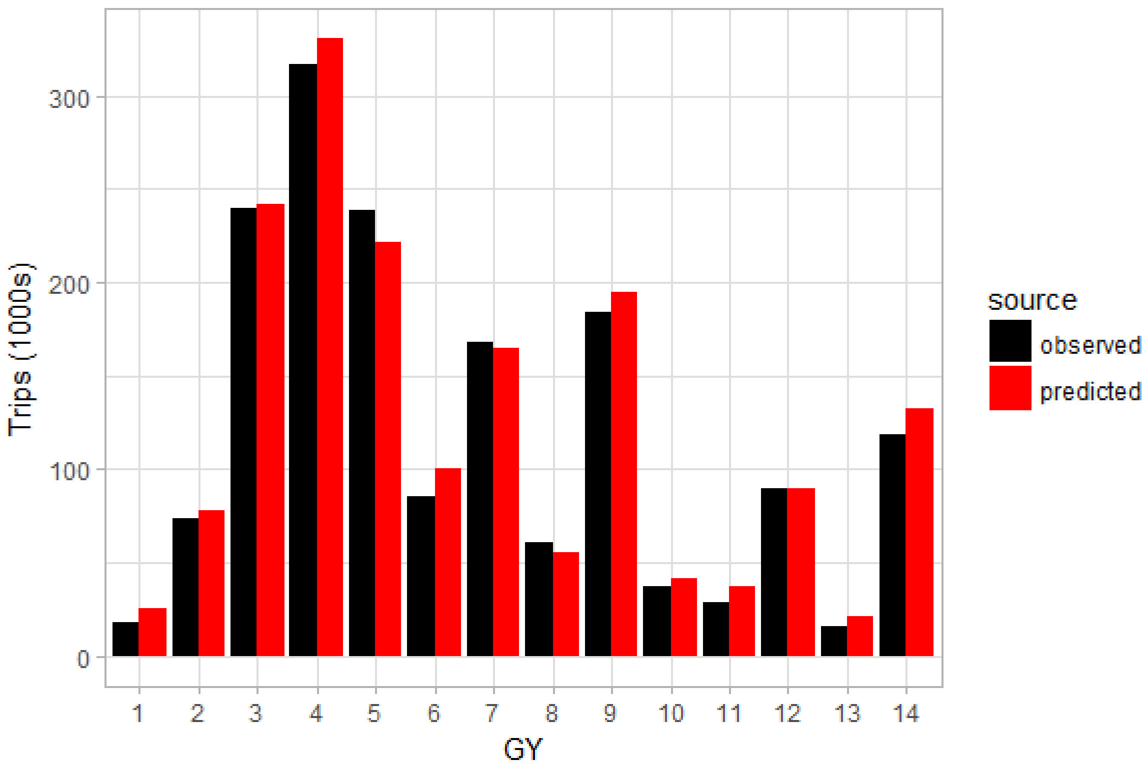

Figure 4-03: Home-based Work Cross-validation Results

[7] Cross-validation could not be performed for home-based university trips. Only a small number of locations attract these trips, and some of the locations (UBC and SFU in particular) dominate the model estimation. As such, if one or both of those institutions was not in the estimation sample a considerably different model would be estimated.

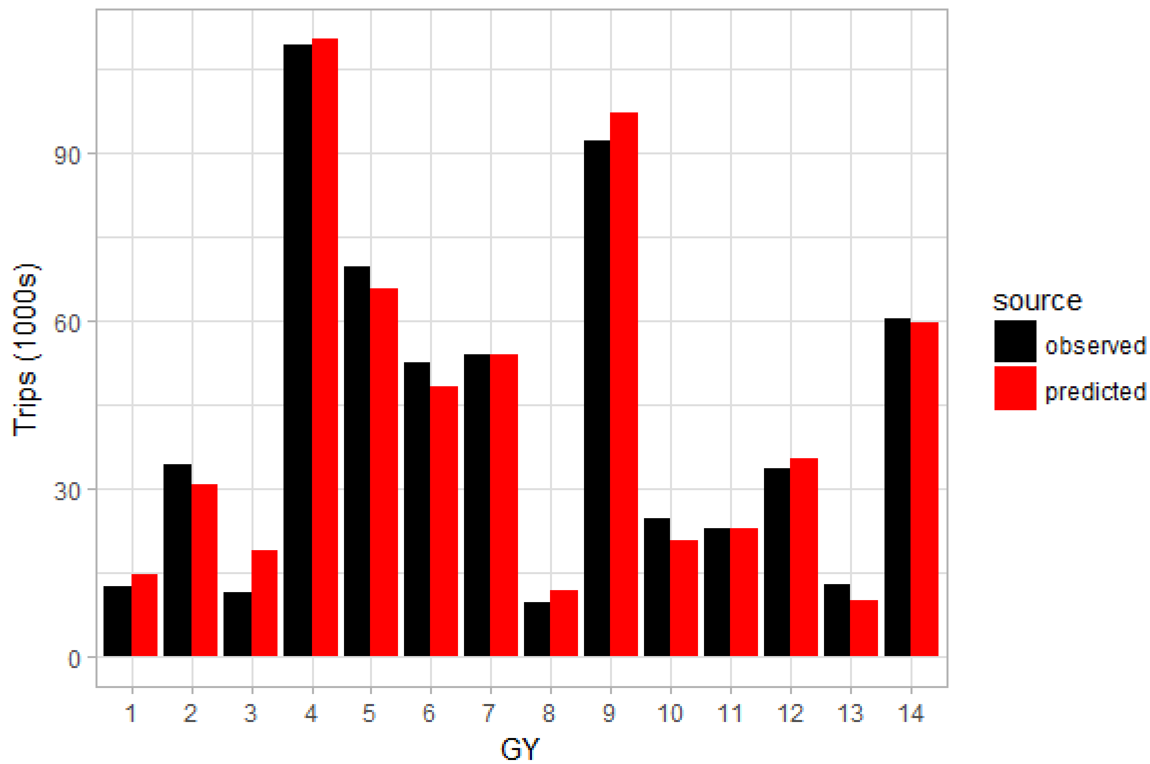

Figure 4-04: Home-based Escorting Cross-validation Results

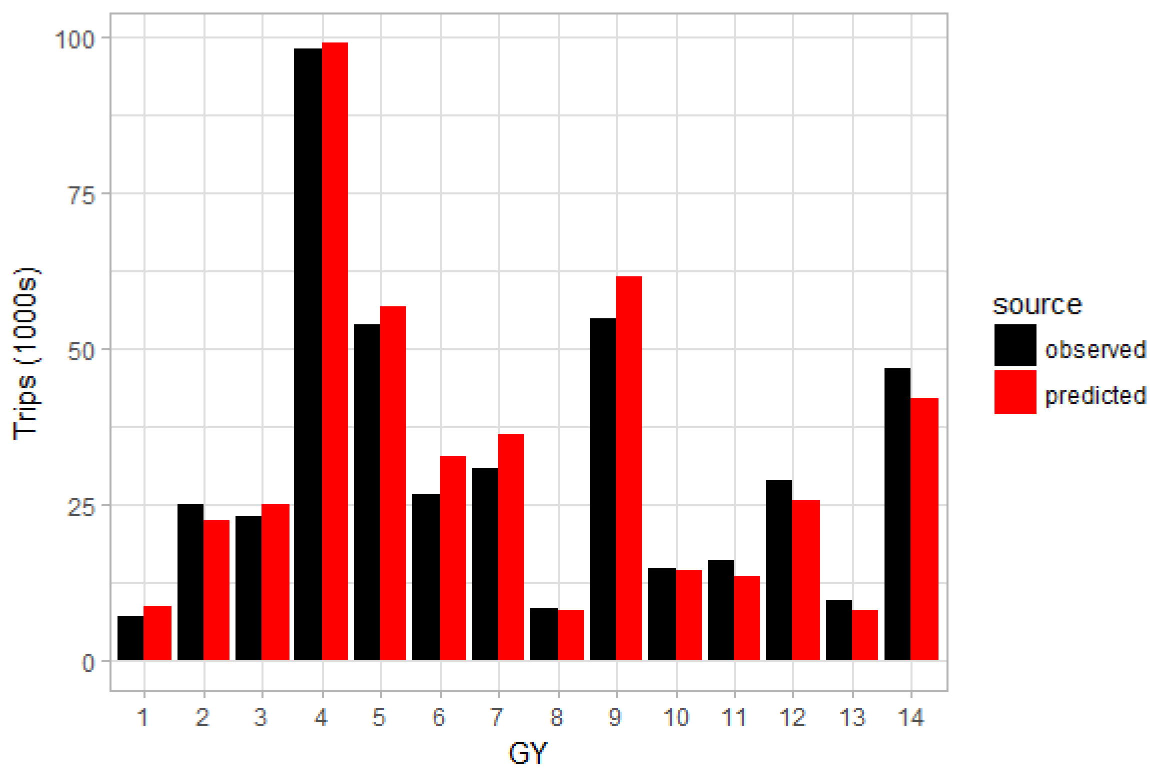

Figure 4-05: Home-based Personal Business Cross-validation Results

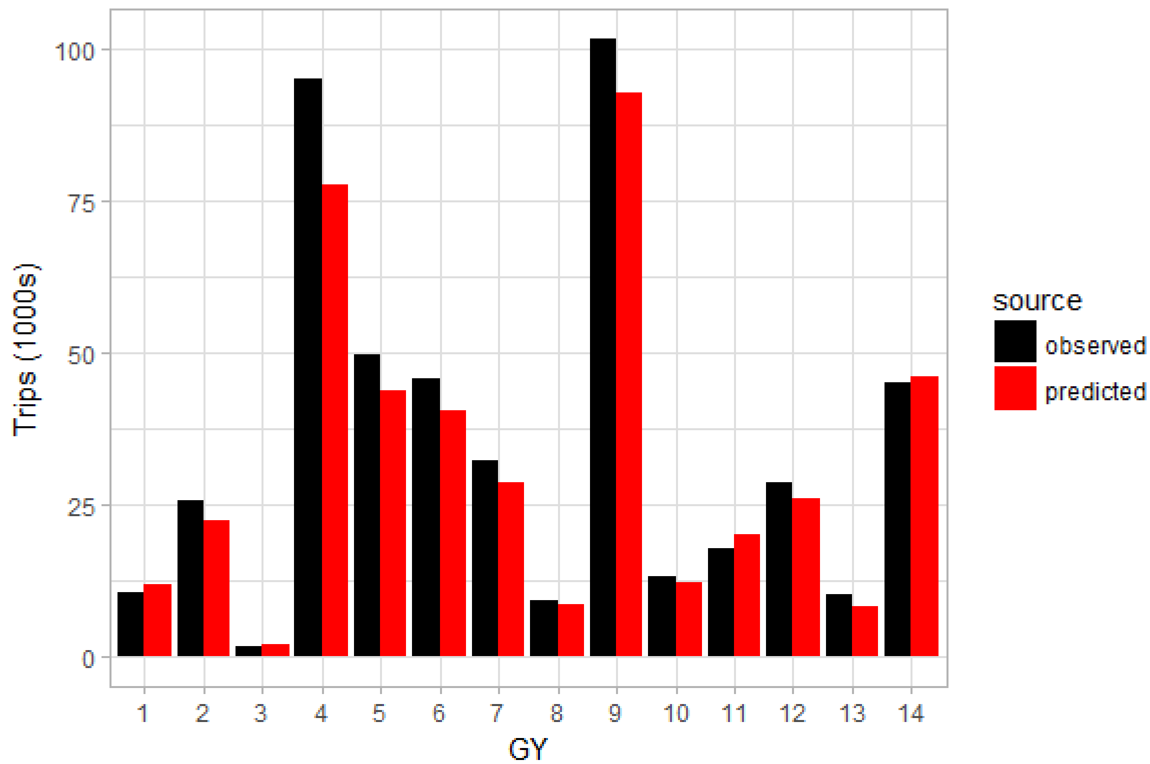

Figure 4-06: Home-based School Cross-validation Results

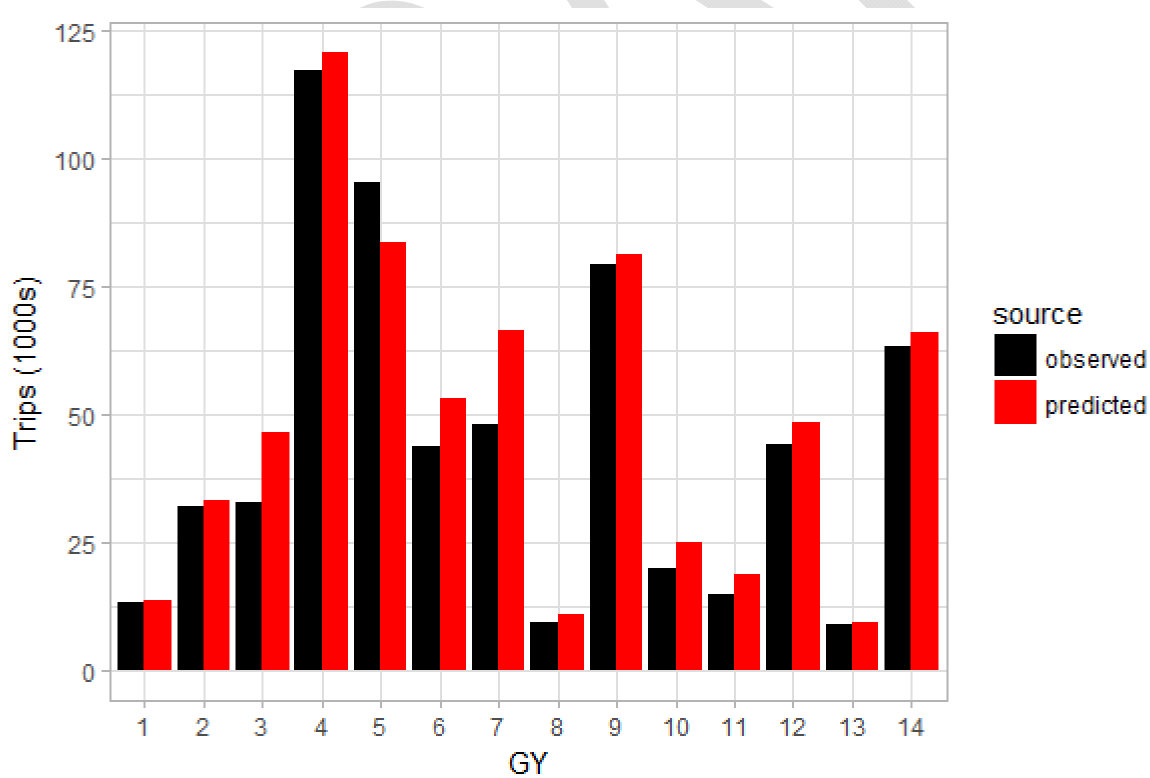

Figure 4-07: Home-based Shopping Cross-validation Results

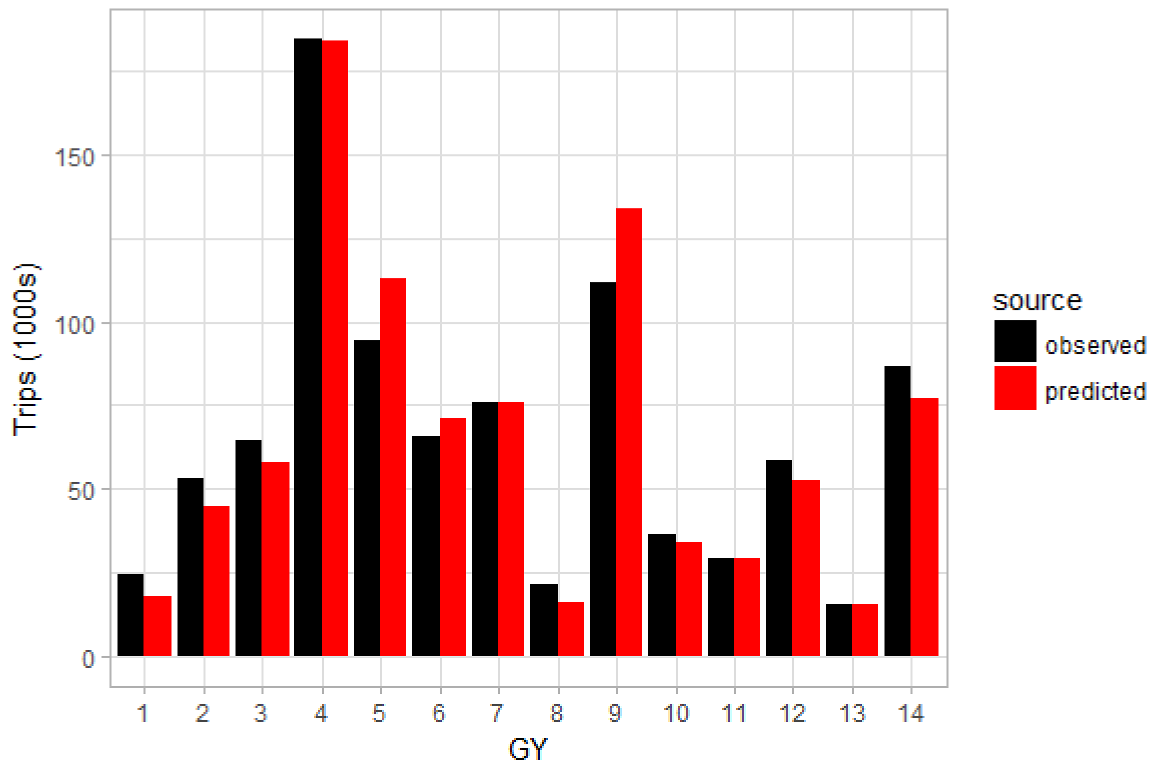

Figure 4-08: Home-based Social/Recreational Cross-validation Results

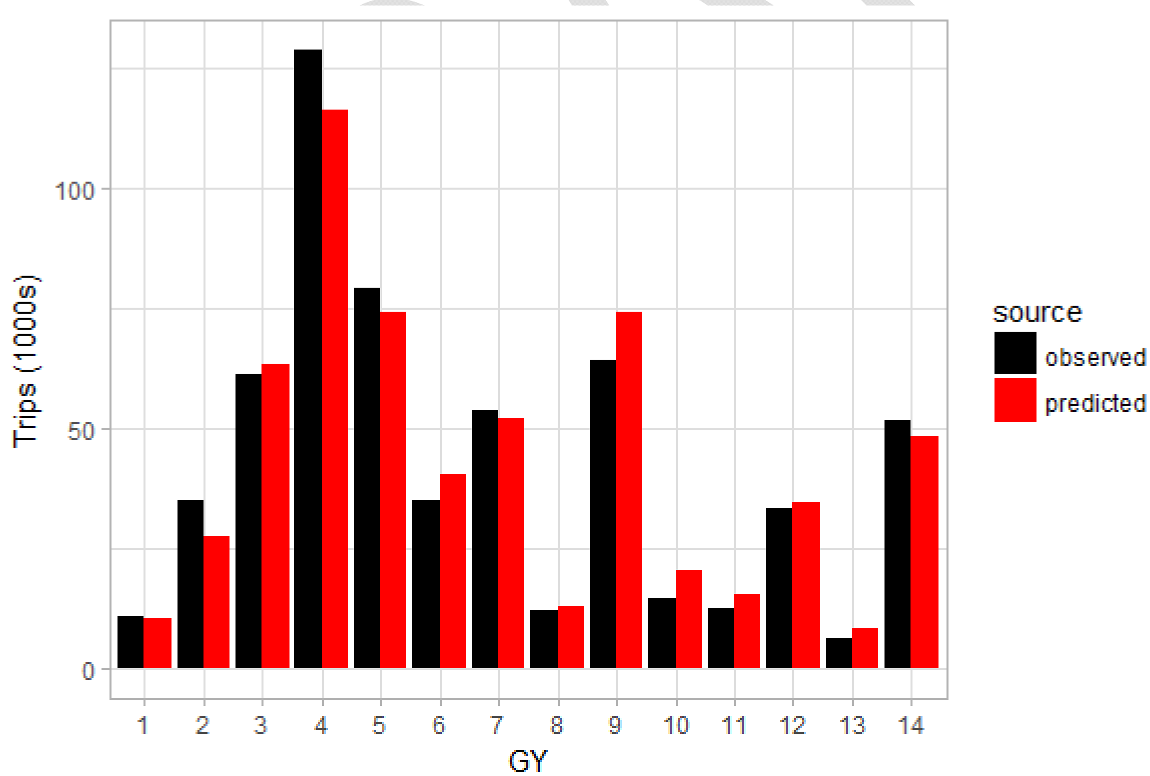

Figure 4-09: Non-home-based Work Cross-validation Results

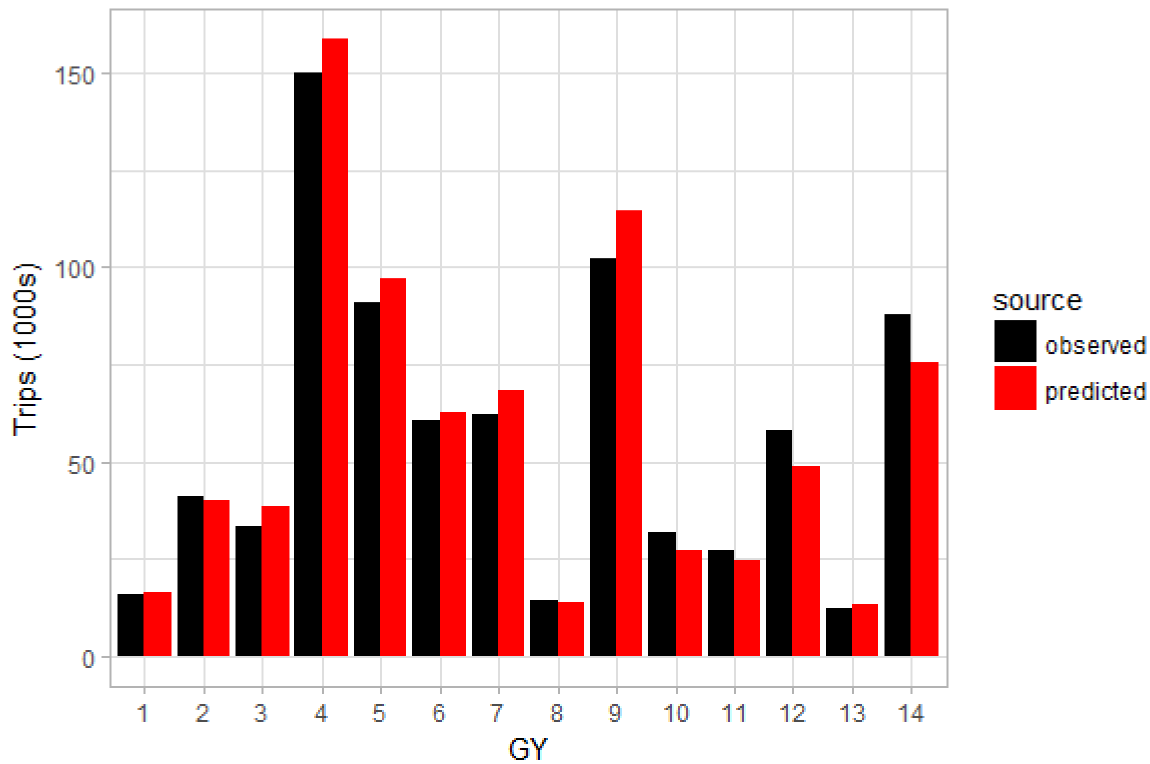

Figure 4-10: Non-home-based Other Cross-validation Results

Aggregate Validation Results

The following figures summarize the aggregate results at the purpose and GY level. Overall the models validate well and show a good fit to the data.

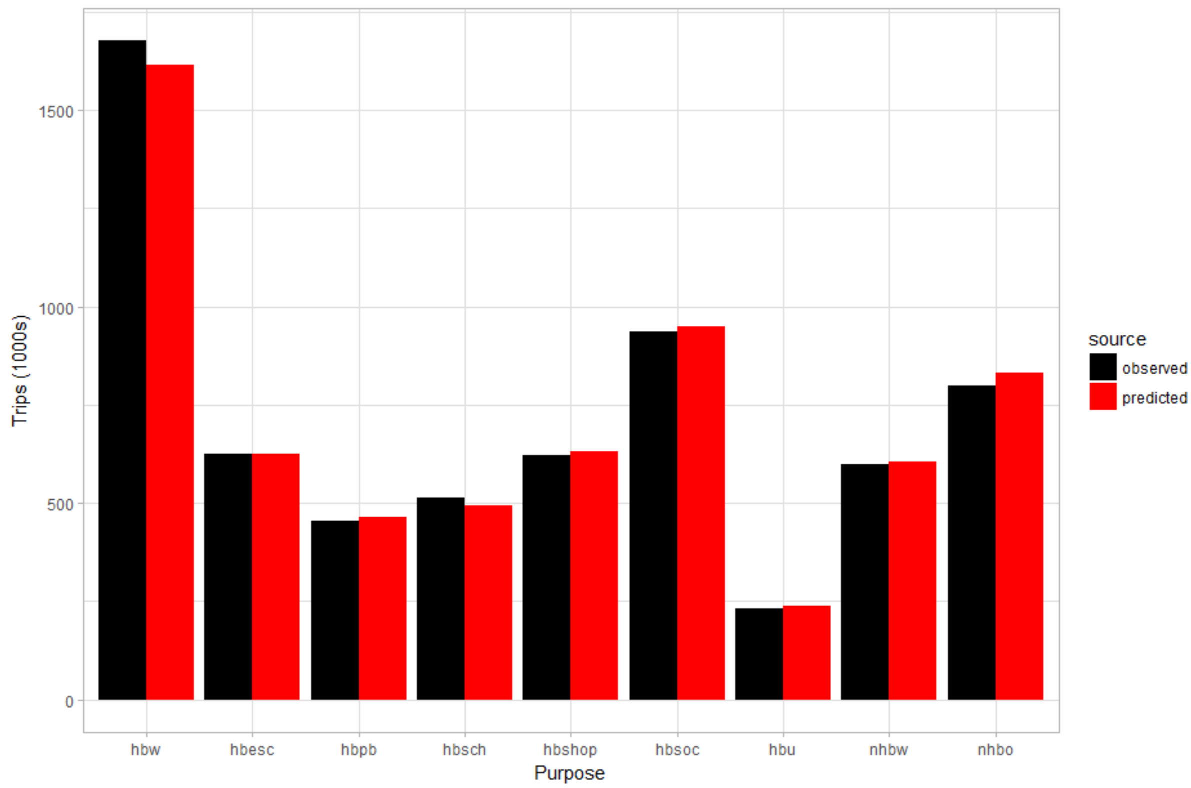

Figure 4-11: Aggregate Trip Attraction Validation by Purpose

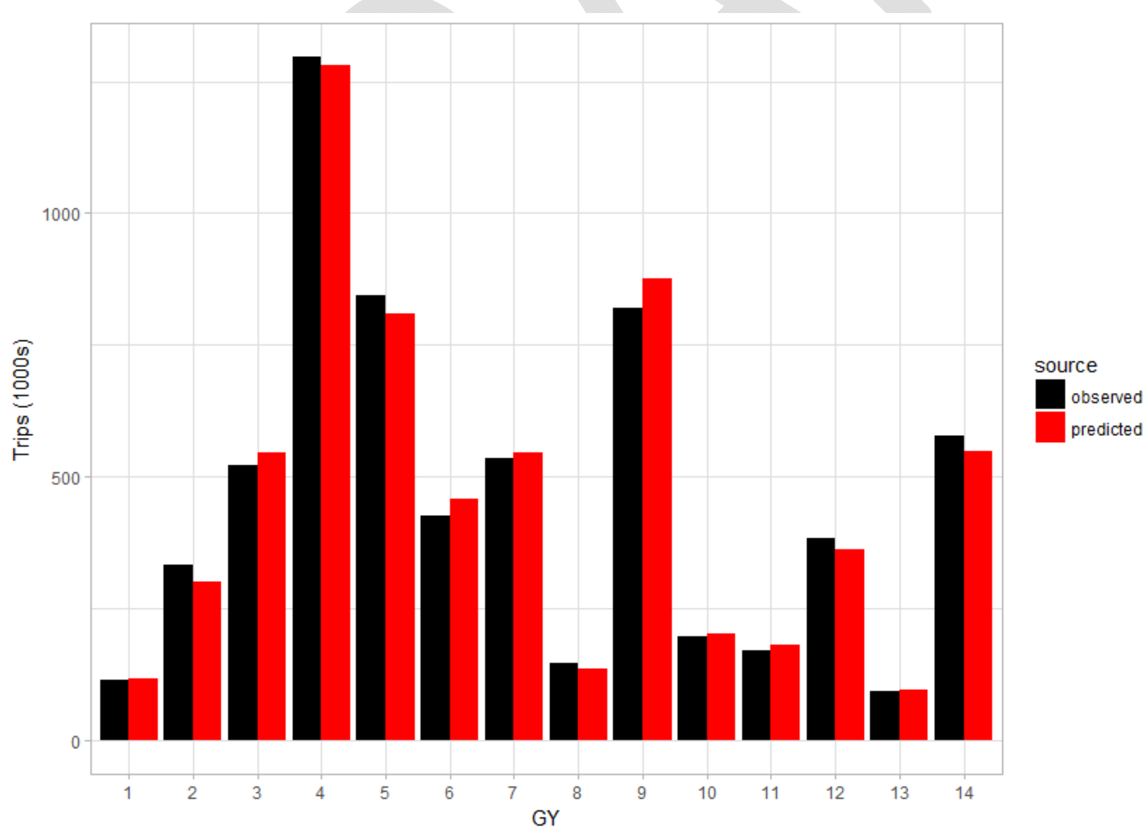

Figure 4-12: Aggregate Trip Attraction Validation by GY

5: Trip Distribution

The trip distribution model is the second component of the four-step model. The model takes the outputs of the trip generation model – total productions and attractions – and estimates the total number of trips from each TAZ to every other TAZ. In total nine trip distribution models are estimated; one for each trip purpose in the RTM3.

The primary data sets used to estimate the trip distribution model are:

- 2011 Trip Diary
- RTM Mode Choice Logsums
- TAZ to TAZ shortest path distance matrix

The trip distribution models are estimated and calibrated to match observed average trip distance lengths and GY-to-GY trip flows for each trip purpose.

Model Structure

The conventional gravity model distributes trips from each production TAZ to each attraction TAZ. The gravity model takes the following general form:

$$T_{ij} = \frac{P_i * (A_j * F_{ij} * K_{ij})}{SUM\ (A_j * F_{ij} * K_{ij})}$$

Where:

T_{ij}: The number of trips produced in Zone i and attracted to Zone j;
P_i: The number of trips produced in Zone i;
A_i: The number of trips attracted to Zone j (also known as the size term);
F_{ij}: A friction factor, which is a function of travel impedance of travel from i to j and
K_{ij}: TAZ-to-TAZ adjustment factor, which takes into account the effect of undefined socioeconomic linkages not otherwise incorporated in the gravity model.

One of the major upgrades made to the RTM3 was changing the form of the friction factor term F_{ij}. In previous RTM versions, the F_{ij} term was defined as follows:

$$Fij = e^{Ɓ*Auto\_GC} + e^{Ɓ*Transit\_GC}$$

Where:

Ɓ: Estimated decay parameter
Auto_GC: Generalized Auto Cost which includes travel time, converted to dollars using purpose-specific values of time, and out-of-pocket costs
Transit_GC: Generalized Transit Cost which includes travel time, converted to dollars using purpose-specific values of time, and out-of-pocket costs

The previous friction factor form did not link trip distribution and mode choice. This form considered only auto and transit level of service attributes and did not account for other mode choice model variables such as active mode level of service, geographic attributes, socioeconomic factors, and accessibilities. As such, the friction factors were dominated by the auto generalized cost because auto travel times are usually shorter than transit travel times. This shortcoming could lead to counter-intuitive model outputs, such as:

- Reduced road capacity or increased congestion would result in a reduction in the number rail trips
- Road tolling would result in a reduction in the number transit trips

In both cases transit trips decreased because the total number of trips between the affected zones decreased as a result of increased auto generalized cost. With that formulation, increased generalized costs converted long trips to short ones (e.g. a commuter trip from Surrey to the Vancouver downtown would convert from SkyTrain to a walk trip within Surrey). While some trips could shift in this way, it is unlikely that many people would change their work location in such an extreme way.

The friction factor equation was revamped for RTM3 to include the mode choice logsum and distance terms. The mode choice logsum accounts for the overall travel impedance between zones for all available modes preventing counterintuitive mode shifts. The distance terms reduce model sensitivity to changes in generalized cost, thereby reflecting the long-term nature of destination choice, especially for commuting purposes. The RTM3 friction factor takes the form:

$$Fij = e^{(\theta*\text{Logsum} + \lambda*\text{distance} + \alpha*\text{distance}^2 + \mu*\text{distance}^3)}$$

The term θ is the mode-destination nesting parameter. In the RTM3, θ is asserted since this is not a combined mode-destination nested logit model. The θ term typically falls between 0 and 1. The closer the value is to 1, the higher the model's sensitivity to mode choice variables all else being equal. The terms λ, α, and μ are calibrated iteratively so that average of each distance term closely matches those observed in the trip diary.

The Logsum term is calculated as follows:

$$\text{Logsum} = \log(e^{Vauto} + e^{Vtransit} + e^{Vactive})$$

Where:

$$V_{auto} = \phi*\log(e^{Vsov} + e^{Vhov2} + e^{Vhov3})$$
$$V_{transit} = \phi*\log(e^{Vbus} + e^{Vrail} + e^{Vwce})$$
$$V_{active} = \phi*\log(e^{Vwalk} + e^{Vbike})$$

And:

Φ is the estimated mode choice nesting parameter
V is the mode-specific utility

Figure 5-01 is a flow chart showing the iterative process used to estimate the parameters λ, α and μ.

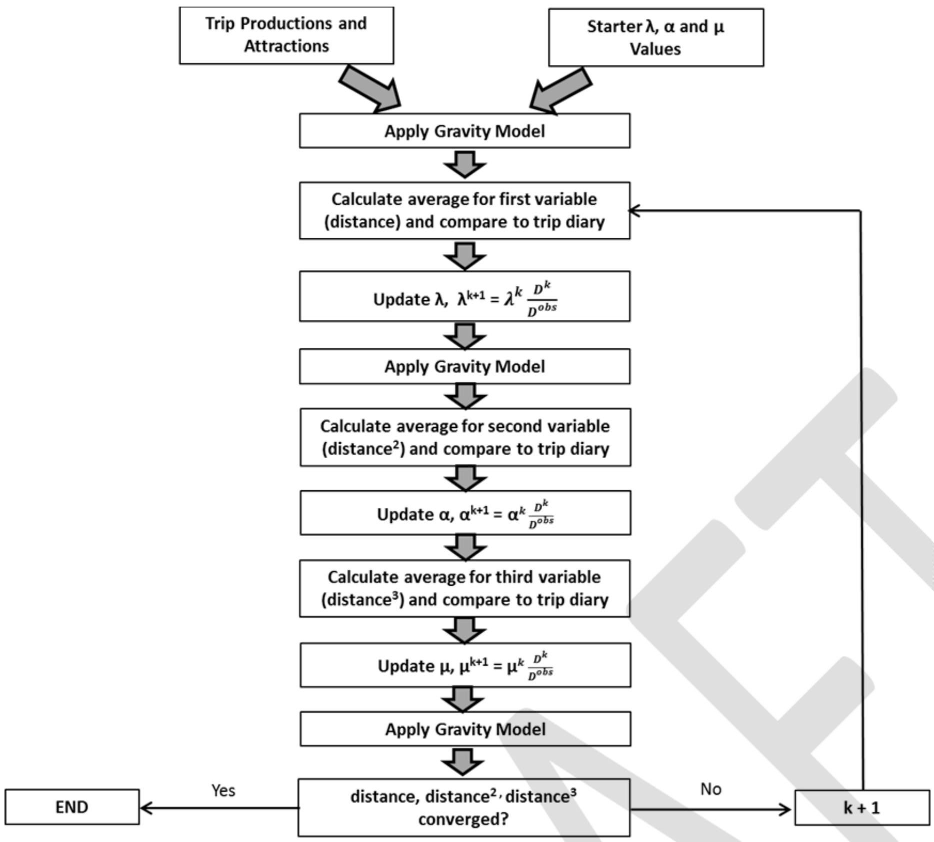

Figure 5-01: Distance Term Coefficient Estimation Process

There are no specific convergence criteria for the distance terms. Figure 5-02 shows the range of convergence thresholds used in the RTM3.

Term	Measure Type	Convergence Range
distance	Absolute difference	+/- (0.05 – 0.25) km
distance^2	Percent difference	+/- (10% - 20%)
distance^3	Percent difference	+/- (10% - 20%)

Figure 5-02: Distance Term Estimation Convergence Thresholds

Note that the number of distance terms varies by trip purpose and are employed only when additional terms add value to the model.

Implementation

In implementation the trip distribution model becomes a sub-module of the mode choice model because calculating friction factors from mode choice logsums requires the execution of several mode choice model stages prior to the trip distribution model execution.

The following process applies to the all trip purposes:

1) Calculate blended skims from traffic assignment for each trip purpose
2) Launch the mode choice module
3) Calculate mode choice utilities for each mode and socio-economic segment
4) Run the trip distribution model sub-module
    i. Calculate the higher nest utility for each high-level
       $V_{car} = \phi * \log\{\exp(V_{sov})+\exp(V_{hov2})+\exp(V_{hov3})\}$
       $V_{transit} = \phi * \log\{\exp(V_{bus})+\exp(V_{rail}) +\exp(V_{WCE})\}$
       $V_{active} = \phi * \log\{\exp(V_{bike})+\exp(V_{walk})\}$
       Where ϕ is the nesting parameter estimated by the mode choice model

    ii. Calculate the 1741x1741 logsum matrix
       $\text{Logsum} = \log\{\exp(V_{car})+\exp(V_{transit})+\exp(V_{active})\}$
    iii. Use the logsum for the friction factor and matrix balancing process of the trip distribution model
    iv. Exit the trip distribution sub-module
5) Calculate mode choice probabilities from the utilities calculated in Step 4
6) Multiply the probabilities with the trip distribution demands estimated in Step 4 to determine the mode-specific demand matrices

Singly-constrained and Doubly-constrained Gravity Models

The RTM3 distributes trips with double-constrained gravity models for compulsory trips (such as home-based work) and singly-constrained gravity models for discretionary trip purposes (such as home-based shopping).

A doubly-constrained gravity model ensures that for every TAZ the total number of productions and attractions estimated in trip generation are maintained after trip distribution. For example if a total of $\sum$p1 productions and $\sum$a1 attractions are estimated for zone 1 in trip generation, the doubly-constrained model ensures that these totals remain the same after trip distribution. This would be true for all TAZs.

Production/Attraction	1	2	3	…	j	Totals
1						∑p1
2						∑p2
3						∑p3
…						…
i						∑pi
Totals	∑a1	∑a2	∑a3	…	∑aj	

Figure 5-03: Trip Distribution Example

A singly constrained gravity model only maintains the total estimated trips for one of these vectors. The RTM3 discretionary purposes maintain the trip production totals but not necessarily the trip attraction totals for each TAZ. For these trip purposes $\sum$p1 in the example above will remain the same before and after trip distribution, but $\sum$a1 may be different.

Doubly-constrained models better capture travel behavior for compulsory trips where the number of trips destined to a TAZ is largely determined by the number of jobs or student enrollment in that zone.

Singly-constrained models, on the other hand, better capture travel behavior for discretionary trips where travelers are not necessarily limited to a single destination for a particular activity. For example, if two shopping malls that are otherwise identical open at the same time and the first is located in an accessible area, while the second is located is an isolated area, then the first mall should attract more trips. Both malls would attract the same number of trips with a doubly-constrained model; with the only difference being that less accessible mall would attract longer distance trips.

Similarly, if the cost to visit one mall increased – for example with the introduction of paid parking – then some shopping trips might choose a new destination. This would happen with a singly-constrained model but not a doubly-constrained model. Thus a singly-constrained model allows level of service attributes, such as travel time and cost, to influence the total number of attractions at a particular TAZ.

Bridge Crossing Penalties

Previous RTM versions overestimated the number of trips that cross the large water bodies, such as the Burrard Inlet and Fraser River. It was initially believed that this crossing over-estimation was due to under-representation of network travel times, especially at congested bridge merge and weave sections. The volume delay functions were updated for RTM3 to better represent network times and the trip distribution and mode choice models were re-estimated using updated skims. This change improved model performance but the RTM still distributed too many trips across large water bodies.

Bridge crossing over-estimation is a common problem for travel demand modeling. One way to explain this phenomenon is that people are more reluctant to cross long bridges than would be projected by distance alone (potentially due to the reduced reliability in these traffic bottlenecks). Experts vary on whether k-factors or link-level bridge penalties better address the underlying travel behavior. For RTM3 it was decided that bridge crossing penalties better represented the perceptual barrier for travelers that factors into the decision of whether a person decides to make a trip across the river.

The penalties were calculated at the GY-to-GY level based on the ratio of weighted average peak travel time to off peak travel time. Figure 5-04 shows the penalties used:

Ratio Peak:Mid-day Skim	Penalty (Additional distance in km)
<1.25 or if difference in time less than 5 minutes	0
1.25 - 1.5	1
1.5 - 2	2
>2	3

Figure 5-04: Bridge Crossing Penalties

Model Examination and Validation

The following section documents the trip distribution models estimated parameters and performance against observed data. Separate parameters were estimated for different income and auto-ownership levels where possible.

Compulsory trip purposes, including home-based work, university, and school, and non-home-based work were estimated as doubly-constrained models. The remaining five trip purposes were estimated as singly-constrained models.

As mentioned, the number of distance terms varies by trip purpose and are employed only when additional terms add value to the model. A coefficient of 0 in the following parameter tables indicates that distance parameter was not included in the model estimation for that purpose. Note that α and μ are multiplied by $distance^2$ and $distance^3$ respectively and so small input values impact the results.

HOME-BASED WORK

For the home-based work purpose, a total of nine production matrices, segmented by income and auto ownership, are balanced to a single attraction matrix. Figure 5-05 shows the estimated model parameters.

Income	Auto	θ	λ	α	μ
Low	0	0.7	-0.15931	0.00391	-0.00007
	1	0.7	-0.13110	0.00164	-0.00001
	2	0.7	-0.13128	0.00158	-0.00001
Medium	0	0.7	-0.15313	0.00273	-0.00002
	1	0.7	-0.10835	0.00180	-0.00001
	2	0.7	-0.10687	0.00143	-0.00001
High	0	0.7	-0.03580	0.00039	0.00000
	1	0.7	-0.11816	0.00215	-0.00002
	2	0.7	-0.10317	0.00161	-0.00001

Balancing Type: Doubly-constrained
K-Factor Range: 0.85 - 1.10

Figure 5-05: Home-based Work Trip Distribution Parameters

Figure 5-06 compares the modelled and observed trip length distributions by distance. The model validates well as indicated by the high coincidence ratio[8].

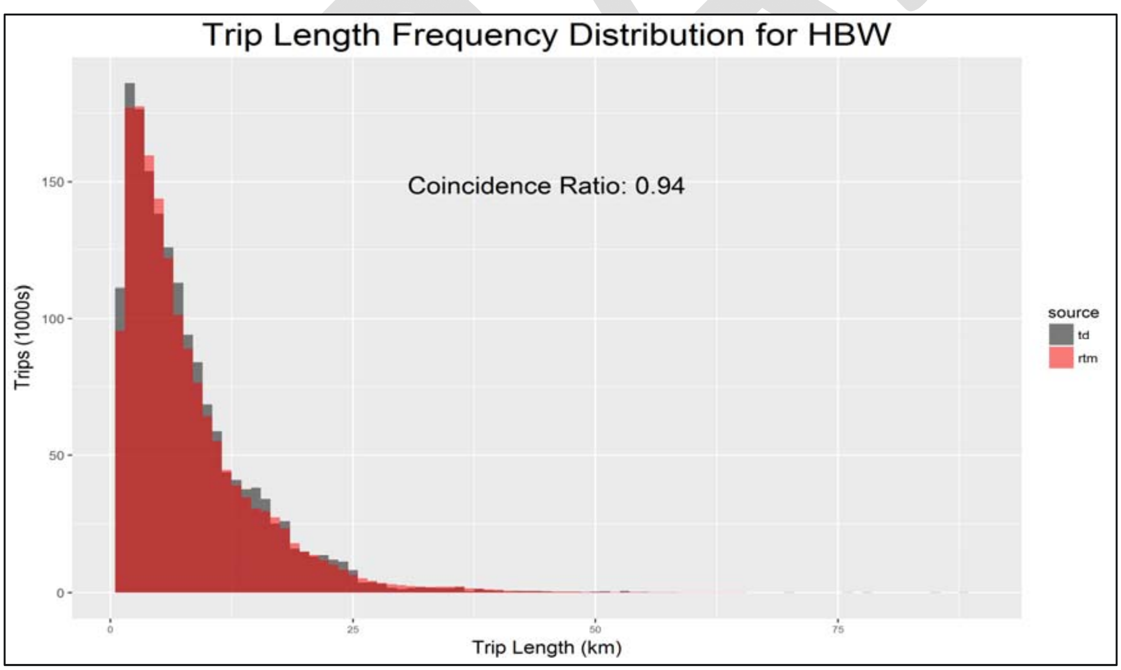

Figure 5-06: Trip Length Frequency Distribution for Home-based Work Trips

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[8] See https://ops.fhwa.dot.gov/freight/publications/qrfm2/sect08.htm for a definition of the coincidence ratio and a discussion of its use. In general the coincidence ratio is a way to compare two distributions, with values that range from 0 to 1. The more similar the distributions are the closer the value will be to 1.

HOME-BASED UNIVERSITY

For the home-based university purpose, a single production matrix is balanced to a single attraction matrix. Figure 5-07 shows the estimated model parameters.

Income	Auto	θ	λ	α	μ
All	All	0.4	-0.106753	0.001030	-0.000005

Balancing Type: Doubly-constrained
K-Factor Range: 0.80 - 1.20

Figure 5-07: Home-based University Trip Distribution Parameters

Figure 5-08 compares the modelled and observed trip length distributions by distance. The model, overall, validates well as indicated by the high coincidence ratio. The model slightly overestimates the number of trips in the three to six kilometer range.

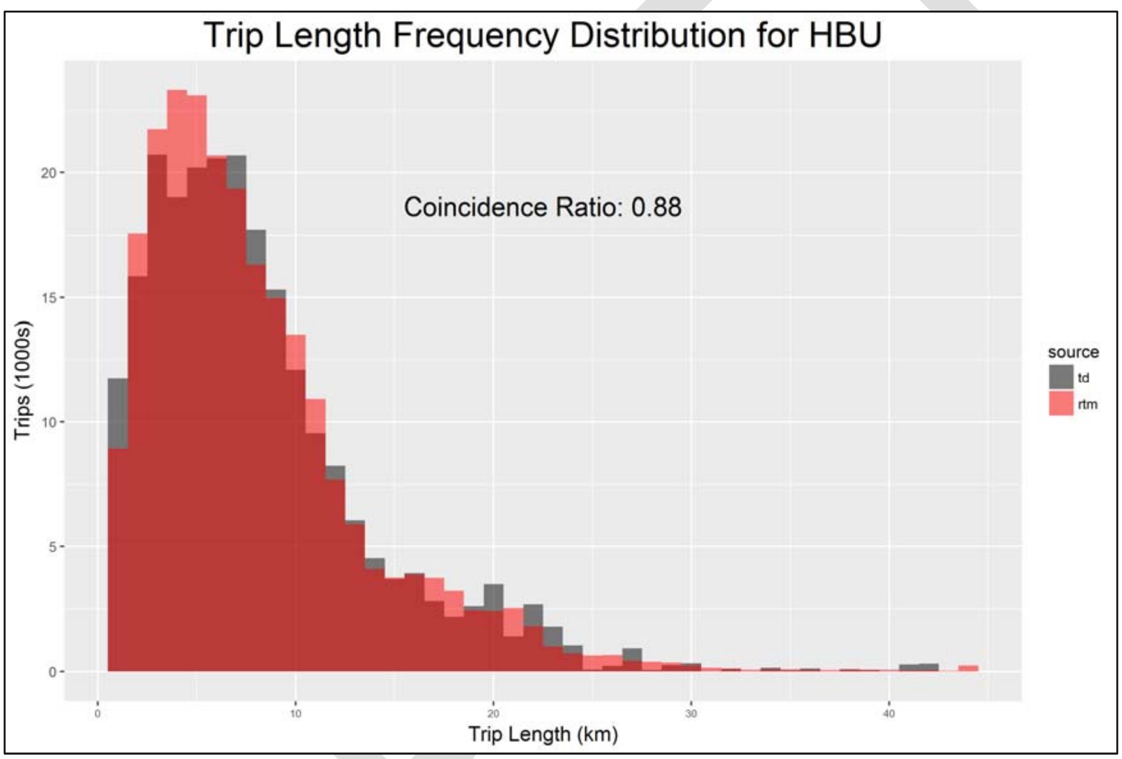

Figure 5-08: Trip Length Frequency Distribution for Home-based University Trips

Home-based School

For the home-based school purpose, a total of nine production matrices, segmented by income and auto ownership, are balanced to a single attraction matrix. Figure 5-09 shows the model's estimated parameters.

Income	Auto	θ	λ	α	μ
Low	0	0.4	-0.93857	0	0
	1	0.4	-0.94446	0	0
	2	0.4	-0.83963	0	0
Medium	0	0.4	-0.93857	0	0
	1	0.4	-0.94446	0	0
	2	0.4	-0.83963	0	0
High	0	0.4	-0.93857	0	0
	1	0.4	-0.94446	0	0
	2	0.4	-0.83963	0	0

Balancing Type: Doubly-constrained

K-Factor Range: 0.90 - 1.10

Figure 5-09: Home-based School Trip Distribution Parameters

Figure 5-10 compares the modelled and observed trip length distributions by distance. The model, overall, validates well as indicated by the high coincidence ratio.

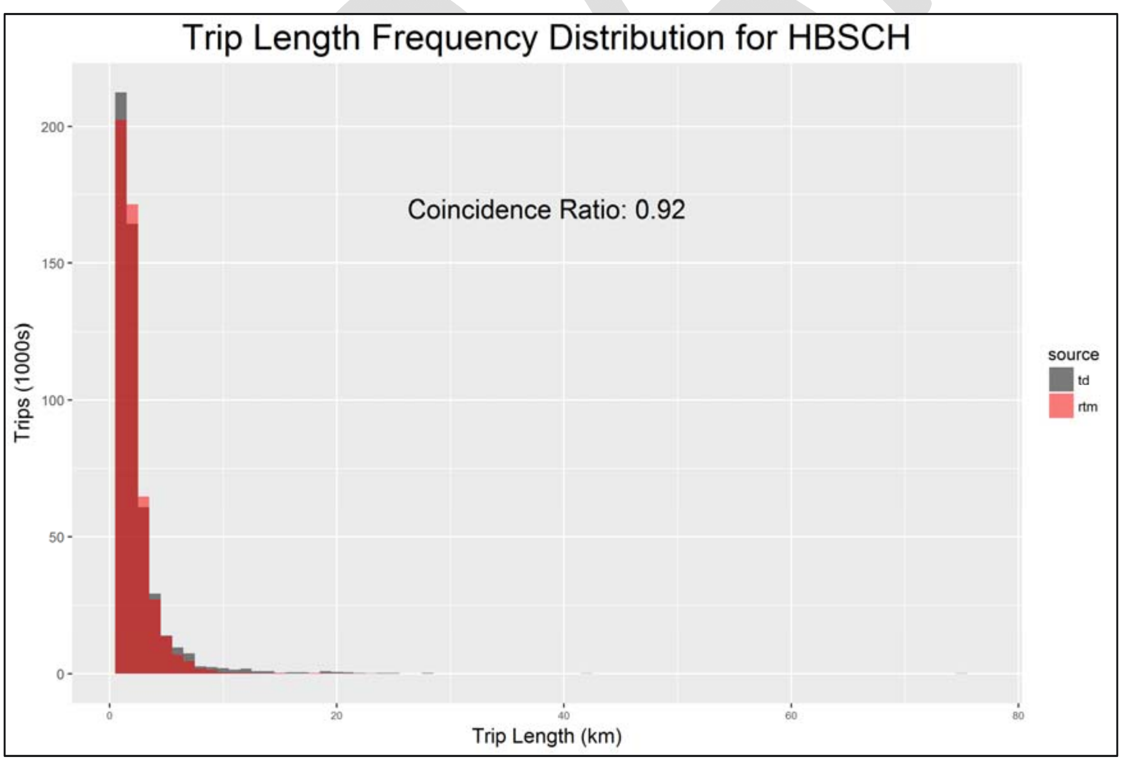

Figure 5-10: Trip Length Frequency Distribution for Home-based School Trips

HOME-BASED SHOPPING

For the home-based shopping purpose, a total of nine production matrices, segmented by income and auto ownership, are balanced to a single attraction matrix. Figure 5-11 shows the estimated model parameters.

Income	Auto	θ	λ	α	μ
Low	0	0.8	-0.269174	0.004639	-0.000065
	1	0.8	-0.308665	0.004853	-0.000066
	2	0.8	-0.288528	0.005203	-0.000092
Medium	0	0.8	-0.269174	0.004639	-0.000065
	1	0.8	-0.308665	0.004853	-0.000066
	2	0.8	-0.288528	0.005203	-0.000092
High	0	0.8	-0.269174	0.004639	-0.000065
	1	0.8	-0.308665	0.004853	-0.000066
	2	0.8	-0.288528	0.005203	-0.000092

Balancing Type: Singly-constrained
K-Factor Range: 0.87 - 1.13

Figure 5-11: Home-based Shopping Trip Distribution Parameters

Figure 5-12 compares the modelled and observed trip length distributions by distance. The model, overall, validates well as indicated by the high coincidence ratio.

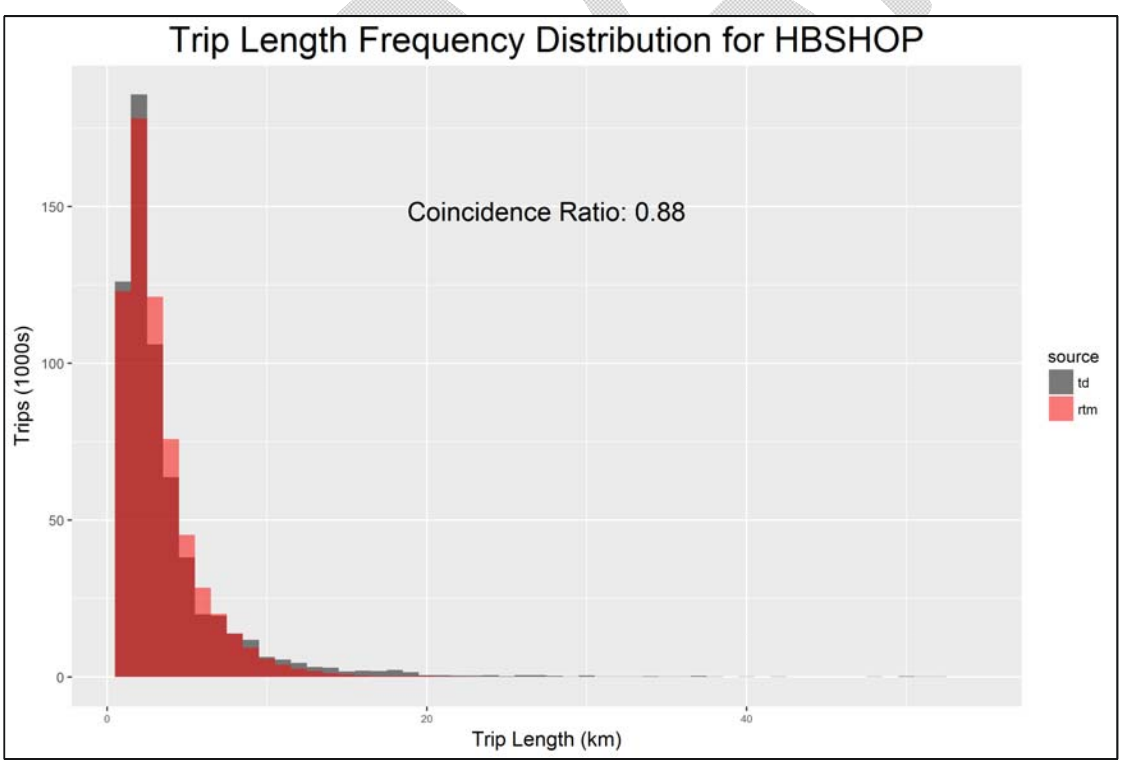

Figure 5-12: Trip Length Frequency Distribution for Home-based Shopping Trips

HOME-BASED PERSONAL BUSINESS

For the home-based personal business purpose, a total of nine production matrices, segmented by income and auto ownership, are balanced to a single attraction matrix. Figure 5-13 shows the estimated model parameters.

Income	Auto	θ	λ	α	μ
Low	0	0.5	-0.293972	0.004422	-0.000039
	1	0.5	-0.256702	0.003497	-0.000025
	2	0.5	-0.265041	0.003786	-0.000033
Medium	0	0.5	-0.293972	0.004422	-0.000039
	1	0.5	-0.256702	0.003497	-0.000025
	2	0.5	-0.265041	0.003786	-0.000033
High	0	0.5	-0.293972	0.004422	-0.000039
	1	0.5	-0.256702	0.003497	-0.000025
	2	0.5	-0.265041	0.003786	-0.000033

Balancing Type: Singly-constrained
K-Factor Range: 0.87 - 1.13

Figure 5-13: Home-based Personal Business Trip Distribution Parameters

Figure 5-14 compares the modelled and observed trip length distributions by distance. The model, overall, validates reasonably well as indicated by the high coincidence ratio. The model tends to underestimate longer distance trips. Personal business trips in the RTM generally have a broad definition and can include short distance trips, such as trips to the bank or potentially longer distance trips such as servicing a car.

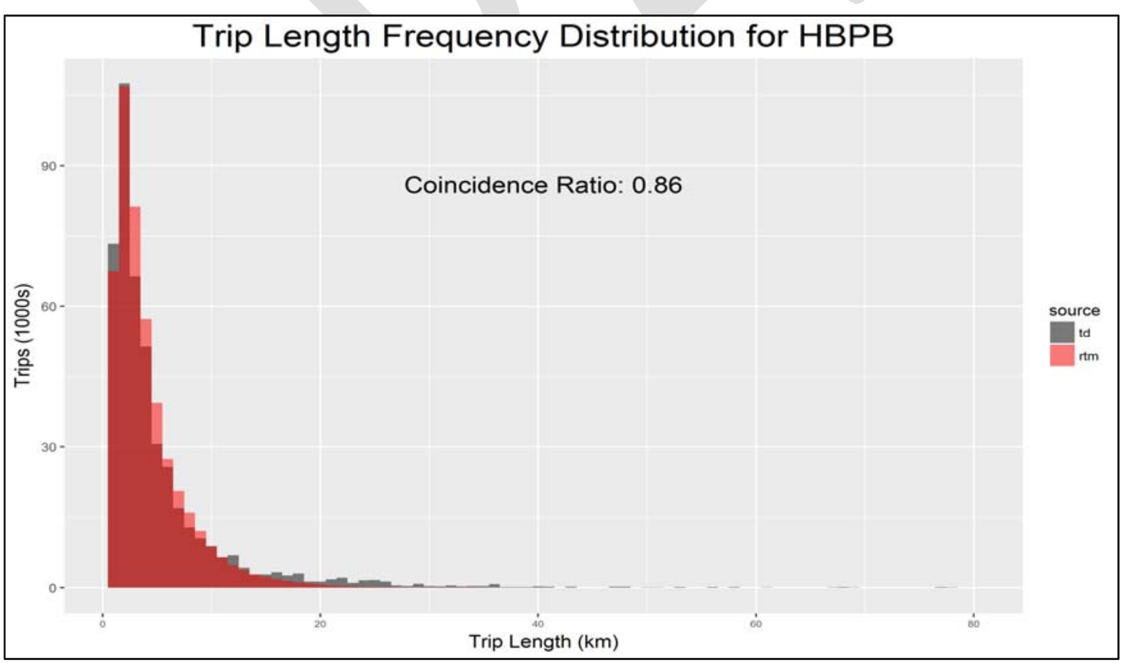

Figure 5-14: Trip Length Frequency Distribution for Home-based Personal Business Trips

Home-based Social-Recreational

For the home-based social-recreational purpose, a total of nine production matrices, segmented by income and auto ownership, are balanced to a single attraction matrix. Figure 51- shows the estimated model parameters.

Income	Auto	θ	λ	α	μ
Low	0	0.8	-0.205104	0.003596	-0.000032
	1	0.8	-0.237037	0.003915	-0.000036
	2	0.8	-0.238268	0.003367	-0.000023
Medium	0	0.8	-0.205104	0.003596	-0.000032
	1	0.8	-0.237037	0.003915	-0.000036
	2	0.8	-0.238268	0.003367	-0.000023
High	0	0.8	-0.205104	0.003596	-0.000032
	1	0.8	-0.237037	0.003915	-0.000036
	2	0.8	-0.238268	0.003367	-0.000023

Balancing Type: Singly-constrained
K-Factor Range: 0.87 - 1.13

Figure 5-15: Home-based Social-recreational Trip Distribution Parameters

Figure 5-16 compares the modelled and observed trip length distributions by distance. The model, overall, validates well as indicated by the high coincidence ratio.

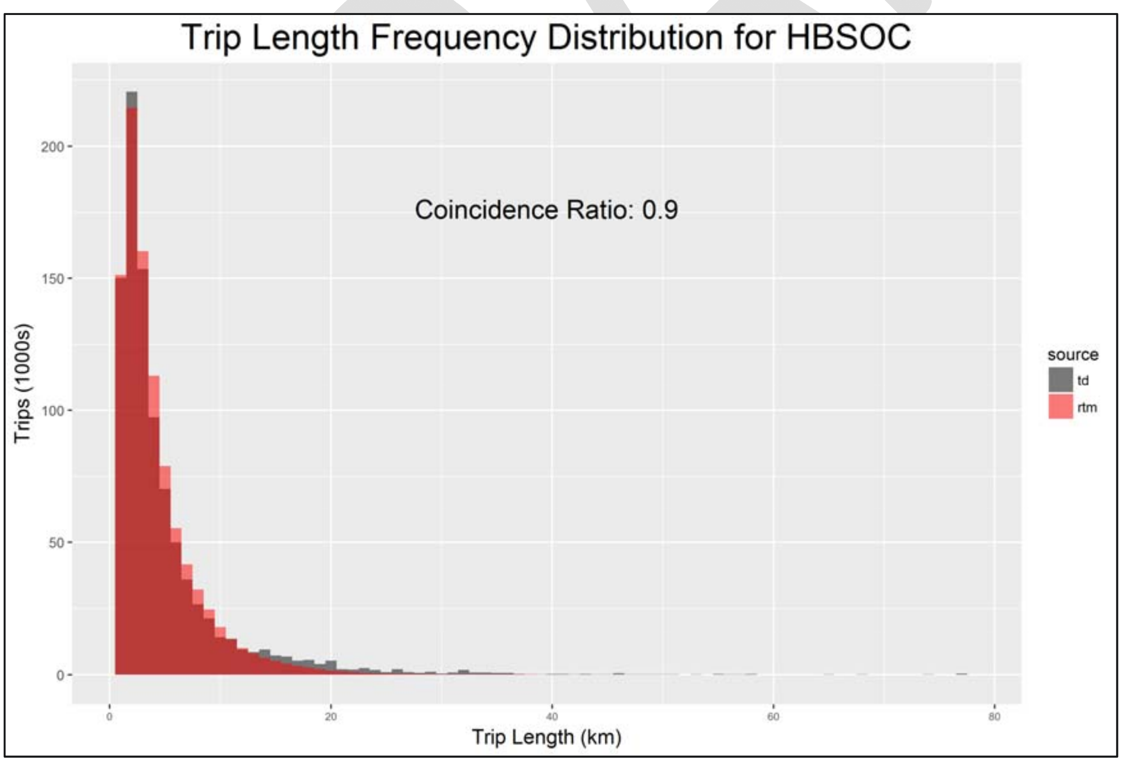

Figure 5-16: Trip Length Frequency Distribution for Home-based Social/Recreational Trips

HOME-BASED ESCORTING

For the home-based escorting purpose, a total of nine production matrices, segmented by income and auto ownership, are balanced to a single attraction matrix. Figure 5-17 shows the estimated model parameters.

Income	Auto	θ	λ	α	µ
Low	0	0.2	-0.406931	0	0
	1	0.2	-0.386407	0	0
	2	0.2	-0.391416	0	0
Medium	0	0.2	-0.406931	0	0
	1	0.2	-0.386407	0	0
	2	0.2	-0.391416	0	0
High	0	0.2	-0.406931	0	0
	1	0.2	-0.386407	0	0
	2	0.2	-0.391416	0	0

Balancing Type: Singly-constrained
K-Factor Range: 0.90 - 1.10

Figure 5-17: Home-based Escorting Trip Distribution Parameters

Figure 5-18 compares the modelled and observed trip length distributions by distance. The model, overall, does not validate as well as other purposes, especially for longer distance trips. This is attributed to the broad definition of escorting trips in the RTM which can include short trips, such as dropping children at school, or longer distance trips such as dropping a friend at the airport or ferry terminal.

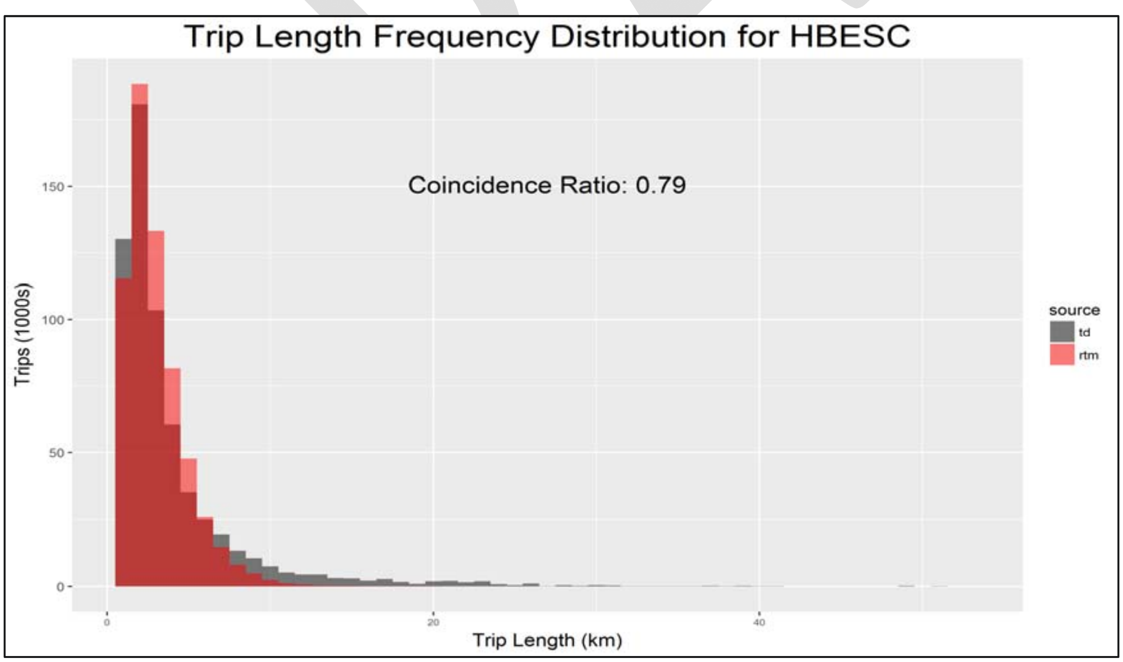

Figure 5-18: Trip Length Frequency Distribution for Home-based Escorting Trips

Non-home-based Work

For the non-home-based work purpose, a single production matrix is balanced to a single attraction matrix. Figure 5-19 shows the estimated model parameters.

Income	Auto	θ	λ	α	μ
All	All	0.7	-0.094648	0	0

Balancing Type: Doubly-constrained
K-Factor Range: 0.90 - 1.10

Figure 5-19: Non-home-based Work Trip Distribution Parameters

Figure 5-20 compares the modelled and observed trip length distributions by distance. The model, overall, does not validate as well as other purposes, especially for shorter distance trips. This is not surprising given that these are non-home base trips that are made as part of a journey. Non-home-work trips can be very short, such as going to a restaurant at lunch hour, or much longer, such as stopping at a shopping center close to home on the way back from the office.

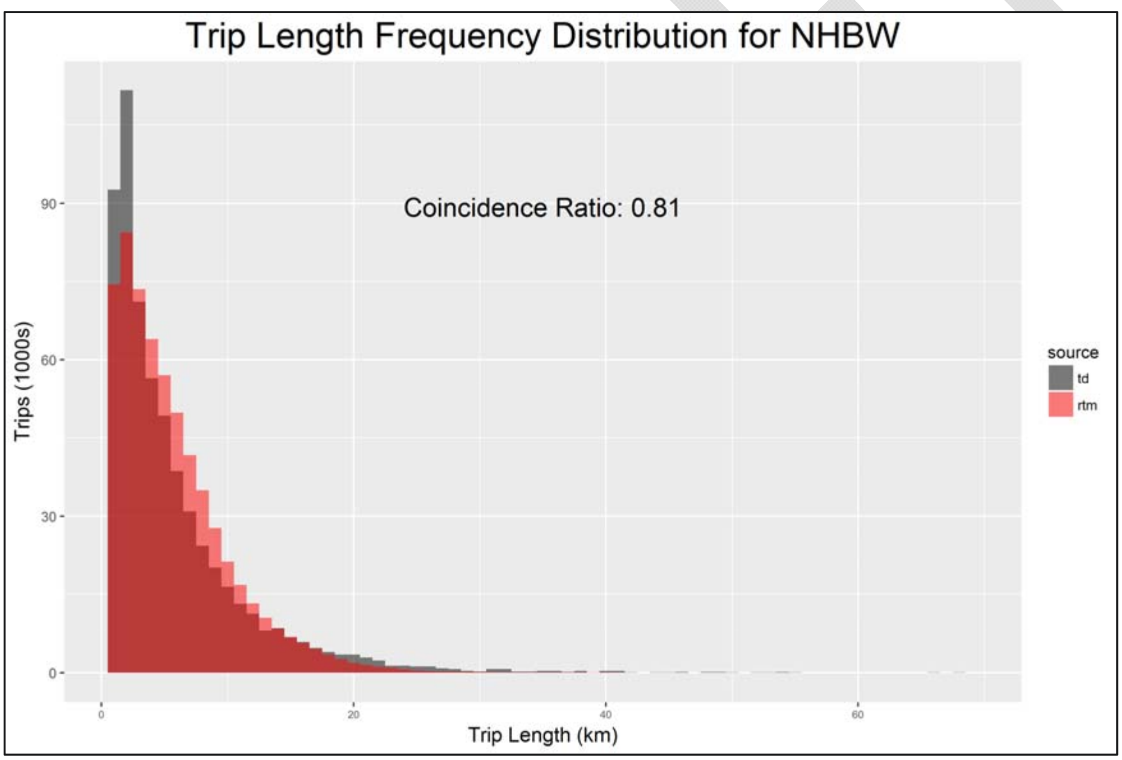

Figure 5-20: Trip Length Frequency Distribution for Non-home-based Work Trips

Non-home-based Other

For the non-home-based other purpose, a single production matrix is balanced to a single attraction matrix. Figure 5-21 shows the estimated model parameters.

Income	Auto	θ	λ	α	µ
All	All	0.8	-0.273022	0.007442	-0.000285

Balancing Type: Singly-constrained
K-Factor Range: 0.90 - 1.10

Figure 5-21: Non-home-based Other Trip Distribution Parameters

Figure 5-22 compares the modelled and observed trip length distributions by distance. The model, overall, validates reasonably well as indicated by the high coincidence ratio. The model under-estimates longer distance trips due to the broad definition of non-home-based trips in the RTM.

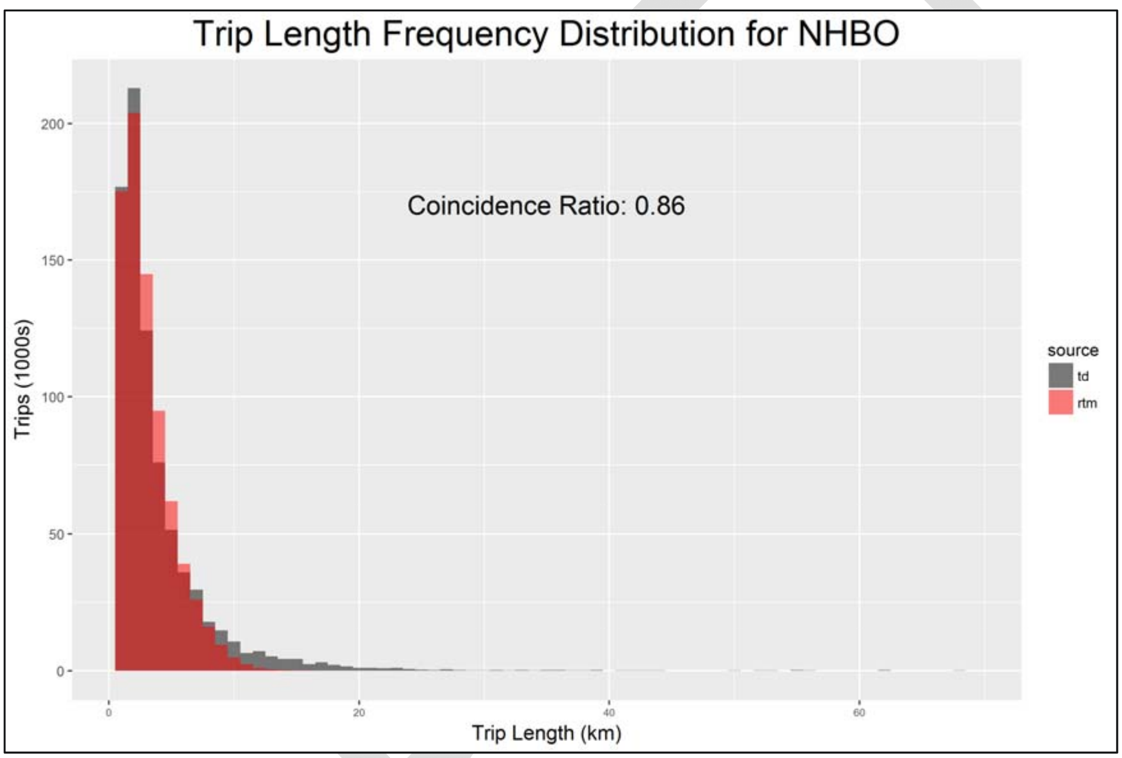

Figure 5-22: Trip Length Frequency Distribution for Non-home-based Other Trips

6: Mode Choice

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The mode choice model is the third component of the four-step model. The model takes the outputs of the trip distribution model – total productions and attractions between TAZs – and assigns each trip to one of several modes based on a variety of trip and trip-maker characteristics. In total nine mode choice models are estimated; one for each trip purpose in the RTM3. The number of travel modes in each of these models differs according to mode applicability and data availability – ranging from five to 11 modes. Some fundamental changes were implemented in RTM3 described in the following sections.

DAILY PRODUCTION/ATTRACTION (ROUND TRIP) ESTIMATION

The mode choice models were estimated at the daily level in production/attraction (round-trip) format except for the non-home based trip purposes. The difference between production/attraction (PA) and origin/destination (OD) format is discussed in section X. Estimating and applying the mode choice model in PA format is beneficial in addressing trip directionality when blending the skims – this was a major problem in the Phase 2 model. This change required a fundamental restructuring of the data flow. Mode choice now requires a daily estimation of the travel impedances at the PA level. However, the model has three assignment hours, the AM and PM peaks and a MD period used to represent off-peak travel. The translation from peak hour to daily impendences is achieved by applying time-of-day slicing factors which are discussed in section X.

MODE CHOICE CONSISTENT WITH TRIP DISTRIBUTION AND ASSIGNMENT

As mentioned previously, the Phase 2 trip distribution model friction factor form did not link trip distribution and mode choice as the impedance functions were not consistent across the two models, and applied attraction-constrained models for all trip purposes. In Phase 3, this consistency is achieved through an improved impedance function using mode choice logsums. In addition, consistency between the mode choice and assignment models is achieved by using the estimated VOTs and other perception factors from mode choice in assignment. More details on VOTs and perception factors used in trip assignment are discussed in section X.

VOT HETEROGENEITY

The models were estimated allowing for user (i.e. household class) heterogeneity by the value of travel time (VOT). VOT can vary widely between users, and an individual's VOT can vary depending on their trip purpose. Capturing these differences reduces aggregation biases and improves forecast accuracy. The mode choice models in RTM3 were estimated with different time and cost perceptions by income level and trip purpose to capture VOT heterogeneity across different household and trip segments. The application of different VOTs allows different user classes to have different responses to a given scenario.

NEW TRAVEL MODES

New travel modes were introduced including transit auto access (park-and-ride) modes and the West Coast Express (WCE) commuter rail. West Coast Express (WCE) is a commuter rail service operating between downtown Vancouver and Mission City during the morning and evening peak periods in the peak direction. It carries about 0.75% of the modelled home-based work trips. In the Phase 2 model, bus and rail were treated as two distinct transit modes in the mode choice and transit assignment models. As such SkyTrain, SeaBus, and WCE were modelled as a single (rail) mode. However, a number of characteristics about the WCE make it district from SkyTrain, for instance, the fare structure, quality of service, availability throughout the day, and headway. The opening of the Evergreen line in December 2016 introduced direct competition between the WCE and SkyTrain services for trips from the North East Sector to parts of Vancouver. A distinct WCE mode was introduced in RTM3 to properly model the competition between WCE and SkyTrain, and to capture the variation in users' perception of service levels and fare structures between the two transit rail modes.

DATA SOURCES

The primary data used to estimate the mode choice models are:

- Trip diary data structured in PA round-trip format, except for non-home-based trip purposes which are modelled in OD format
- RTM skims extracted by time-of-day and VOT class.
- Land use data, such as population and employment by TAZ
- Parking cost data
- Outputs of upstream modules, such as household workers, income and auto availability

These data sources were joined to create an estimation dataset for each trip purpose. The data processing for the estimation data set proceeded as follows:

- A PA identifier was assigned to each trip leg based on the purpose, origin, destination, and mode of travel.
- Skims from the RTM for travel time and cost were joined to trip legs of each PA based on household VOT class (generally related to the household income levels and trip purpose) and the trip origin, destination, and time-of-day.
- A set of mode availability conditions was defined for trip leg based on observed patterns from the trip diary of each trip purpose.
- Trip legs were aggregated to PAs and the skims were blended to produce average skims for each PA according to the trip legs' time-of-day and PA level mode availability.
- Trip legs that do not have a matching trip in the opposite direction (e.g. driving from home to work in the morning but stopping at a grocery store on the way back) were treated as single-trip PAs with a weight of 0.5 compared to a weight of 1 for complete PAs.
- Land use variables were joined to trip origin, destination, or both, as needed. Finally, parking cost data were joined to trips' non-home ends.

Model Structure

Mode choice was specified as a nested-logit model where travel modes that share similar characteristics are grouped in nests. Several nesting structures were considered and empirically tested. Two candidate structures were closely investigated for final model selection – one is shown in figure XX below (the successful candidate) and the other is similar expect for the transit nest which included two sub-nests: transit main modes (bus, rail, and WCE) and transit access mode (walk, and auto). Both nesting structures are empirically valid; however, the first nesting structure outperformed the second one in terms of goodness-of-it. It is worth noting that the nesting structure can vary between trip purposes because the modeled travel modes can be different across trip purposes. For instance, park-and-ride (PNR) modes are only available for home-based work trips and SOV is not available as a mode for home-based school trips. Figure 6-01 shows the adopted nesting structure for the home-based work mode choice model, which is the most detailed nesting structure among the nine mode choice models.

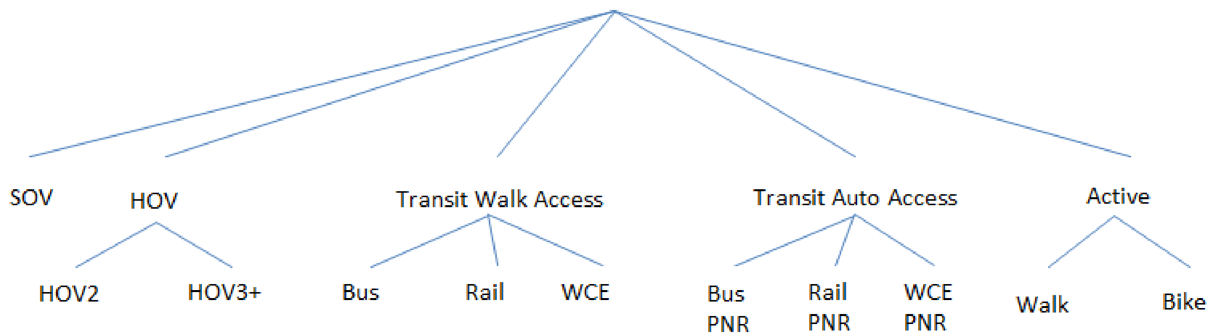

Figure 6-01: Mode Choice Nesting Structure

Model Form

The systematic utility of each of the lower level nest alternatives 'i' can be defined in a linear form as:

$$V_i = ASC + \sum_{j}^{m} \beta_j \cdot x_j$$

Where:

'ASC' represents alternative-specific constants,
'x_j' represents a set of 'm' explanatory variables and
'β_j' represents their corresponding estimated coefficients.

These utilities are used directly for calculating the conditional choice probabilities of each alternative within each of the nests as follows:

$$P_{i|n} = \frac{e^{V_i}}{\sum_j^k e^{V_j}}$$

Where 'k' is the number of alternatives in a given nest 'n'. The utilities each of the upper level nest alternatives (composite alternatives) or the 'logsums', are given by:

$$V_n = \theta \cdot \log(\sum_{j}^{k} e^{V_j})$$

Where 'θ' is the structural or tree coefficient of nest 'n' and the sum is taken over its elementary alternatives. The logsums are used to define the probabilities of the higher level nest alternatives 'n':

$$P_n = \frac{e^{V_n}}{\sum_j^c e^{V_j}}$$

Where 'c' is the number of nests. Finally, the probability of the lower level nest alternatives 'i' can be defined as follows:

$$P_i = P_{i|n} * P_n$$

Model Examination

The following section presents the nine mode choice models estimated for RTM3. Various model specifications were attempted for each model to determine the ideal variable set and ensure that all of the coefficients have a logical magnitude and direction (sign). Almost all of the estimated variables' coefficients were significant at the 95% confidence level and any variables below this level were retained because they had the correct sign and magnitude and the wider confidence interval is believed to be due to low sample size.

The SOV mode is the reference level for most of the model choice models, with the following exceptions:

- The SOV mode is not available for home-based school so walk was selected as the reference mode
- Home-based escorting uses a collapsed auto mode (i.e. a single auto mode without differentiation between SOV and HOV) because at least one leg of the PA journey must be HOV
- Non-home-based other uses a collapsed auto mode due to data-availability in the trip diary

Mode Availability

Mode availability conditions define users' choice set in mode choice. Including choices that are not feasible (which are assumed to be excluded from the individuals' choice sets) reduces the models' abilities to accurately replicate the observed mode shares. Using observed distributions of different trip purposes from the trip diary, a list of conditions were identified to determine whether a travel mode is available or not based on level of service attributes between each pair of TAZs and/or household attributes. For example, if the walking (access) time to transit is more than 30 mins, transit is excluded from the choice set for trips between the two zones. Similarly, if a household has zero available vehicles and is not within the catchment area of carshare zones, SOV is excluded from this household's choice set. Other conditions include but not limited to:

- For transit modes: maximum number of transfers, minimum in-vehicle travel time
- For active modes: maximum travel distance
- For drive-alone mode: auto availability and possession of a driver license

VARIABLE RELATIONSHIPS

The relationships between certain estimated mode choice coefficients imply travelers' values and perceptions of travel that warrant further consideration.

The relationship between the travel cost and in-vehicle travel time coefficients implies the value of travel time savings (VOT). VOT is commonly used in transportation planning cost/benefit analysis to estimate how much money a traveler is willing to pay to reduce travel times; or conversely, the economic benefit of reduced travel times from a given policy or infrastructure project. VOT is also used within the model to convert between cost units of time and money when both must be considered simultaneously. This measure is referred to as generalized cost or generalized time depending on the end units.

In RTM3, VOT varies by trip purpose and the income level of the traveler's household. Compulsory trip purposes typically (but not necessarily) show higher VOTs than discretionary purposes and travelers from high-income households typically have higher VOTs than travelers from lower income ones. It is worth noting that VOTs were estimated econometrically expect for a few cases where they were asserted. Estimated VOTs for each trip purpose are presented below.

For transit modes, out-of-vehicle travel time components indicate individuals' perception of waiting, walking and transferring relative to being in the vehicle. For example, a ratio of 2.5 between the waiting time coefficient and the in-vehicle travel time coefficient means travelers on average perceive waiting time as 2.5 times more onerous than in-vehicle time, even when the actual time spent in each situation is equal. In addition, the perception of in-vehicle travel time differs between bus and rail and is captured by the ratio of in-vehicle travel time coefficients across modes. In general, all else being equal, travelers *perceive* bus travel time as taking longer than rail travel time and thus prefer travel on rail modes to travel on buses.

HOV COST SHARING AND DAMPENING

HOV drivers and passengers are modeled together in RTM3 and the mode represents both inter- and intra-household shared vehicles. This distinction has implications for cost sharing. Inter-household HOV trips are expected to represent carpooling with costs shared amongst vehicle occupants. Intra-household HOV trip costs may be borne by the driver regardless of the number occupants. On the other hand the per-person trip costs decrease as occupants are added to the vehicle as opposed to transit, for example, where the same additional fares must be paid for each passenger. Therefore, assumptions about the level of cost-sharing for HOV trips in RTM3 are based on the expected proportion of inter- vs intra-household HOV trips by trip purpose. In general compulsory trip purposes, such as home-based work, are assumed to have a higher proportion of inter-household HOV trips, while discretionary purposes, such as home-based shopping, are assumed to have a higher proportion of intra-household HOV trips.

Shared rides also affect individual and vehicle VOT. The presence of other people in the vehicle tends to raise aggregate VOT and as such vehicles with more people tend to be more willing to pay for travel times savings compared to SOVs. It was shown empirically that the effect of occupancy on VOT appears to be non-linear[9].

[9] For more information see *Improving Our Understanding of How Highway Congestion and Pricing Affect Travel Demand*.

For instance an increase of auto occupancy from 1 to 2 is expected to have an increase of VOT by a factor less than 2.

The incorporation of auto occupancy effects is implemented through a HOV scaling parameter. HOV monetary costs are divided by the number of occupants raised to the scaling parameter[1]. The scaling parameter ranges from 0 to 1 where 0 results in no cost dampening and 1 results in full cost dampening. Since it is assumed that in inter-household trips the travel costs are mostly shared between the vehicle users, trip purposes with more inter-household HOV trips use a larger scaling parameter (closer to 1) and trip purposes with more intra-household HOV use a lower scaling parameter. Another aspect that may affect the cost sharing mechanism for intra-household HOV trips is that adults are more likely share costs among themselves compared to sharing costs between adults and children – this was factored in for trip purposes such as home-based school by further lowering the scaling parameter. The HOV scaling parameter values were asserted for all purposes.

HOME-BASED WORK (HBW)

The HBW model includes all possible (11) travel modes – distinguishing between drive-alone and shared-drive modes, different types of transit services, and different transit access modes. Figure 6-02 shows the variables' definitions and the estimated coefficients. Almost all variables' coefficients are statistically significant at the 95% confidence level and all were estimated with the expected sign and relative magnitude. The reported rho-squared values are 0.19 and 0.49 w.r.t. constant-only and null models, respectively. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Mode	Coefficient	t-Statistics
Alternative Specific Constant	HOV2	0.9578	2.1894
Alternative Specific Constant	HOV3+	-0.8391	-1.9115
Alternative Specific Constant	Bus	-0.1646	-0.2484
Alternative Specific Constant	Bus PNR	-2.0271	-3.2111
Alternative Specific Constant	Rail	1.6577	2.4215
Alternative Specific Constant	Rail PNR	0.7259	1.3042
Alternative Specific Constant	WCE	3.2035	4.0500
Alternative Specific Constant	WCE PNR	0.1176	0.1956
Alternative Specific Constant	Walk	6.7431	11.2089
Alternative Specific Constant	Bike	1.3421	2.3865
Travel Cost/Transit Fare - Low Income	All modes except Walk and Bike	-0.2564	-10.5832
Travel Cost/Transit Fare - Medium Income	All modes except Walk and Bike	-0.1833	-11.3039
Travel Cost/Transit Fare - High Income	All modes except Walk and Bike	-0.1583	-11.1007
Wait Time	All transit modes	-0.1472	-9.6657
Access Time	All transit modes	-0.1016	-12.6979
Number of Boardings	All transit modes	-0.6562	-8.4367
Distance	Walk	-1.5120	-20.1865
Distance	Bike	-0.4318	-11.8376
In-vehicle Travel Time	SOV, HOV2, and HOV3+	-0.0482	-10.7650
In-vehicle Travel Time	Bus	-0.0598	-12.4687
In-vehicle Travel Time	Rail and WCE	-0.0476	-5.0724
One Available Vehicle - Dummy	SOV	5.4791	11.4033
Two+ Available Vehicle - Dummy	SOV	7.5052	14.0239
One Available Vehicle - Dummy	HOV2 and HOV3+	1.5899	5.6285
Two+ Available Vehicle - Dummy	HOV2 and HOV3+	2.8379	9.5000
No Available Vehicle - Dummy	Bus and Rail	1.2134	6.4082
Log Percentage of Population 55 and over (at production end)	Walk	-0.1963	-1.9880
Log Percentage of Population 55 and over (at production end)	Bike	-0.3349	-3.3508
Log Transit Accessibility (at production end)	Bus	0.3515	6.3647
Log Transit Accessibility (at production end)	Rail and WCE	0.3214	5.7238
Log Total Density (at production and attraction ends)	Walk	0.1156	1.7978
Intra-CDB - Dummy	Walk	1.6165	7.3418
Bike Score	Bike	0.5502	6.5984
Distance	All transit modes	-0.1355	-4.8449
Distance Squared	All transit modes	0.0013	4.5166
Log Distance	All transit modes	2.1226	10.5244
Nesting Parameter		0.5858	21.5950

Figure 6-02: Home-based Work Mode Choice Model

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As expected, people from households with more vehicles have a greater propensity to use auto modes and those with fewer or no vehicles are more likely to choose transit or active modes. Similarly, households that are located in areas with higher transit accessibility are more likely to use transit modes and trips within the CBD have a higher propensity to use active modes. Conversely, a higher proportion of older people in the home zone is associated with a lower active mode share. Finally, including distance terms in the transit modes' utility functions allows mode choice preferences to be sensitive to trip lengths and as such it helps in replicating mode shares by trip length bins. In order to define individuals' share of trip costs and to factor in the share of inter-/intra-household HOV trips, the cost is divided by the auto occupancy raised to the power of 0.85 to account for an increased willingness to pay for travel time savings when more people are in the vehicle.

A summary of the estimated variable relationships is presented in Figure 6-03 below.

Variable	Value
VOT – Low Income	$11.3 /hr
VOT – Medium Income	$15.8 /hr
VOT – High Income	$18.3 /hr
Wait perception w.r.t. in-vehicle travel time	2.5
Walk perception w.r.t. in-vehicle travel time	1.7
Boarding perception w.r.t. in-vehicle travel time (transfer penalty)	11
Bus in-vehicle travel time w.r.t. rail in-vehicle travel time	1.26
Vehicle occupancy scale	0.85

Figure 6-03: Home-based Work VOT and Perception Factors

HOME-BASED UNIVERSITY (HBU)

Figure 6-04 shows the variables' definitions and the estimated coefficients for HBU trips. Almost all variables' coefficients are statistically significant at the 95% confidence level and all were estimated with the expected sign and relative magnitude. The reported rho-squared values are 0.20 and 0.29 w.r.t. constant-only and null models, respectively. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Mode	Coefficient	t-Statistics
Alternative Specific Constant	HOV2+	-2.6553	-7.0207
Alternative Specific Constant	Bus	2.7679	4.5145
Alternative Specific Constant	Rail	4.1123	5.6751
Alternative Specific Constant	Walk	5.7272	7.2357
Alternative Specific Constant	Bike	-0.4392	-0.7310
Travel Cost/Transit Fare	All modes except Walk and Bike	-0.3530	-5.5469
In-vehicle Travel Time	All modes except Walk and Bike	-0.0616	-7.1552
Wait Time	Bus and Rail	-0.2123	-6.2764
Access Time	Bus and Rail	-0.1123	-7.0365
Number of Boardings	Bus and Rail	-0.6958	-5.9126
Distance	Walk	-2.7679	-8.1066
Distance	Bike	-0.8077	-5.6533
Log University Accessibility (at production end)	Bus and Rail	0.1225	2.5418
Distance	Bus and Rail	0.0977	4.6334
Nesting Parameter		0.4598	8.5328

Figure 6-04: Home-based University Mode Choice Model

Due to data availability the HOV2 and HOV3+ modes were collapsed to a single HOV2+ mode and the park-and-ride and WCE modes were not included.

Public post-secondary students in Metro Vancouver are required to purchase a significantly discounted transit pass as part of their student fees. To reflect post-secondary students' discounted fares and account for the fact that transit prices do not play a major role in short term mode choice decisions regular transit fares are reduced by 90% in RTM3 for the HBU purpose.

A summary of the estimated variable relationships is presented in Figure 6-05 below.

Variable	Value
VOT	$10.5 /hr
Wait perception w.r.t. in-vehicle travel time	3.4
Walk perception w.r.t. in-vehicle travel time	1.8
Boarding perception w.r.t. in-vehicle travel time (transfer penalty)	11.3
Vehicle occupancy scale	0.75

Figure 6-05: Home-based University VOT and Perception Factors

HOME-BASED SCHOOL (HBSCH)

Figure 6-06 shows the variables' definitions and the estimated coefficients. Almost all variables' coefficients are statistically significant at the 95% confidence level and all were estimated with the expected sign and relative magnitude. The reported rho-squared values are 0.14 and 0.38 w.r.t. constant-only and null models, respectively. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Mode	Coefficient	t-Statistics
Alternative Specific Constant	HOV2+	-5.1331	-8.3290
Alternative Specific Constant	Bus	-4.5127	-6.1778
Alternative Specific Constant	Rail	-5.2264	-5.5733
Alternative Specific Constant	Bike	-4.0129	-21.7789
Generalized Cost (VOT $5 /hr)	All modes except Walk and Bike	-0.4459	-8.5369
Distance	Walk	-1.8750	-32.0291
Distance	Bike	-1.3204	-16.3236
One Available Vehicle - Dummy	HOV2+	1.3859	3.4915
Two+ Available Vehicle - Dummy	HOV2+	2.9053	7.4612
Log Total Density (at production zone)	Bus and Rail	0.3705	2.7767
Log Total Density (at production and attraction zones)	Walk and Bike	0.2224	2.2107
Nesting Parameter – asserted		0.5000	N/A

Figure 6-06: Home-based School Mode Choice Model

A person must be at least 17 years old to drive alone in British Columbia. Therefore, few students are old enough to drive alone and as such, the SOV mode was not included for the home-based school purpose. Due to data availability the HOV2 and HOV3+ modes were collapsed to a single HOV2+ mode and the park-and-ride and WCE modes were not included. Finally trip diary observations were removed from the estimation dataset where school bus or another un-modeled mode was chosen (about 12% of the sample).

The VOT and transit modes' perception factors could not be estimated empirically and were asserted. That is, the model was estimated based on a generic generalized cost variable across all motorized modes. The VOT is set to $5/hr and the other perception factors are consistent with the perception factors used in trip assignment (see section XX).

In order to define individuals' share of trip costs and to factor in the share of inter-/intra-household HOV trips, the cost is divided by the auto occupancy raised to the power of 0. 5 to account for an increased willingness to pay for travel time savings when more people are in the vehicle as well as the high share of HOV passenger (children) compared to HOV drivers (adults). The total cost of HOV trips did not include parking cost since the majority of these trips are escorting trips. In addition, regular transit fares are reduced by 15% to reflect students' concession fares.

A summary of the asserted variable relationships is presented in Figure 6-07 below.

Variable	Value
VOT	$5 /hr
Wait perception w.r.t. in-vehicle travel time	2.5
Walk perception w.r.t. in-vehicle travel time	2.0
Boarding perception w.r.t. in-vehicle travel time (transfer penalty)	10.0
Vehicle occupancy scale	0.85

Figure 6-07: Home-based School VOT and Perception Factors (Asserted)

HOME-BASED SHOPPING (HBSHOP)

Figure 6-08 shows the variables' definitions and the estimated coefficients. Almost all variables' coefficients are statistically significant at the 95% confidence level and all were estimated with the expected sign and relative magnitude. The reported rho-squared values are 0.15 and 0.32 w.r.t. constant-only and null models, respectively. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Mode	Coefficient	t-Statistics
Alternative Specific Constant	HOV2+	1.3891	1.5396
Alternative Specific Constant	Bus	8.8908	6.2555
Alternative Specific Constant	Rail	10.3330	7.0425
Alternative Specific Constant	Walk	10.3917	5.2698
Alternative Specific Constant	Bike	4.6373	2.3069
Travel Cost/Transit Fare – Low/Medium Income	All modes except Walk and Bike	-0.7728	-5.9096
Travel Cost/Transit Fare – High Income	All modes except Walk and Bike	-0.4204	-4.4762
In-vehicle Travel Time	All modes except Walk and Bike	-0.1060	-5.7295
Wait Time	Bus and Rail	-0.1386	-3.7500
Access Time	Bus and Rail	-0.1862	-7.3197
Number of Boarding	Bus and Rail	-0.3787	-2.9178
Distance	Walk	-3.3674	-7.0484
Distance	Bike	-2.4194	-5.0151
One Available Vehicle - Dummy	SOV	9.8003	5.8390
Two+ Available Vehicles - Dummy	SOV	12.4948	6.0603
One Available Vehicle - Dummy	HOV2+	6.8814	6.2152
Two+ Available Vehicles - Dummy	HOV2+	9.6258	6.3777
No Available Vehicle - Dummy	Bus and Rail	2.6049	4.4667
Log Total Density (at production and attraction zones)	Walk and Bike	0.6721	3.9548
Bike Score	Bike	0.4712	3.7545
Nesting Parameter		0.3036	6.6433

Figure 6-08: Home-based Shopping Mode Choice Model

Due to data availability the HOV2 and HOV3+ modes were collapsed to a single HOV2+ mode and the park-and-ride and WCE modes were not included. A summary of the estimated variable relationships is presented in Figure 6-09 below.

Variable	Value
VOT – Low/Medium Income	8.2 $/hr
VOT – High Income	15.1 $/hr
Wait perception w.r.t. in-vehicle travel time	1.3
Walk perception w.r.t. in-vehicle travel time	1.8
Boarding perception w.r.t. in-vehicle travel time (transfer penalty)	3.6
Vehicle occupancy scale	0.75

Figure 6-09: Home-based Shopping VOT and Perception Factors

HOME-BASED PERSONAL BUSINESS (HBPB)

Figure 6-10 shows the variables' definitions and the estimated coefficients. Almost all variables' coefficients are statistically significant at the 95% confidence level and all were estimated with the expected sign and relative magnitude. The reported rho-squared values are 0.16 and 0.33 w.r.t. constant-only and null models, respectively. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Mode	Coefficient	t-Statistics
Alternative Specific Constant	HOV2+	6.3409	3.2717
Alternative Specific Constant	Bus	-17.9009	-3.3005
Alternative Specific Constant	Rail	-16.2246	-2.9992
Alternative Specific Constant	Walk	9.7409	3.7987
Alternative Specific Constant	Bike	5.7407	2.2250
Travel Cost/Transit Fare – Low/Medium Income	All modes except Walk and Bike	-0.3512	-4.5390
Travel Cost/Transit Fare – High Income	All modes except Walk and Bike	-0.2786	-3.7165
In-vehicle Travel Time	All modes except Walk and Bike	-0.0546	-3.7343
Wait Time	Bus and Rail	-0.1111	-2.3982
Access Time	Bus and Rail	-0.1180	-5.2297
Number of Boarding	Bus and Rail	-1.1163	-6.6791
Distance	Walk	-2.9840	-5.7729
Distance	Bike	-2.2737	-4.3366
One Available Vehicle - Dummy	SOV	12.4290	4.6518
Two+ Available Vehicles - Dummy	SOV	14.7557	4.8870
One Available Vehicle - Dummy	HOV2+	4.0807	4.6218
Two+ Available Vehicles - Dummy	HOV2+	6.7363	5.2351
No Available Vehicles - Dummy	Bus and Rail	3.2316	4.2191
Log Total Density (at production zone)	Bus and Rail	2.1729	4.5088
Log Total Density (at production and attraction zones)	Walk and Bike	1.2338	4.5340
Distance	Bus and Rail	0.1922	5.8227
Nesting Parameter		0.3193	5.7010

Figure 6-10: Home-based Personal Business Mode Choice Model

Due to data availability the HOV2 and HOV3+ modes were collapsed to a single HOV2+ mode and the park-and-ride and WCE modes were not included. A summary of the estimated variable relationships is presented in Figure 6-11 below.

Variable	Value
VOT – Low/Medium Income	9.3 $/hr
VOT – High Income	11.8 $/hr
Wait perception w.r.t. in-vehicle travel time	2
Walk perception w.r.t. in-vehicle travel time	2.2
Boarding perception w.r.t. in-vehicle travel time (transfer penalty)	20
Vehicle occupancy scale	0.70

Figure 6-11: Home-based Personal Business VOT and Perception Factors

HOME-BASED SOCIAL/RECREATIONAL (HBSOC)

Figure 6-12 shows the variables' definitions and the estimated coefficients. Almost all variables' coefficients are statistically significant at the 95% confidence level and all were estimated with the expected sign and relative magnitude. The reported rho-squared values are 0.14 and 0.31 w.r.t. constant-only and null models, respectively. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Mode	Coefficient	t-Statistics
Alternative Specific Constant	HOV2+	3.3213	4.4070
Alternative Specific Constant	Bus	-1.6535	-1.0674
Alternative Specific Constant	Rail	0.6821	0.4436
Alternative Specific Constant	Walk	4.4987	4.7178
Alternative Specific Constant	Bike	-0.2980	-0.2979
Travel Cost/Transit Fare – Low Income	All modes except Walk and Bike	-0.3102	-5.7979
Travel Cost/Transit Fare – Medium/High Income	All modes except Walk and Bike	-0.1550	-5.0376
In-vehicle Travel Time	All modes except Walk and Bike	-0.0455	-4.4768
Wait Time	Bus and Rail	-0.0967	-3.5967
Access Time	Bus and Rail	-0.1442	-8.1404
Number of Boarding	Bus and Rail	-0.4641	-4.3791
Distance	Walk	-1.7911	-8.3380
Distance	Bike	-0.8787	-4.3117
One Available Vehicle - Dummy	SOV	5.7981	5.8638
Two+ Available Vehicles - Dummy	SOV	6.8251	6.1910
One Available Vehicle - Dummy	HOV2+	2.6307	6.1063
Two+ Available Vehicles - Dummy	HOV2+	4.0385	6.7530
No Available Vehicles - Dummy	Bus and Rail	1.4005	4.9822
Log Transit Social Accessibility (at production zone)	Bus and Rail	0.7566	4.2858
Log Total Density (at production and attraction zones)	Walk and Bike	0.8982	6.4987
Bike Score	Bike	0.2409	2.4588
Nesting Parameter		0.5549	7.5180

Figure 6-12: Home-based Social/Recreational Mode Choice Model

Due to data availability the HOV2 and HOV3+ modes were collapsed to a single HOV2+ mode and the park-and-ride and WCE modes were not included. A summary of the estimated variable relationships is presented in Figure 6-13 below.

Variable	Value
VOT – Low Income	8.8 $/hr
VOT – Medium/High Income	17.6 $/hr
Wait perception w.r.t. in-vehicle travel time	2.1
Walk perception w.r.t. in-vehicle travel time	3.2
Boarding perception w.r.t. in-vehicle travel time (transfer penalty)	10.2
Vehicle occupancy scale	0.70

Figure 6-13: Home-based Social/Recreational VOT and Perception Factors

HOME-BASED ESCORTING (HBESC)

Figure 6-14 shows the variables' definitions and the estimated coefficients. Almost all variables' coefficients are statistically significant at the 95% confidence level and estimated with the expected sign and relative magnitude. The reported rho-squared values are 0.20 and 0.82 w.r.t. constant-only and null models, respectively. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Mode	Coefficient	t-Statistics
Alternative Specific Constant	Bus	-4.1210	-4.4010
Alternative Specific Constant	Rail	-0.8634	-0.7497
Alternative Specific Constant	Walk	2.3877	4.9452
Alternative Specific Constant	Bike	-1.4711	-2.6463
Generalized Cost (VOT 10 $/hr)	All modes except Walk and Bike	-0.3998	-5.7195
Distance	Walk	-2.4834	-25.6411
Distance	Bike	-1.7698	-12.4108
One Available Vehicle - Dummy	Auto	1.0285	2.1445
Two+ Available Vehicle - Dummy	Auto	2.7314	5.7632
No Available Vehicle - Dummy	Bus and Rail	4.7892	7.0621
Nesting Parameter		0.5000	N/A

Figure 6-14: Home-based Escorting Mode Choice Model

The SOV, HOV2 and HOV3+ modes are aggregated to one auto mode since the nature of escorting trips involves the use of the auto mode with different occupancy levels depending on the PA direction of the trip. The park-and-ride and WCE modes were not included due to data availability.

The VOT and transit mode perception factors could not be estimated empirically and were asserted. This model was estimated based on a generalized cost variable across all motorized modes. The VOT is set to $10/hr and the other perception factors are consistent with the perception factors used in trip assignment (see section XX). The generalized cost for the auto mode does not include parking costs because most escorting trips do not require the driver to exit the vehicle.

A summary of the asserted variable relationships is presented in Figure 6-15 below.

Variable	Value
VOT	$10 /hr
Wait perception w.r.t. in-vehicle travel time	2.5
Walk perception w.r.t. in-vehicle travel time	2.0
Boarding perception w.r.t. in-vehicle travel time (transfer penalty)	10.0
Vehicle occupancy scale	0.70

Figure 6-15: Home-based Escorting VOT and Perception Factors (Asserted)

Non-home-based Work (NHBW)

The non-home-based work model is estimated and applied in OD trip (single-trip PA) format. Figure 6-16 shows the variables' definitions and the estimated coefficients. Almost all variables' coefficients are statistically significant at the 95% confidence level and all were estimated with the expected sign and relative magnitude. The reported rho-squared values are 0.13 and 0.45 w.r.t. constant-only and null models, respectively. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Mode	Coefficient	t-Statistics
Alternative Specific Constant	HOV2+	-2.8233	-10.6476
Alternative Specific Constant	Bus	-15.6427	-5.4028
Alternative Specific Constant	Rail	-13.6698	-4.7738
Alternative Specific Constant	Walk	-5.7875	-8.6548
Alternative Specific Constant	Bike	-10.5889	-11.5555
Travel Cost/Transit Fare	All modes except Walk and Bike	-0.1767	-7.3320
In-vehicle Travel Time	All modes except Walk and Bike	-0.0453	-5.7365
Wait Time	Bus and Rail	-0.1583	-5.3522
Access Time	Bus and Rail	-0.1121	-7.3624
Number of Boardings	Bus and Rail	-0.4143	-3.7636
Distance	Walk	-2.0904	-12.8177
Distance	Bike	-0.6206	-5.4164
Log Transit Accessibility (at production end)	Bus and Rail	1.0895	5.1386
Log Total Density (at production and attraction ends)	Walk	1.2427	10.3626
Log Total Density (at production end)	Bike	0.6734	4.5403
Bike Score	Bike	0.9372	4.9367
Nesting Parameter		0.5423	11.0510

Figure 6-16: Non-home-based Work Mode Choice Model

Due to data availability the HOV2 and HOV3+ modes were collapsed to a single HOV2+ mode and the park-and-ride and WCE modes were not included. A summary of the estimated variable relationships is presented in Figure 6-17 below.

Variable	Value
VOT	15.4 $/hr
Wait perception w.r.t. in-vehicle travel time	3.5
Walk perception w.r.t. in-vehicle travel time	2.5
Boarding perception w.r.t. in-vehicle travel time (transfer penalty)	9.1
Vehicle occupancy scale	0.85

Figure 6-17: Non-home-based Work VOT and Perception Factors

NON-HOME-BASED OTHER (NHBO)

The non-home-based other model is estimated and applied in OD trip (single-trip PA) format. Figure 6-18 shows the variables' definitions and the estimated coefficients. Almost all variables' coefficients are statistically significant at the 95% confidence level and estimated with the expected sign and relative magnitude. The reported rho-squared values are 0.18 and 0.67 w.r.t. constant-only and null models, respectively. In addition, the log likelihood ratio test indicates that the reported model fits the data significantly better than a constant-only model.

Variable	Mode	Coefficient	t-Statistics
Alternative Specific Constant	Bus	-2.7973766	-5.1004
Alternative Specific Constant	Rail	-1.6135827	-2.9957
Alternative Specific Constant	Walk	-2.4369258	-6.5949
Alternative Specific Constant	Bike	-7.3169414	-12.6732
Travel Cost/Transit Fare	All modes except Walk and Bike	-0.4714344	-6.0598
In-vehicle Travel Time	All modes except Walk and Bike	-4.94E-02	-4.5590
Wait Time	Bus and Rail	-0.1383701	-5.9693
Access Time	Bus and Rail	-6.38E-02	-4.8507
Number of Boardings	Bus and Rail	-0.3079639	-3.0871
Distance	Walk	-1.5966088	-7.4431
Distance	Bike	-0.6588046	-3.4070
Log Total Density (at production end)	Bus and Rail	0.23577843	3.1373
Log Total Density (at production and attraction ends)	Walk	0.42575156	6.7668
Bike Score	Bike	0.81746279	6.2215
Nesting Parameter		0.63940811	7.1702

Figure 6-18: Non-home-based Other Mode Choice Model

Due to data availability the SOV, HOV2 and HOV3+ modes were collapsed to a single auto mode and the park-and-ride and WCE modes were not included. A summary of the estimated variable relationships is presented in Figure 6-19 below.

Variable	Value
VOT	6.3 $/hr
Wait perception w.r.t. in-vehicle travel time	2.8
Walk perception w.r.t. in-vehicle travel time	1.3
Boarding perception w.r.t. in-vehicle travel time (transfer penalty)	6.2
Vehicle occupancy scale	0.7

Figure 6-19: Non-home-based Other VOT and Perception Factors (Asserted)

Model Validation

A cross-validation test was conducted for each mode choice model to assess the estimated model's performance at the disaggregate level (household level). Each model was re-estimated using a stratified random sample of the full dataset (80%) and then applied to a hold-out sample (20%). For the HBW purpose, a 5-fold cross-validation was applied and the remaining purposes were validated with one hold-out sample. The observed shares and the resulting aggregate shares of the models are shown in Figures 6-20 through 6-28 below. In general, the models predict the observed modal shares with slight variations. This suggests that the models were reasonably specified and that the model estimations were not performed on a dataset that was uniquely well-suited to returning the desired results (i.e., no signs of overfitting).

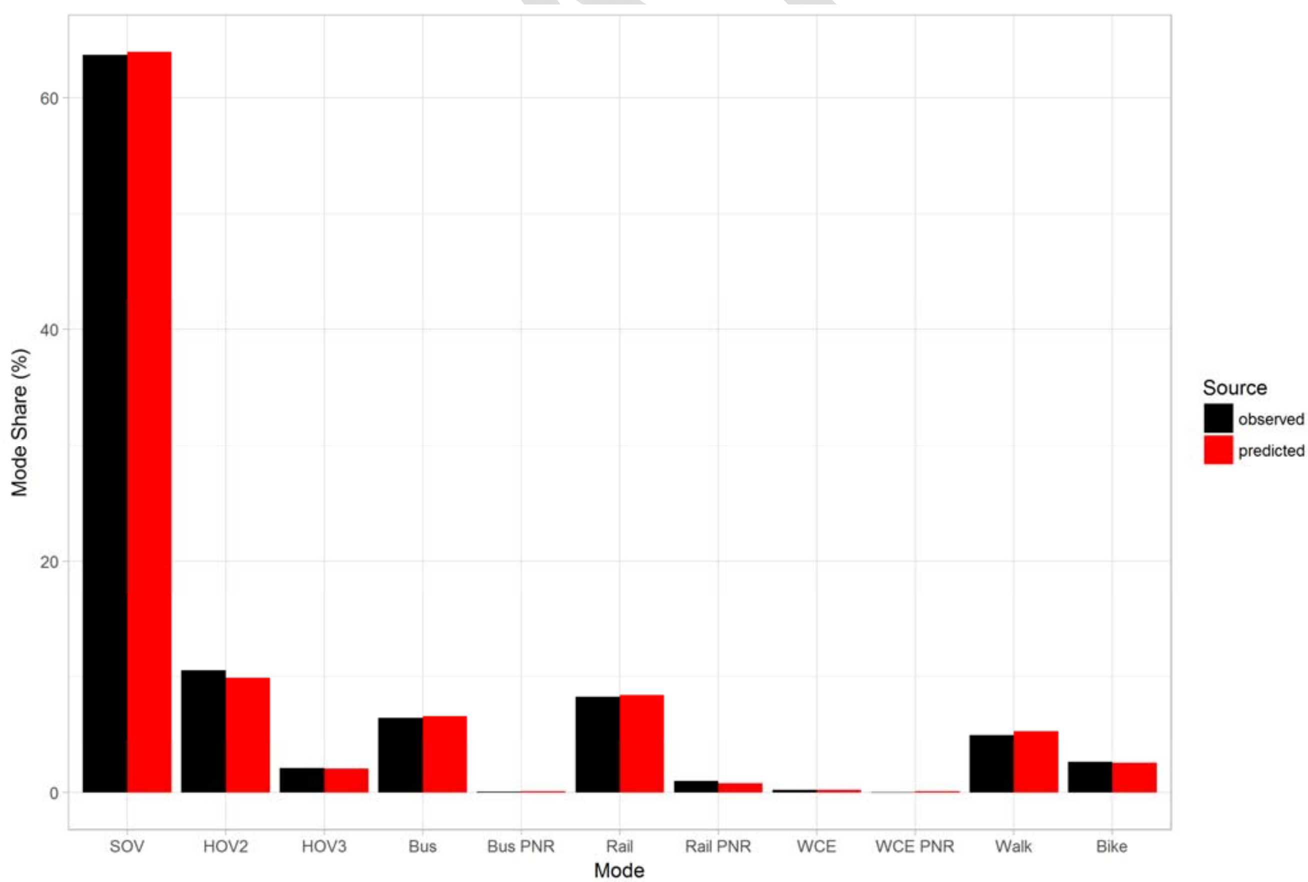

Figure 6-20: Home-based Work Cross-validation Results

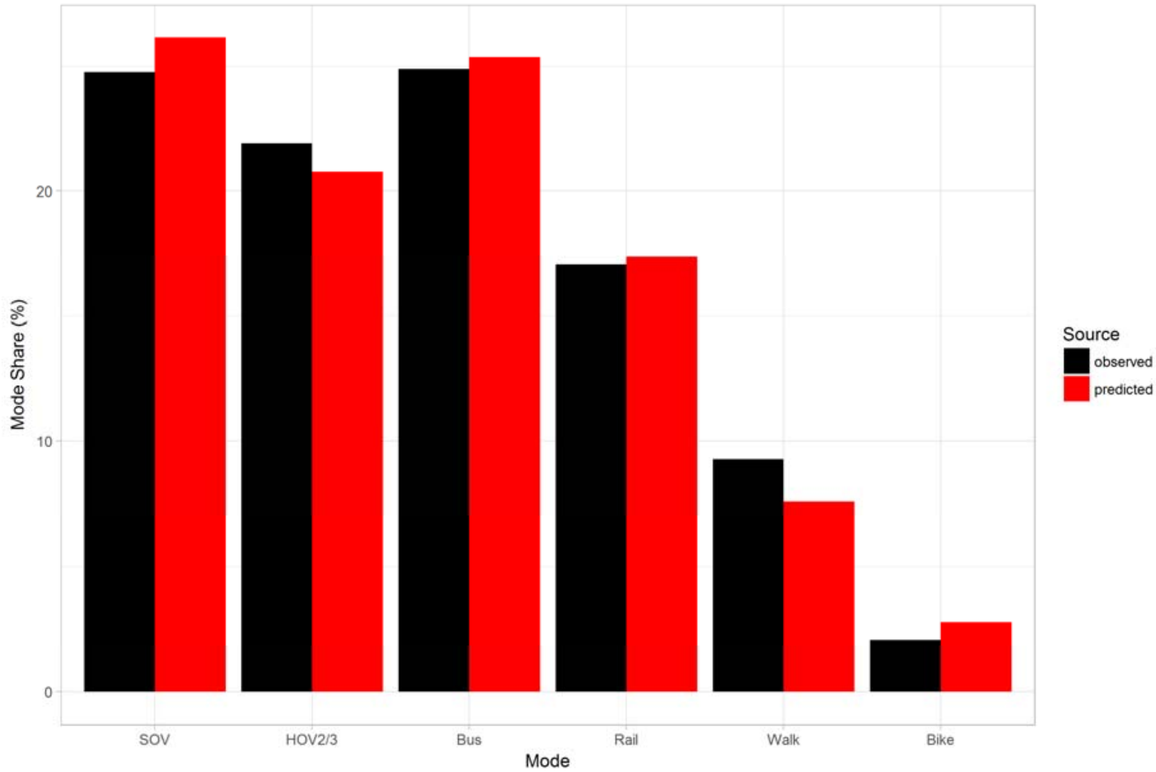

Figure 6-21: Home-based University Cross-validation Results

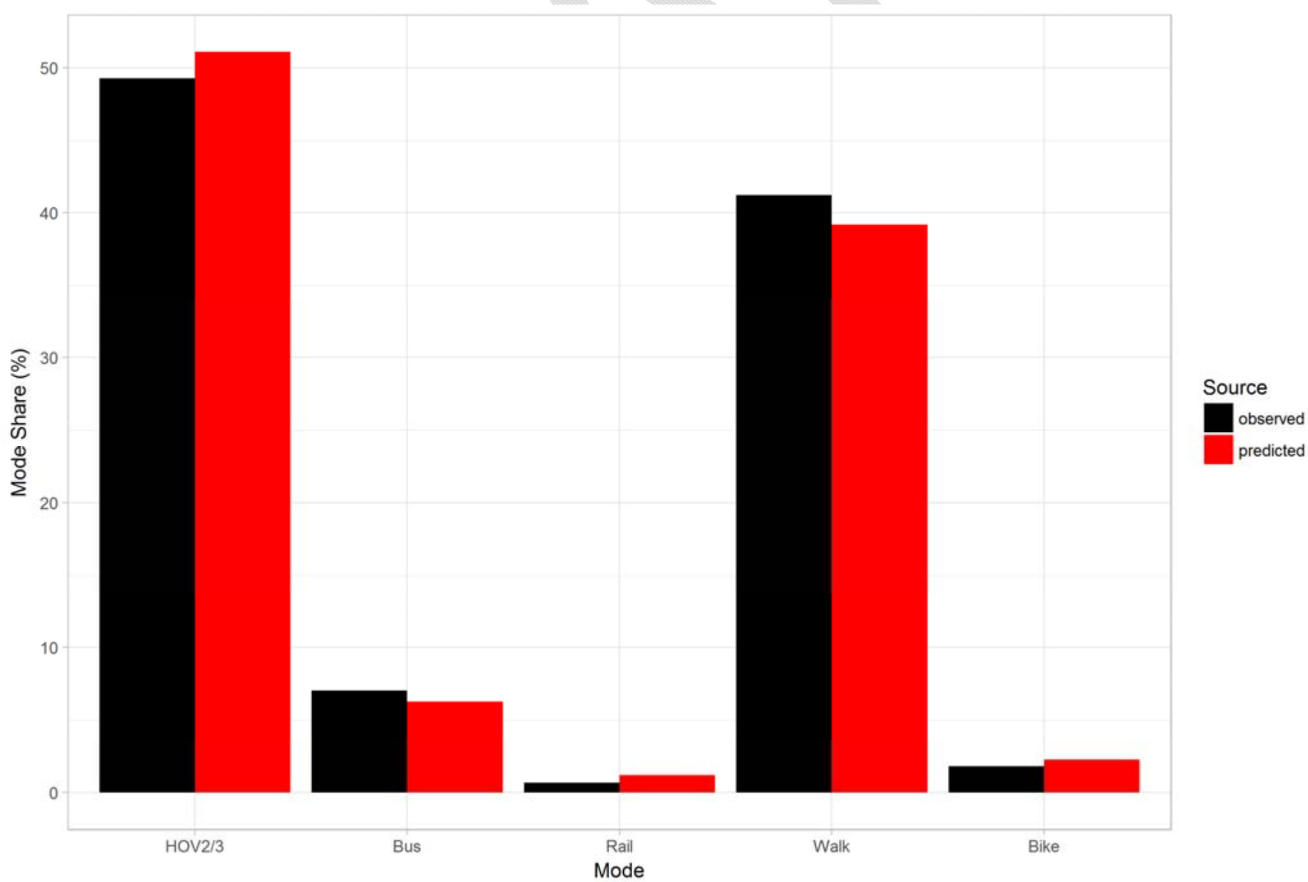

Figure 6-22: Home-based School Cross-validation Results

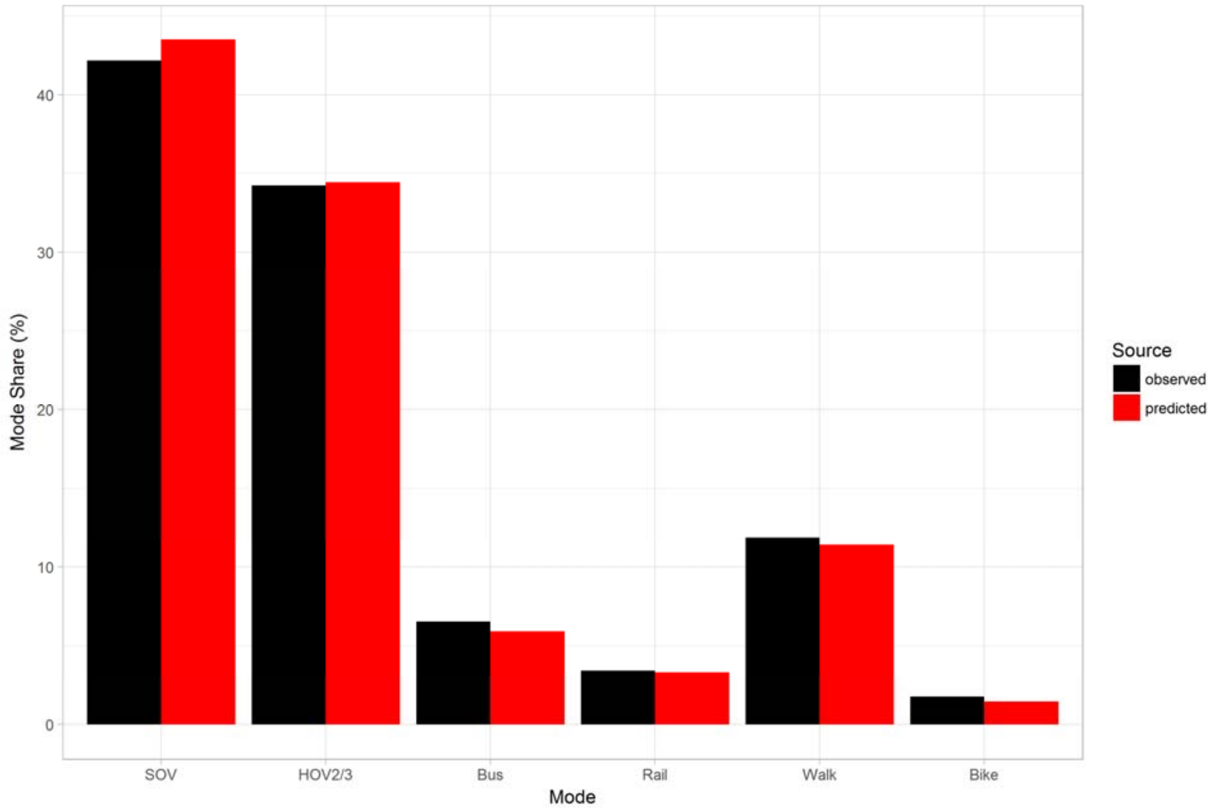

Figure 6-23: Home-based Shopping Cross-validation Results

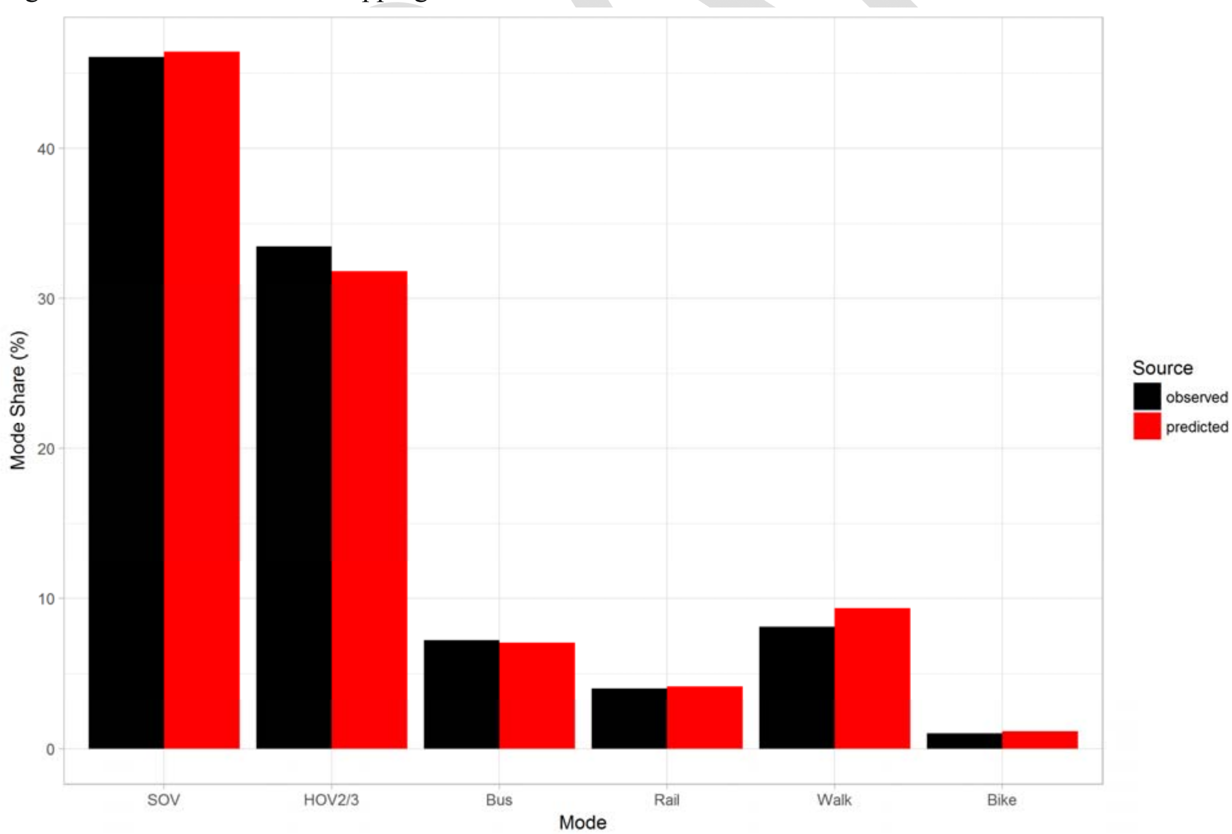

Figure 6-24: Home-based Personal Business Cross-validation Results

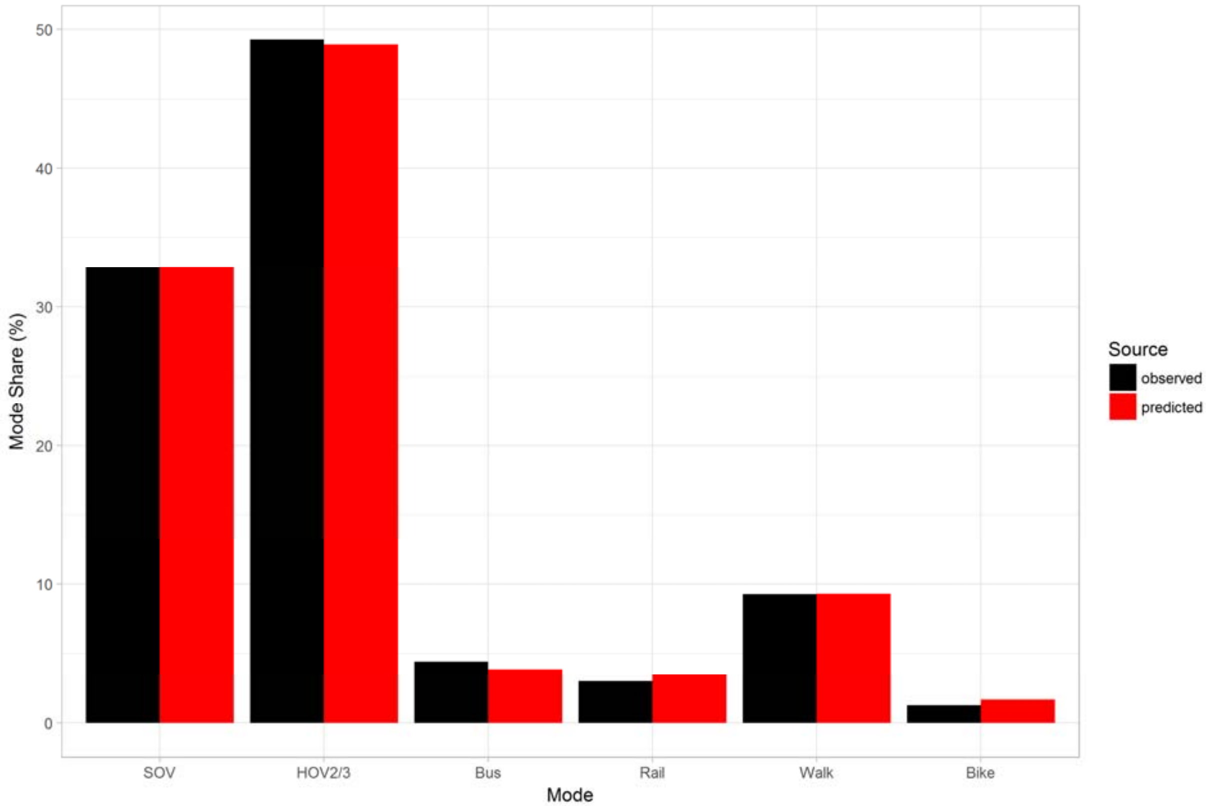

Figure 6-25: Home-based Social/Recreational Cross-validation Results

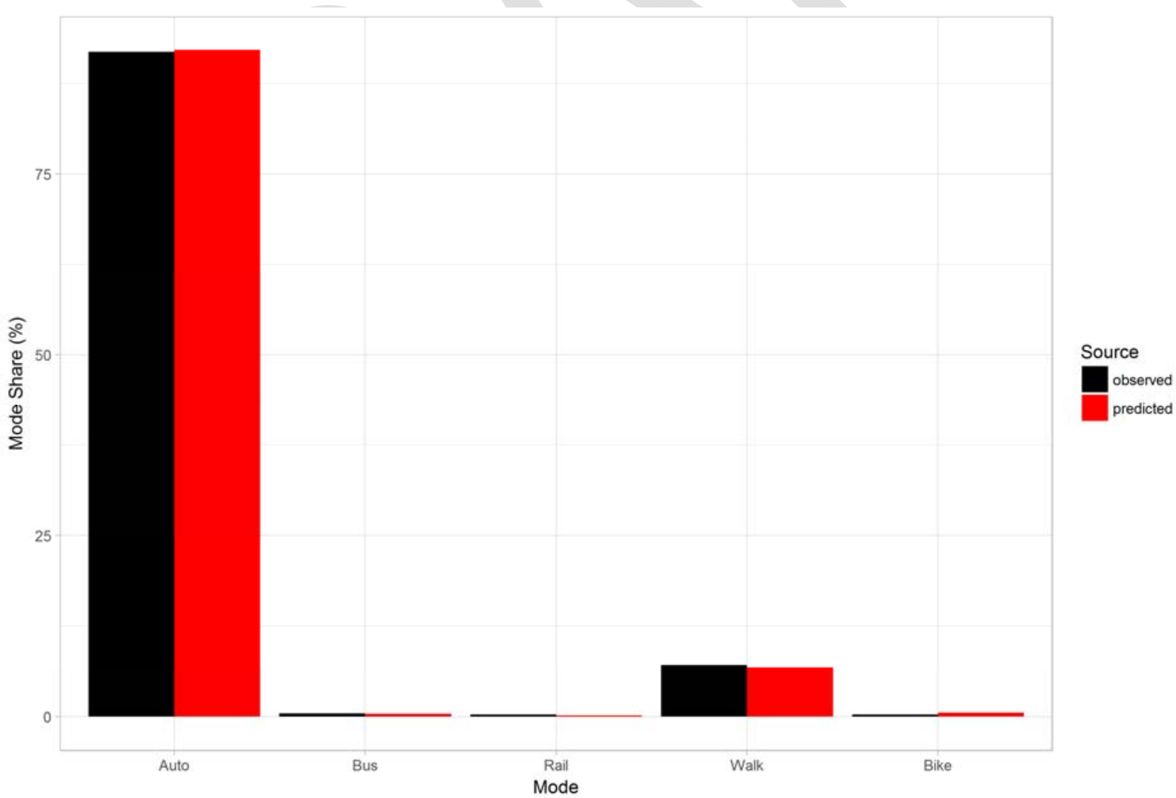

Figure 6-26: Home-based Escorting Cross-validation Results

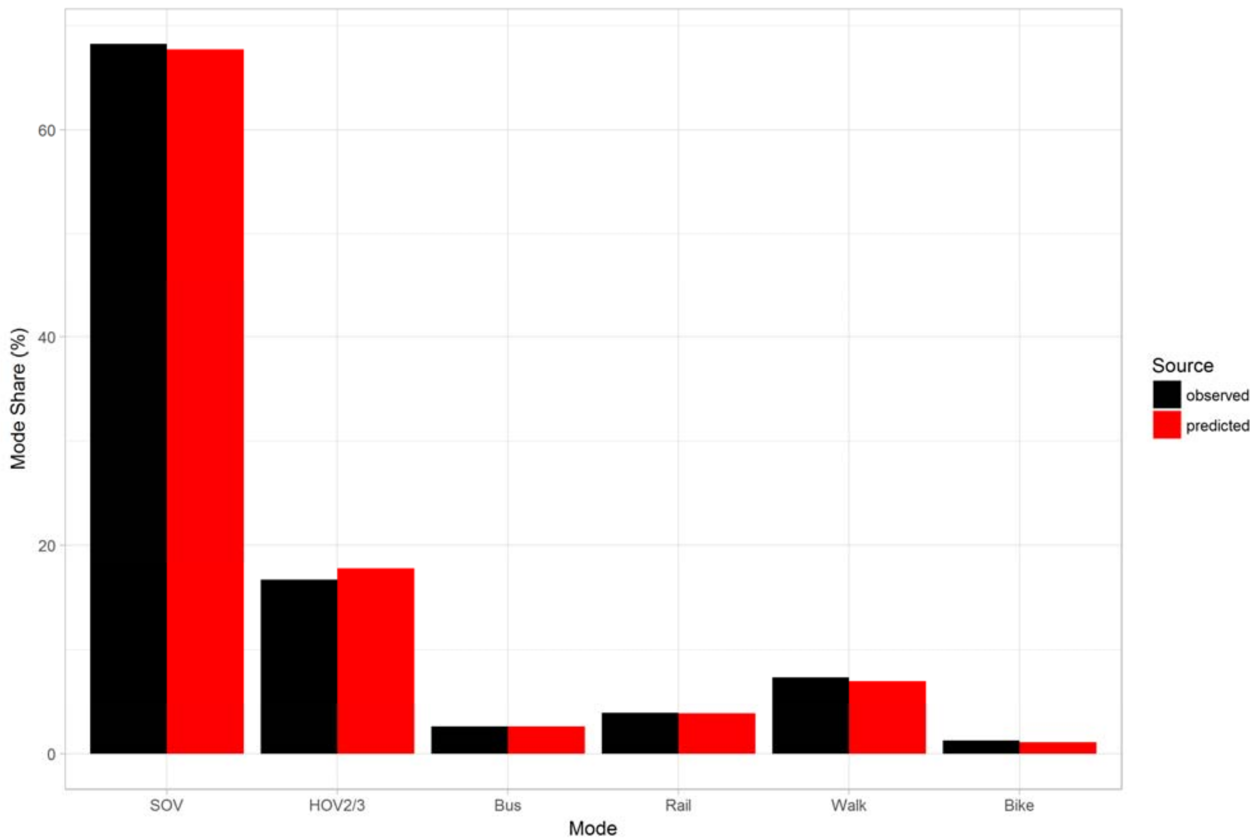

Figure 6-27: Non-home-based Work Cross-validation Results

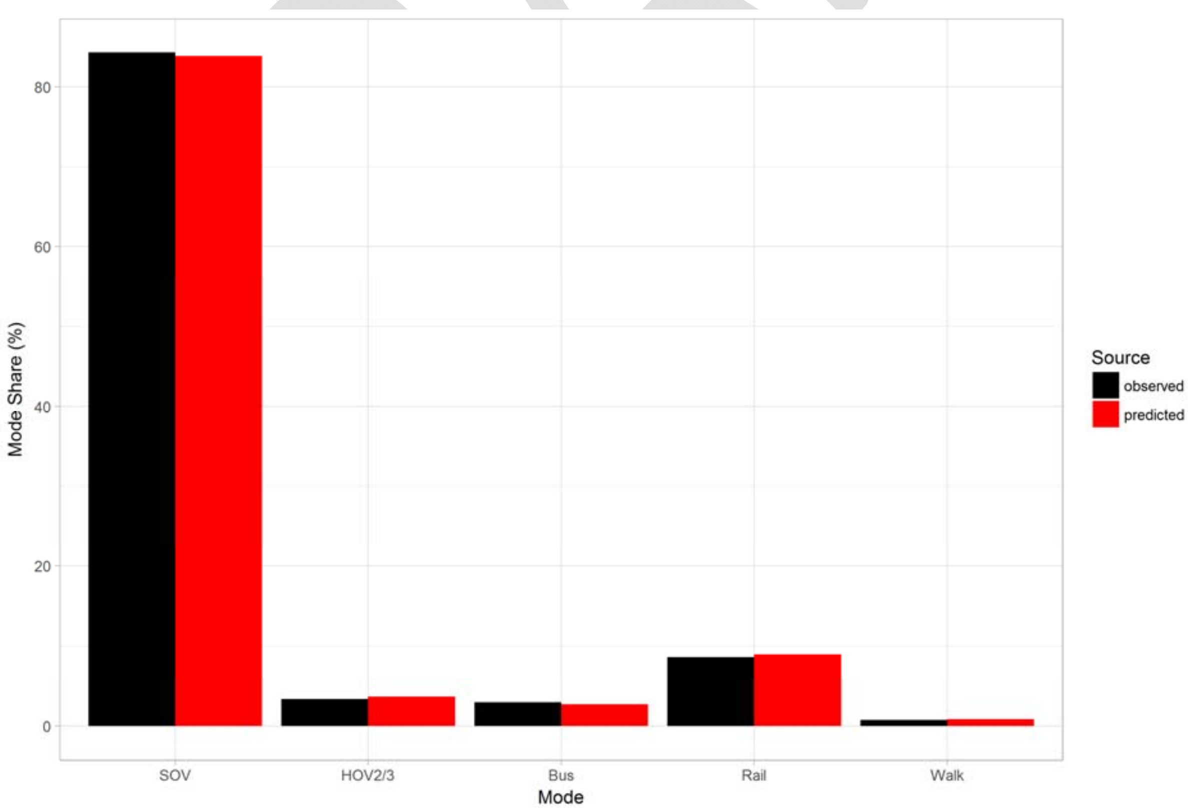

Figure 6-28: Non-home-based Other Cross-validation Results

7: Time Scales

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The RTM interacts travel demand with transportation network supply. Model estimates of travel demand, (generation, distribution, mode choice) operate at the daily (24hr) level, while model estimates of network impendences (assignment) operate at the hourly level. Only three out of the 24 daily hours are assigned. Similarly the RTM stores travel demand in different ways. Daily demand is treated at the production/ attraction (PA) level while hourly demand is treated at the origin/destination (OD) level.

The RTM, therefore, needs methods to translate between these two time scales and units. Due to the iterative nature of the RTM, this translation takes place twice. Once it happens in the skim-blending procedure which combines skims from the three assigned hours to create daily values. It then happens a second time in the time-slicing procedure where OD demand for the three assignment hours is extracted from the daily demand tables. The following sections describe:

- The difference between PA and OD trips
- The method for skim-blending to move from peak hour to daily
- The method for time-slicing to move from daily to peak hour

PRODUCTIONS /ATTRACTIONS (PA) VS. ORIGINS/DESTINATIONS (OD)

The following description and figure are provided to illustrate the distinction between productions/attractions and origins/destinations and its importance in the context of the RTM.

The PA trip format is the simplest representation of a tour in a transportation model. This is possible since the PA level considers the entire trip chain (e.g. home-to-work and back) while the OD level considers each direction separately. This feature of PA allows modeling choices based on costs and impedances on both trip legs and prevents users from illogical mode switches (e.g. it prevents a user from taking auto in one direction and transit back). In addition, it allows retention of knowledge about trip directionality so that, for example, 95% of the morning commute trips are specified as going from home-to-work and only 5% in the work-to-home direction.

For more information see the *Time-slicing in PA (Round-Trip) Format* presentation given at the Phase 3 model release meeting in Appendix C.

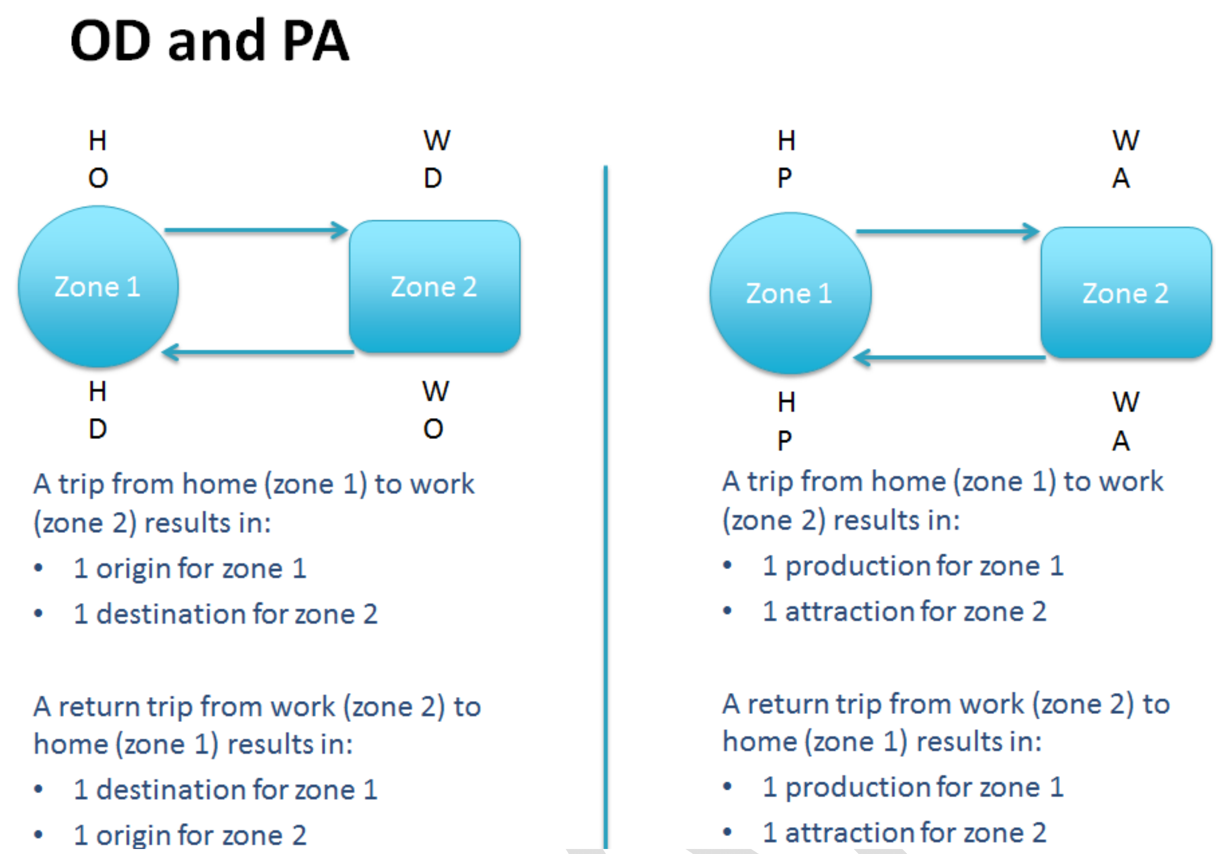

Figure 7-01: PA vs. OD

Skim Blending

RTM3 maintains trip tables in 24 hour PA format for trip generation, distribution and mode choice. The trip distribution and mode choice models are heavily dependent on travel times and out of pocket cost skims by mode, which are held at the hourly level. Skim blending is the process of creating weighted average daily impedance from the model's three peak hour assignments to be used in trip distribution and mode choice.
RTM3 has three one-hour assignments:

- AM: 0730 – 0830
- MD: 1200 – 1300
- PM: 1630 – 1730

Each one-hour assignment is used to represent various periods throughout the day as show in Figure 7-02.

Peak Hour Assignment	Hours of the day represented
AM (07:30 – 08:30)	06:00 – 10:00
MD (12:00 – 13:00)	10:00 – 15:00 and 18:00 – 06:00
PM (16:30 – 17:30)	15:00 – 18:00

Figure 7-02: Peak Period Representation for Skim Blending

Blended daily skims are constructed from the peak hour skims, with weights given to each peak hour skim depending on the trip purpose. For example work trips have a higher weight for peak assignments (AM and PM) compared to MD and shopping trips place more weight on the MD than the AM and PM. The trip direction is accounted for similarly; for example the AM work to home direction gets more weight than the AM home to work direction. Both sets of weights are calculated based on Trip Diary data which includes the temporal and directional distribution of trips by purpose throughout the day.

Thus the factors account for the likelihood of the trip occurring in each peak hour in addition to the likelihood that it will be going from home to the destination or from the destination to home. Six peak hour skims are used to create each daily skim.

The general form of the blended skim function for a trip between two TAZs is:

$$\begin{aligned} Bl\_skim_{p\text{-}a} = \; & W_{p\text{-}a,AM}*Skim_{p\text{-}a,AM} + W_{p\text{-}a,MD}*Skim_{p\text{-}a,MD} + W_{p\text{-}a,PM}*Skim_{p\text{-}a,PM} + \\ & W_{a\text{-}p,AM}*Skim_{a\text{-}p,AM} + W_{a\text{-}p,MD}*Skim_{a\text{-}p,MD} + W_{a\text{-}p,PM}*Skim_{a\text{-}p,PM} \end{aligned}$$

Where:

p-a represents the home to destination direction
a-p represents the return direction

The weight factors ($W_{p\text{-}a}$ and $W_{a\text{-}p}$) are calculated by purpose and the weights should always sum to 1. Non-home based trips only use the first half of the equation (p-a) as the trip is not tied to a home end.
Figure 7-03 summarizes the blend factors used in RTM3. These weights are used for the following skim types:

- Auto travel time, operating costs, and tolls
- Transit travel time components (wait, walk, boarding, and in-vehicle)

Trip Purpose	p-a direction			a-p direction		
	AM	MD	PM	AM	MD	PM
Home-based work	0.39	0.12	0.03	0.01	0.14	0.32
Home-based work (west coast express)	0.52	0.00	0.00	0.00	0.00	0.47
Home-based university	0.34	0.16	0.04	0.04	0.20	0.22
Home-based school	0.54	0.02	0.01	0.00	0.12	0.31
Home-based shopping	0.05	0.25	0.10	0.01	0.33	0.26
Home-based personal business	0.14	0.26	0.10	0.03	0.28	0.20
Home-based social	0.08	0.20	0.19	0.02	0.36	0.15
Home-based escorting	0.23	0.17	0.12	0.09	0.17	0.21
Non-home-based work	0.20	0.45	0.35	-	-	-
Non-home-based other	0.12	0.54	0.34	-	-	-

Figure 7-03: Skim Blending Factors

Daily blended transit fares are calculated with separate weights. System wide transit fares are set to the 1-zone fare ($2.1) after 18:30 so an additional two values are used in the blending.

Time Slicing

Time slicing is the reverse process of skim blending; assignment hours' OD trips are extracted from the daily PA tables by purpose, mode, and geography. The auto and transit trips are then assigned to their respective networks and all modes used for mode share calculations.

Time of day (TOD) factors are calculated from the trip diary based on the share of trips by direction, mode, and production geography in each assignment period. Transit demand slices are also done by sub-mode; Bus, Rail, and West Coast Express.

TIME

A Trip Diary trip is said to occur during one of these hours if the trip's mid-point[10] falls in the one-hour assignment window. The three assignment hours are:

1. AM : 07:30 – 08:30
2. MD: 12:00 – 13:00
3. PM: 16:30 – 17:30

DIRECTION

Time-slicing factors account for direction of the trip. Production to attraction factors differ from attraction to production factors. For instance, during the AM peak period more people go from home to work than from work to home and so the PA factor is greater than the AP factor. During the PM peak hour the opposite is true and more people go from work to home than home to work. This type of directional accounting is not possible for trips on an OD basis

MODE

Time slicing factors account for different peaking across modes. Certain modes such as SkyTrain in Vancouver peak later than auto and the WCE does not operate during the MD assignment period.

GEOGRAPHY

Peak assignment periods are for the whole region across all modes. Local areas within the region may have different peaks. The time slicing factors also account for regional variation in the regional peak times. Suburban areas, south of the Fraser for example, tend to peak earlier in the morning while core areas such as the City of Vancouver and the CBD tend to peak later. In order to account for this, separate factors were produced depending on the trip's production end and direction (PA vs AP and core vs suburbs).

Production geography was defined according to the five-zone GB ensemble, shown in Figure 7-04, which generally follows the main regional land masses:

[10] Midpoint is the time half-way between the start time and the end time of the trip

1. North Shore
2. Burrard Peninsula
3. Richmond
4. South of Fraser
5. North of Fraser, East of Pitt River

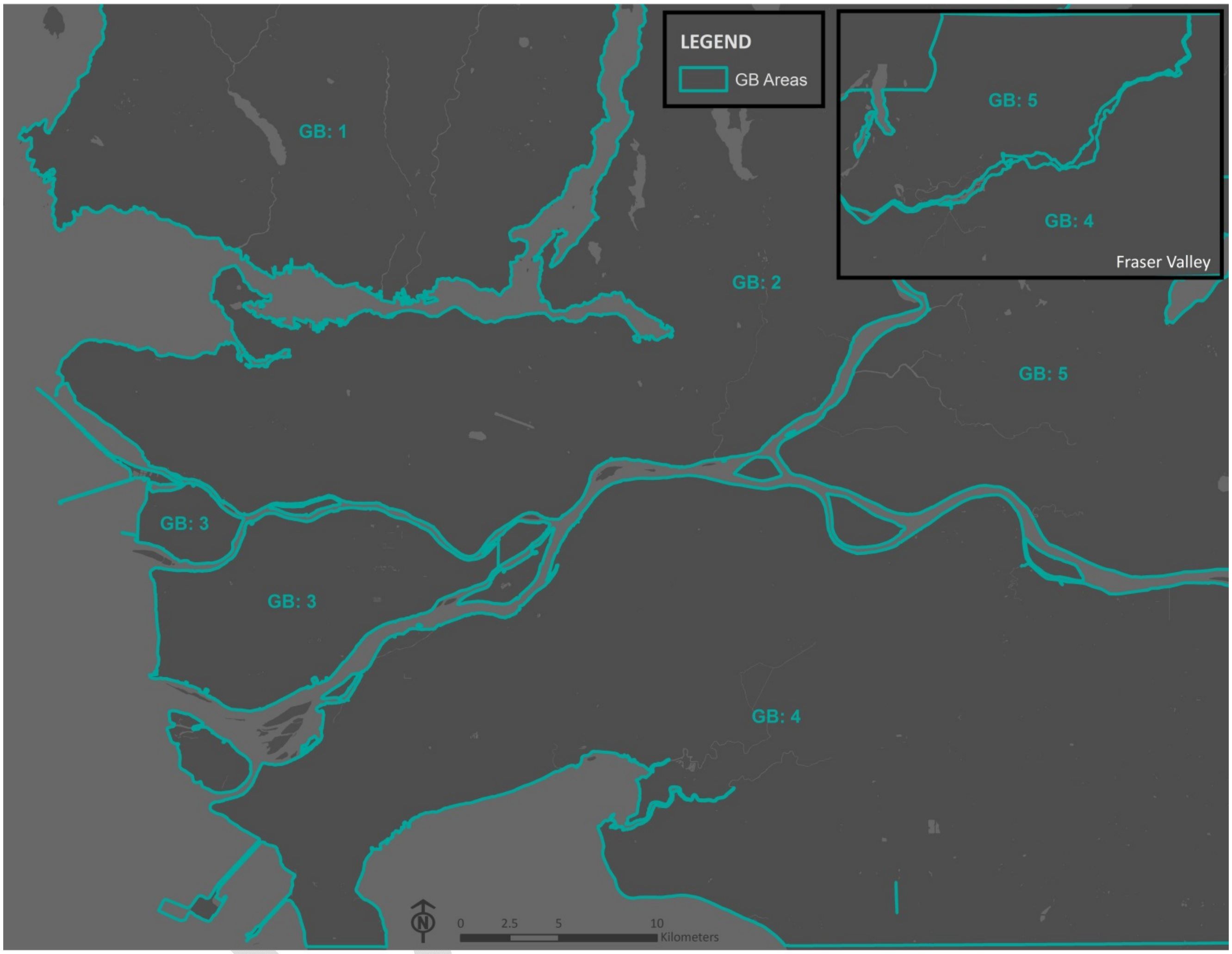

Figure 7-04: Map of the GB Ensemble

There are numerous combinations of time, direction, mode and geography. As a result, the table of time slicing factors is available in the RTM3 files in the Basenetworks/Inputs folder of the model distribution.

8: Auto Assignment

Trip assignment is the last of the primary model components of the four-step model. The trip assignment model estimates the auto volume and transit ridership on each link in the transportation system.
The trip assignment model has two main objectives:

1) Produce measures of impedance (skims) that are cycled back to trip distribution and mode choice
2) Generate important model outputs such as travel volumes and times on the network

RTM3 employs a multi-class user-equilibrium assignment. Auto assignment is a complex optimization problem requiring 70% - 75% of the total model run time.

TIME PERIODS

Three time periods are assigned in the RTM as described below:

- AM Peak Hour: 0730 – 0830
- MD Peak Hour: 1200 – 1300
- PM Peak Hour: 1630 – 1730

USER CLASSES

In total, nine vehicle classes are assigned onto the road network, four single occupancy vehicles (SOV) classes, three high occupancy vehicles (HOV) and two truck classes. Figure 8-01 summarizes the assignment parameters used in the RTM for each class.

Class	VOT $/hr	Operating Cost $/km	Passenger Car Equivalent (PCE)	Occupancy
SOV - VOT 1	6.3	0.18	1.00	1.00
SOV - VOT 2	10.3	0.18	1.00	1.00
SOV - VOT 3	15.5	0.18	1.00	1.00
SOV - VOT 4	18.2	0.18	1.00	1.00
HOV - VOT 1	6.3	0.18	1.00	2.25
HOV - VOT 2	10.3	0.18	1.00	2.25
HOV - VOT 3	16.9	0.18	1.00	2.25
Light Trucks	30.0	0.24	1.50	1.00
Heavy Trucks	42.0	0.56	2.50	1.00

Figure 8-01: Auto Assignment Parameters

The assignment module VOTs are based on the mode choice model estimated VOTs. In general, trips with similar VOTs were placed into the same VOT bin as shown in Figure 8-02. Binning assignment VOTs based on the mode choice estimated VOTs strikes a desirable balance between assignment accuracy, consistency between sub-models, and model run time.

Home-based shopping low and medium income trips have the same estimated VOT ($8.2/hr). Low income home-based shopping trips were placed in the VOT-1 bin and medium income home-based shopping trips in the VOT-2 bin, which resulted in a weighted average VOT close to $8.2/hr.

Home-based social/recreational medium and high income trips have the same estimated VOT ($17.4/hr). Medium income home-based social/recreational trips were placed in the VOT-2 bin and high income home-based social/recreational trips in the VOT-3 bin because $17.4/hr seemed too high for medium income social/recreational trips based on professional judgement, particularly when compared to the home-based work VOTs for the same income levels.

VOT Bin	Purpose	% of Auto Trips	Income Categories	Mode Choice VOT ($/hr)	SOV Assignment VOT ($/hr)
1	HBSCH	5%	All	5.0	
1	NHBO	13%	All	6.3	6.3
1	HBSHOP	3%	Low	8.2	
2	HBSHOP	3%	Medium	8.2	
2	HBSOC	3%	Low	9.0	
2	HBPB	2%	Low	9.6	
2	HBPB	3%	Medium	9.6	
2	HBESC	12%	All	10.0	10.3
2	HBU	3%	All	10.8	
2	HBW	3%	Low	11.2	
2	HBPB	2%	High	11.9	
2	HBSOC	5%	Medium	17.4	
3	HBSHOP	3%	High	14.6	
3	HBW	9%	Medium	15.6	15.5
3	NHBW	10%	All	15.7	
3	HBSOC	6%	High	17.4	
4	HBW	13%	High	18.2	18.2

Figure 8-02: VOT Bins

Assignment Impedance Functions

Figure 8-03 shows the assignment impedance functions for SOV, HOV and trucks in RTM3. Costs in dollars are converted to minutes using the inverse of the VOT term, 60/VOT.

Heavy trucks are required to use established truck routes and minimize time on other roads. However, heavy trucks must be able to make deliveries to all areas, and so must be allowed to access these local roads at the beginning and end of their runs. To minimize truck usage of non-truck route links a truck dummy link attribute (‘truck_penalty’) with a sentinel value of $100 is coded onto the network.

Class	Impedance Function
SOV	time + (VOC*length + toll)*60/VOT
HOV	time + ((VOC*length + toll)*60/VOT)/Occupancy
Light Trucks	time + ((VOC*length + 2*toll)*60/VOT)
Heavy Trucks	time + ((VOC*length + 3*toll + truck_penalty)*60/VOT)

Figure 8-03: Assignment Impedance Functions

The travel time component of the impedance formula (time) is calculated based on the link's volume-delay function (VDF) as shown in Figure 8-04. The 15-second[11] time penalty was introduced at controlled intersection functions to simulate base intersection delay.

Function	Facility Type	Equation
fd1	Centroid Connector	length*60/40
fd2	Bowen Ferry	40 + ((volume)-100)*60/(volume)*((volume).ge.100)
fd3	Merge Section	length*60/posted_speed + 0.85*((volume)/(600*lanes))5
fd4	Merge Section	length*60/posted_speed + 0.85*((volume)/(800*lanes))5
fd5	Merge Section	length*60/posted_speed + 0.85*((volume)/(1000*lanes))5
fd6	Merge Section	length*60/posted_speed + 0.85*((volume)/(1200*lanes))5
fd7	Merge Section	length*60/posted_speed + 0.85*((volume)/(1400*lanes))5
fd25	Controlled Instersection	0.25 + length*60/posted_speed + 0.85*((volume)/(400*lanes))4
fd35	Controlled Instersection	0.25 + length*60/posted_speed + 0.85*((volume)/(600*lanes))4
fd45	Controlled Instersection	0.25 + length*60/posted_speed + 0.85*((volume)/(800*lanes))4
fd55	Controlled Instersection	0.25 + length*60/posted_speed + 0.85*((volume)/(1000*lanes))4
fd65	Controlled Instersection	0.25 + length*60/posted_speed + 0.85*((volume)/(1200*lanes))4
fd75	Controlled Instersection	0.25 + length*60/posted_speed + 0.85*((volume)/(1400*lanes))4
fd85	Uninterrupted flow	length*60/posted_speed*(1+0.6*0.85*((volume)/(1600*lanes1.05))5)
fd88	Uninterrupted flow	length*60/(posted_speed*1.1)*(1+0.6*0.85*((volume)/(1600*lanes1.05))5.25)

Figure 8-04: Volume Delay Functions (VDFs)

Auto Assignment Outputs

Each assignment generates skims by time period. These skims are blended and fed back to trip generation, distribution, and mode choice in the subsequent cycle as described in Section 7. Figure 8-05 summarizes the relevant skims generated by class and time period. The travel time matrix is calculated by subtracting the trip cost matrix from the generalized cost matrix. The distance and toll skims are optional and are generated in the last cycle. Intra-zonal skims are estimated at half of the value of the shortest non-zero inter-zonal travel.

Skim	Unit
Generalized Cost	Minutes
Trip Cost	Dollars
Trip Time	Minutes
Trip Distance	Kilometers
Tolls	Dollars

Figure 8-05: Auto Assignment Outputs and Units

[11] Volume delay functions return travel time in minutes so 15 seconds is represented as 0.25 minutes

Validation

Traffic volumes from RTM3 were compared to traffic counts from the 2011 Screenline Survey for validation purposes. Figures 8-06 through 8-08 are scatterplots comparing AM, MD, PM traffic counts to RTM3 volumes. In general the AM and PM peak hour assigned volumes fit the data well while the RTM3 generally underestimates MD travel. The MD period has a number of known trips that were unobserved in the trip diary, such as service and visitor trips, that are the subject of additional study for Phase 4

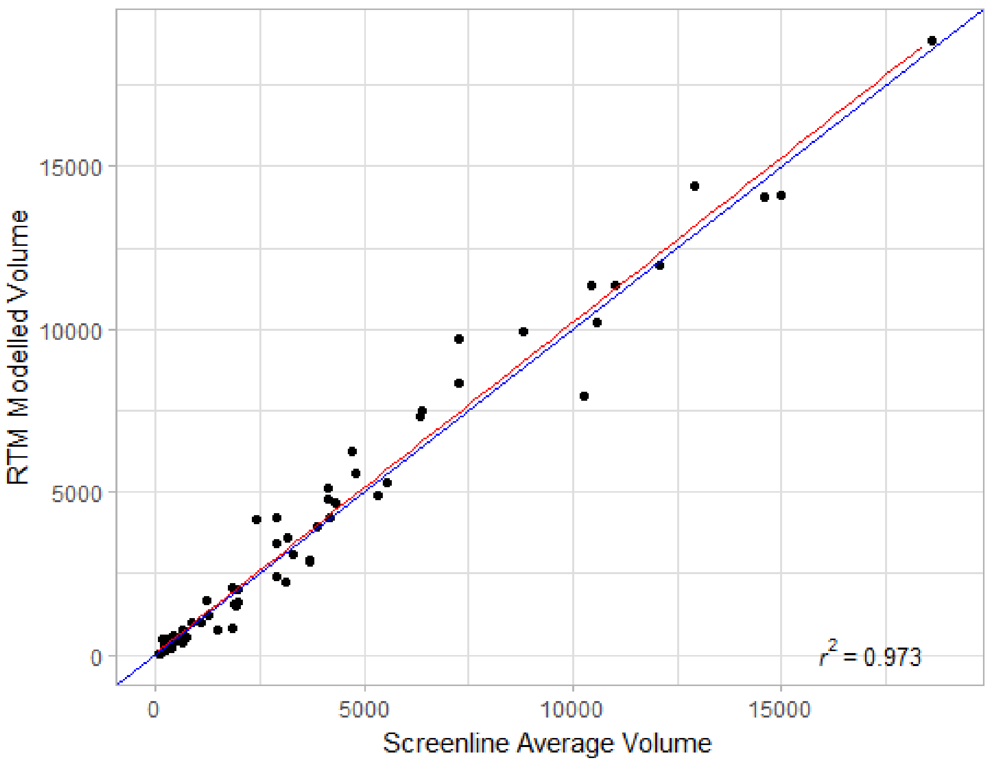

Figure 8-06: RTM Volume vs Screenline Volume – AM Peak Hour

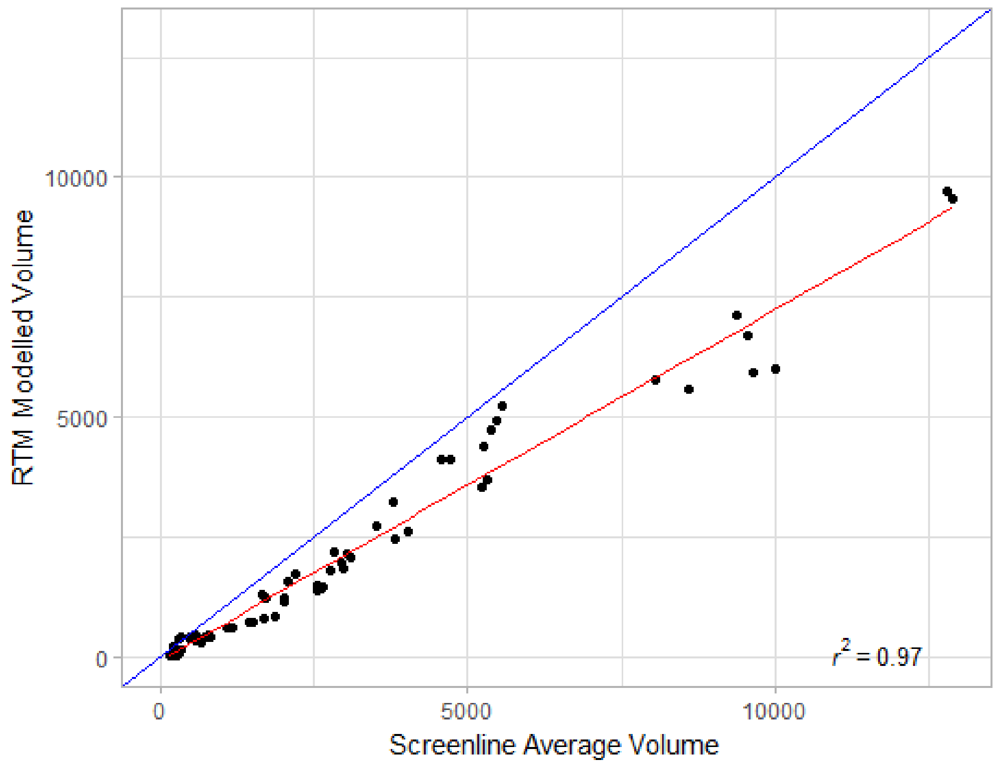

Figure 8-07: RTM Volume vs Screenline Volume – MD Peak Hour

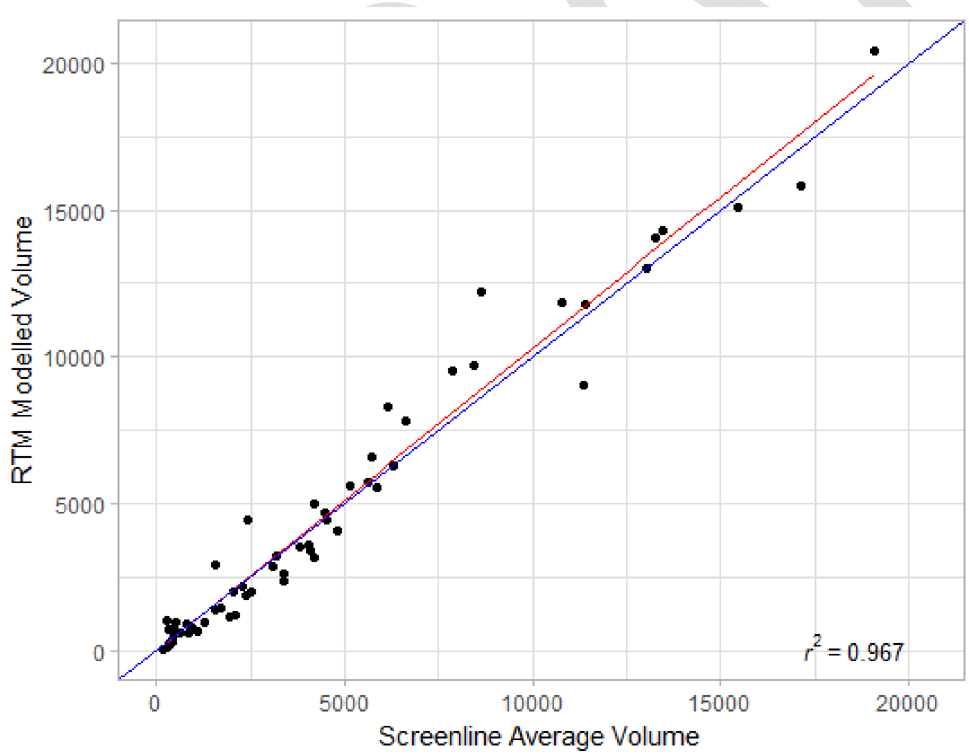

Figure 8-08: RTM Volume vs Screenline Volume – PM Peak Hour

Detailed volume plots were developed to expand understanding of the facility and screenline operations. Model volumes were tested for validity against GEH standards. Figure 8-09 shows the detailed volume plot for Screenline 9: South Arm Fraser River, which comprises the Deas (Massey) Tunnel and the Alex Fraser Bridge. As shown in the preceding figures the model replicates the AM and PM peak hours very well, but tends to under-predict the MD peak hour. Additionally, Figure 8-09 illustrates that peak hour directionality issues present in Phase 2 have been corrected for Phase 3, largely due to time-slicing the PA matrices as opposed to the OD matrices.

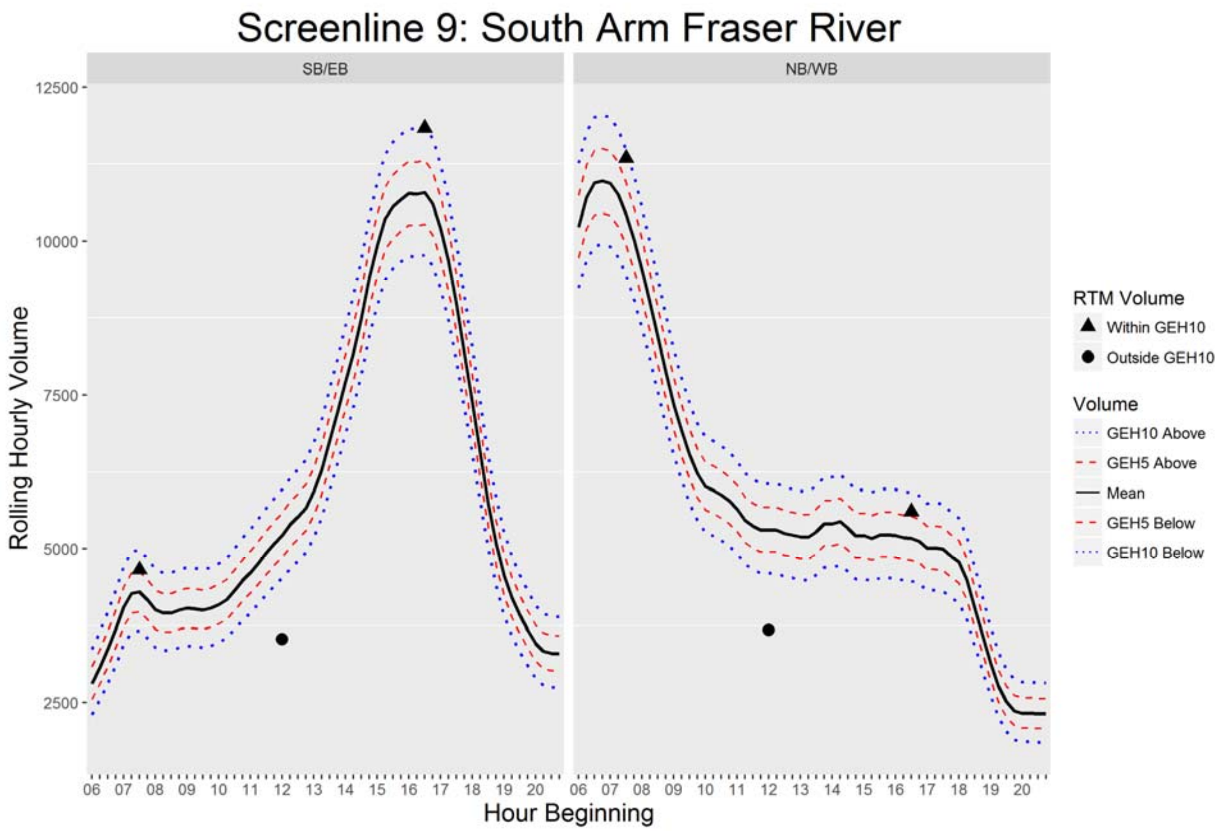

Figure 8-09: Detailed Screenline Volume Plot

9: Transit Assignment

The transit assignment module assigns the time-sliced peak hour transit demand to the transit network to generate segment level person trip volumes and matrix level impedance measure skims. Transit assignment has been significantly revamped for the Phase 3 model; numerous changes improved the representation of transit time and cost impedances including:

- West Coast Express (WCE) sub-mode introduced
- Crowding measured and the effect on routing cycled back to trip distribution and mode choice
- Capacity constrained, accounting for the effect of pass-ups on headways
- Headway calculations were updated to better represent arrival patterns for infrequent services
- Transit time functions (TTFs) were updated and with dwell times explicitly modeled
- Transit time perception factors were updated based on estimates from the mode choice models
- Transit fares skimmed from the network as opposed to using fixed transit fare matrices
- Journey-levels assignment introduced to enforce transit sub-mode choice without distorting impedances
- Park-n-ride updated to be fully integrated in the mode choice model and allow best lot choice based on generalized cost

Transit Assignment Sub-Modes and Demand

As discussed in the mode choice chapter, West Coast Express is represented as a distinct transit sub-mode in RTM3. Three transit demand matrices are now assigned hierarchically:

- West Coast Express: Trips with at least one leg on the West Coast Express
- Rail: Trips with at least one leg on SkyTrain, Seabus, Gondola, or LRT
- Bus: Trips with only bus leg(s)

Figure 9-01 shows the transit modes available in the RTM as they are coded in EMME.

EMME Mode	Description	Demand Matrix
b	Bus	Bus
f	LRT	Rail
g	BRT	Bus
h	Gondola	Rail
l	SkyTrain	Rail
r	West Coast Express	WCE
s	Seabus	Rail

Figure 9-01: Mode Designation and Grouping

Transit Assignment Sequence

In total 10 transit assignment iterations are performed per cycle. Each iteration assigns the three transit demands sequentially, bus followed by rail followed by West Coast Express. Figure 9-02 summarizes the transit assignment process.

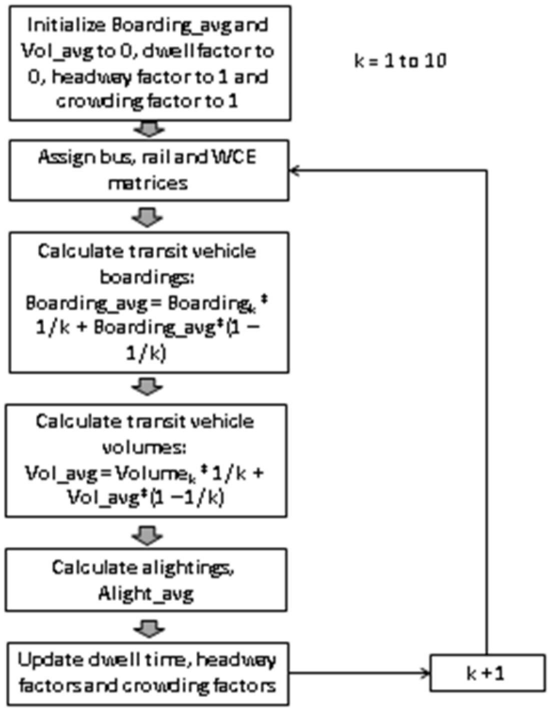

Figure 9-02: Transit Assignment Process

Transit Time Impedance

Transit time impedance estimation was significantly updated for RTM3. Both the actual travel times (e.g. additional travel time from pass-ups) and the perception of travel times (e.g. the unpleasantness of crowded transit vehicles, or the aversion to waiting) were updated.

Transit time impedances were improved by the introduction of crowding and capacity constraints. Headway calculations were updated to allow for the fact that people can plan their arrival to the schedule for infrequent routes. In addition, the transit time factors were updated to directly account for stopping activity. If no one boards or alights at a particular stop, the transit vehicle does not experience that delay. Finally, mode specific transit time perception factors were estimated from the mode choice models.

Congested Transit Assignment

Transit assignment procedures are now capacity constrained and iterative. The transit assignment module calculates both the seated and total capacity on a transit vehicle as follows:

$$Seated\ Capacity\ (per\ hour) = Total\ Seats\ x\ 60/headway$$
$$Total\ Capacity\ (per\ hour) = (Total\ Seats + Standing\ Capacity)\ x\ 60/headway$$

The assigned volume is compared to the seated and standing capacities to determine a crowding factor. These crowding factors are then used to adjust the perception of in-vehicle travel time during the assignment module. The crowding factors for bus and rail are shown in Figures 9-03 and 9-04, respectively.

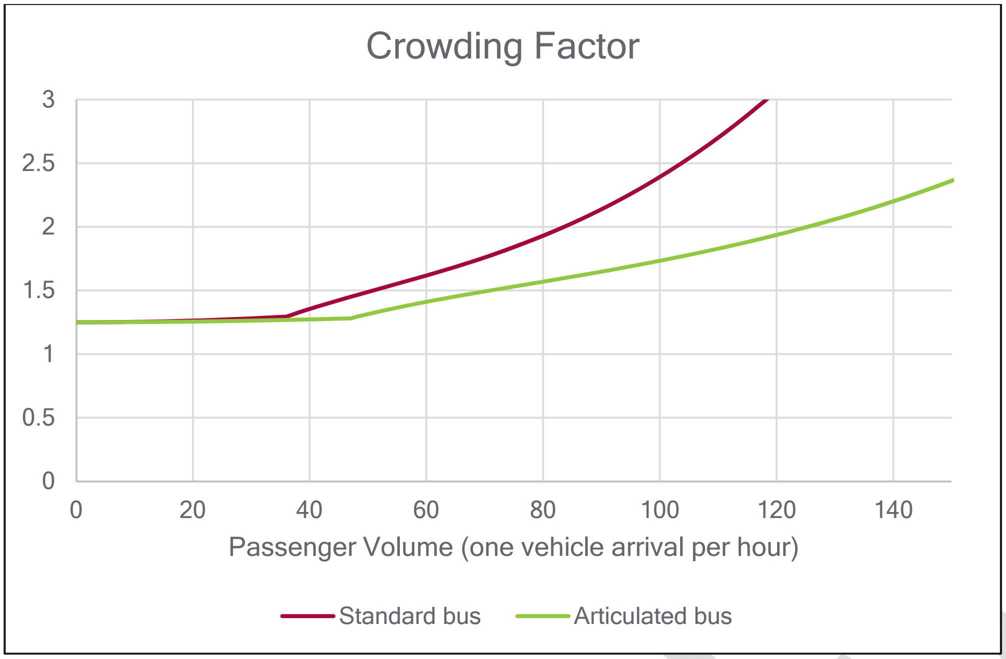

Figure 9-03: Bus Crowding Factors

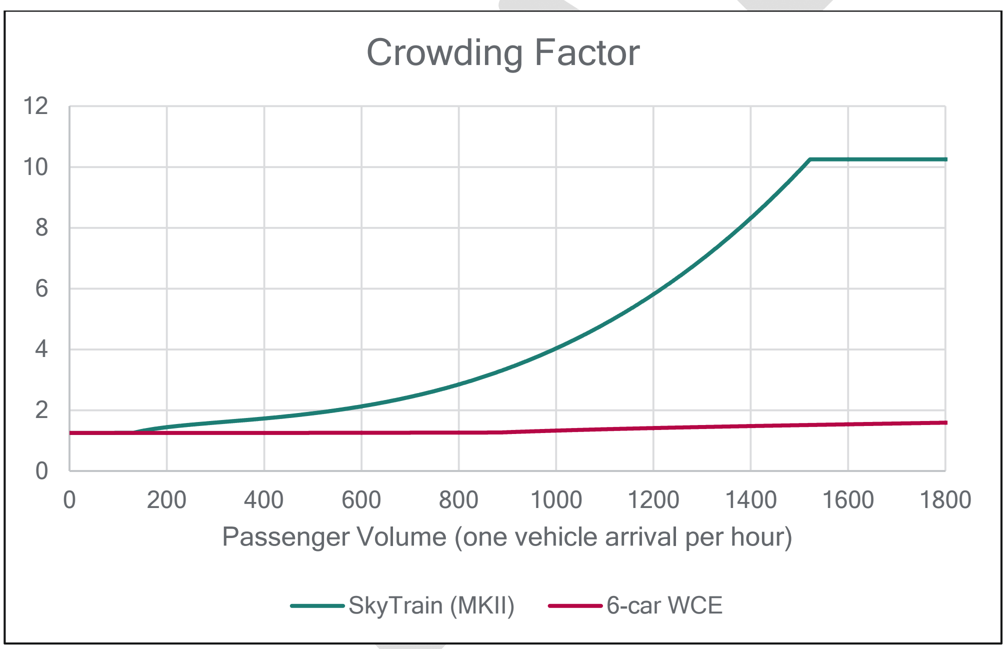

Figure 9-04: Rail Crowding Factors

During each transit assignment iteration users select their route by minimizing the perceived travel time, which accounts for crowding from the previous iteration; similar to the effect of congestion in auto-assignment. As a result, some users may choose a route with a longer actual travel time to avoid crowding because the perceived travel time of the new route is lower than the perceived travel time of the crowded route. However, the skim passed back to distribution and mode choice is the travel time of the actual route selected as opposed to the perceived time.

`

Capacitated Transit Assignment and Headway Calculations

Transit assignment was not capacity constrained in previous RTM versions. As such, all demand was served within the assignment hour regardless of the system capacity. In practice this is not the case; users cannot board a full transit vehicle. These events are referred to as 'pass-ups' and in practice this means the user must wait for multiple bus arrivals before boarding. In RTM3 this is simulated by adjusting the headway at the stop level, extending it to match the estimated number of buses that would pass the user by. This approach accounts for pass-ups and where they occur. Vehicles often fill-up early in the run and pass-ups occur in the middle or end of the route. This adjustment is calculated as the headway factor or *hdwyfac*, bound between 1 and 3[12] as follows:

$$@hdwyfac = \frac{@boardavg}{\max(@totcapacity - @voltravg + @boardavg, 1)}$$

Where :

@boardavg = Number of boardings at the stop
@totcapacity = Transit vehicle capacity
@voltravg = Volume on transit vehicle

Previous RTM versions assume that people wait for half the service headway on average. While this works reasonably well for frequent service, this assumption tends to overestimate wait times for infrequent routes, especially premium type service such as the West Coast Express[13]. A new approach was adopted for RTM3 that accounts for the fact that people can, to some extent, adjust their arrival to match the schedule on lower frequency routes. This value is calculated as the headway fraction or *hfrac*.

In RTM3, wait times are calculated as follows:

Bus Modes:

$$@hfrac = \begin{cases} 0 + 0.5 \times h, & if\ 0 < h < 10 \\ 5 + 0.4 \times (h - 10), & if\ 10 < h < 20 \\ 9 + 0.35 \times (h - 20), & if\ 20 < h < 30 \\ 12.5 + 0.08333 \times (h - 30), & if\ h > 30 \end{cases}$$

Rapid Transit Modes:

$$@hfrac = \begin{cases} 0 + 0.5 \times h, & if\ 0 < h < 10 \\ 5 + 0.15 \times (h - 10), & if\ 10 < h < 20 \\ 6.5 + 0.1 \times (h - 20), & if\ 20 < h < 30 \\ 7.5 + 0.03333 \times (h - 30), & if\ h > 30 \end{cases}$$

For example, if the headway on a rapid transit service is 25 minutes, the waiting time is calculated as follows:

Wait time = 6.5 + 0.1*(25 – 20) = 7 minutes.

Using the half method, the wait time would be 12.5 minutes.

[12] The upper bound prevents the first assignment iteration from overly impacting the number of iterations for the assignment to converge
[13] People will time their travel to match the schedule or based on information from transit apps.

Combining the headway factor and headway fraction yields the effective headway as follows:

$$@hdwyeff = @hdwyfac \times @hfrac$$

The effective headway represents user waiting time at transit stops in other RTM3 sub-modules. The effective headway accounts for the actual bus headway, the user's ability to time their arrival, and additional waiting time associated with full-bus pass-ups.

Dwell Time

Transit Time Functions (TTFs) were updated to specifically account for stop delays. A dwell time model was estimated using Automated Passenger Count (APC) data collected over four months during the fall of 2011. The resulting model estimates dwell time in RTM3.

Bus dwell time at a stop location is calculated as follows:

$$us1 = mdwt + \left\{max[(@dwtboard \times @boardavg), (@dwtalight \times @alightavg)] \times \frac{h}{60}\right\}$$

Where:

mdwt = min dwell time = 0.33 min (20 s) adds to dwell time if boarding or alighting occurs to account for door operations + acceleration + deceleration

h = headway

@dwtboard = Dwell time board factor bus = 0.025 min (1.5 s) per boarding

@dwtalight = Dwell time alight factor bus = 0.0083 min (0.5 s) per alighting

Since, boardings and alightings happen simultaneously the maximum of the board and alight dwell times is used. For rapid transit, dwell times are hard-coded directly into the RTM based on actual design dwell times at various stations.

Transit Perception Factors

RTM3 includes transit travel time perception factors estimated from the mode choice models. Previously, these factors were asserted based on typical values recommended by literature.

Time Component	RTM3		RTM2	
	Bus	Rail & WCE	Bus	Rail & WCE
Wait	2.50	2.50	2.25	2.25
Walk	2.00	2.00	1.75	1.75
Board	10.00	10.00	4.00	4.00
In vehicle time	1.25	1.00	1.00/3.50	1.00

Figure 9-05: Transit Perception Factors

While the wait and walk perception factors changed slightly, the boarding penalty increased by a factor of 2.5, indicating that transfers are a significant inconvenience to transit users in the region. Mode choice econometric modeling indicated that transit users prefer travel time on rail to travel time on bus. Therefore, the bus in-vehicle perception time was set to 1.25 times that of rail in-vehicle time.

Phase 2 used two different in-vehicle bus perception factors; during the bus assignment the perception factor was 1.0, while in the rail assignment is was 3.5. At the time, there was no way to guarantee that rail trips used rail while still allowing bus access to the rail network. The high bus perception factor was therefore used as a way to ensure that rail trips indeed use rail rather than make long bus trips. RTM3 transit assignment uses INRO's relatively new Journey Level Assignment (JLA) algorithm which forces rail trips to use the rail network at least once in the journey without artificially penalizing the bus leg of a trip leading to sub-optimal path choices. See more on JLA below.

Transit Cost Impedance

RTM3 transit fares are coded directly onto the network and used as part of the optimal path-finding algorithm that minimizes generalized cost-minutes for trips between two zones. Bus and rail fares are skimmed directly from the network and used in mode choice and trip distribution models. This allows for more flexible fare policy testing and simplified fare coding. Network-based fares are used to calculate the optimal path for WCE trips; however the skims are computed at the matrix level depending on the origin and destination of the trip due to the complex WCE fare structure, particularly as it relates to transfers to other parts of the system.

TRANSIT FARES

For model years 2011, 2030, and 2045[14] the RTM3 bus and rail fares in are based on the region's three-zone fare system as shown in Figure 9-06. The first boarding costs $2.10 and an add-fare value of $1.05 is coded on each network link that traverses a fare zone boundary.

[14] At the time of model development it was assumed that the 3-zone system would return for future years.

Figure 9-06: Fare Zone Map

In 2016, the regional fare system was changed to a single bus zone (flat fare) while maintaining the three zone system on rail. As such, for year 2016 assignments the first boarding is charged $2.10 and transfers to another bus cost $0. For rail, the first boarding is charged $2.10. Subsequent bus boardings are charged at $0.Conversly, transit fares are incremented by $1.05 each time a trip traverses a zone boundary on rail. For example, if a person boards a bus in Surrey, transfers onto SkyTrain at Scott Road Station and alights in downtown Vancouver, their total fare is $4.20 since two fare zone boundaries are crossed on rail (i.e. a 3-zone rail trip). The 2016 add-fare network links are shown in Figure 9-07.

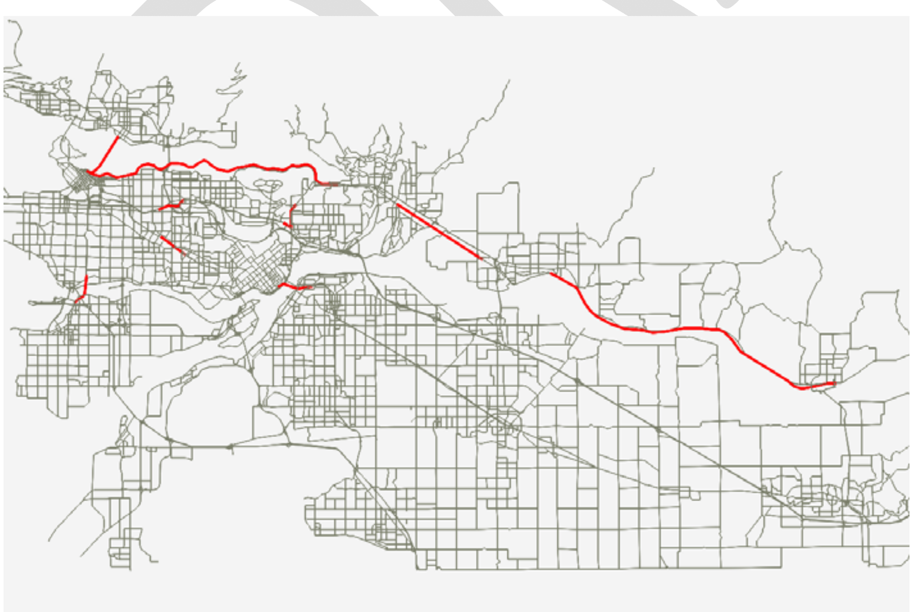

Figure 9-07: 2016 Network Add-fare Links

The West Coast Express has a different fare structure and fare calculation. When the first boarding is WCE the fare varies by station and time of day as shown in table below:

Station	AM Boarding Cost ($)	PM Boarding Cost ($)
Mission	3.80	0.00
Pitt Meadows/Maple Ridge Stations	2.10	2.10
Tri-cities	2.10	2.70
Waterfront	0.00	5.00

Figure 9-08: West Coast Express Initial Boarding Charges

When the first boarding is bus or rail the trip would have been charged $2.10 already, so transfer boardings at WCE stations are charged as follows:

Station	AM Boarding Cost ($)	PM Boarding Cost ($)
Mission	1.70	0.00
Pitt Meadows/Maple Ridge Stations	0.00	0.00
Tri-cities	0.00	0.60
Waterfront	0.00	2.90

Figure 9-09: West Coast Express Transfer Boarding Charges

If the trip then traverses a WCE zone boundary the fare is incremented as follows:

Link	AM ($)	PM ($)
Pitt Meadows to Tricities	1.70	0.00
Tricities to Vancouver	2.90	0.00
Tricities to Pitt Meadows	0.00	1.10
Pitt Meadows to Mission	0.00	1.70

Figure 9-10: West Coast Express Add-Fares

Transit Structural Changes

JOURNEY LEVELS ASSIGNMENT

The RTM3 mode choice model produces three distinct transit sub-mode demand tables defined hierarchically as:

1) WCE: A transit trip that has at least one leg on the WCE. Bus and rail are treated as feeder modes.
2) Rail: A transit trip that has at least one leg on the SkyTrain or SeaBus. Bus is treated as a feeder.
3) Bus: A transit trip that uses buses only.

The EMME standard transit assignment module does not guarantee that the conditions highlighted above are met. For example, bus and rail service must remain available in the network for WCE trips to use them as an access mode. However, if these services are in the network, there is no guarantee that a trip allocated to the WCE mode in the mode choice step will indeed use the West Coast Express mode in the assignment step.

RTM2 had two distinct transit modes, bus and rail, with the West Coast Express demand included with rail trips. In order to address the issue above, a bus in-vehicle time perception factor of 3.5[15] was implemented in the rail trip assignment to encourage rail trips to use the rail network. While this mostly solved the issue it was supposed to address, this 'fix' resulted in the unintended consequence of producing sub-optimal path choices; for example some people walked long distances to access a SkyTrain station when bus access to the station would have been faster without the large perception factor.

RTM3 corrected this issue by using INRO's Journey-Level Assignment (JLA) module that was released in 2016. JLA finds the optimal transit path in generalized cost-minutes conditioned on:

- Bus trips only use the bus network
- Rail trips have at least one leg on the rail network
- WCE trips have at least one leg on the WCE network

Thus JLA results in more realistic assignment paths and better skims for mode choice estimation and application.

PARK-N-RIDE

Park-n-ride is available for home-based work trips for all transit sub-modes in RTM3. The available data did not support park-n-ride as an access mode for the other trip purposes. The park-n-ride lot choice was updated to allow for the best-lot based on the minimum generalized cost. RTM2 assigned certain zones to specific park-n-ride lots. The best lot selection is based on the minimized AM peak hour generalized cost and held constant through the tour. This ensures that trips using a lot for their AM to work leg use the same lot on their way home.

In addition, park-n-ride was fully integrated into the mode choice model; RTM2 split park-n-ride trips from the transit demand after mode choice. The new implementation allows park-n-ride transit access to compete with auto modes where it could not previously.

Transit Assignment Outputs

Transit assignment generates skims for each of the AM, MD, and PM peak hour assignment periods. These skims are blended and fed back to trip generation, distribution and mode choice in the subsequent cycle. Figure 9-11 is a summary of relevant skims generated by time period in transit assignment.

[15] This means that every actual minute on bus, in this assignment, was felt as 3.5 minutes, thereby supressing bus usage.

Skim	Unit
Wait Time	Minutes
Walk Time	Minutes
Boarding	Number of Boardings
In Vehicle Time	Minutes
Fare	Dollars

Figure 9-11: Transit Assignment Outputs and Units

Validation

Assigned transit volumes compared to Automated Passenger Count (APC) data at the screenline level are shown in Figures 9-12 through 9-14 for the AM, MD, and PM assignment periods. As with the auto assignment, the AM and PM assignment passenger volumes fit the observed data well while the MD assigned passenger volumes tend to under-predict the observed data.

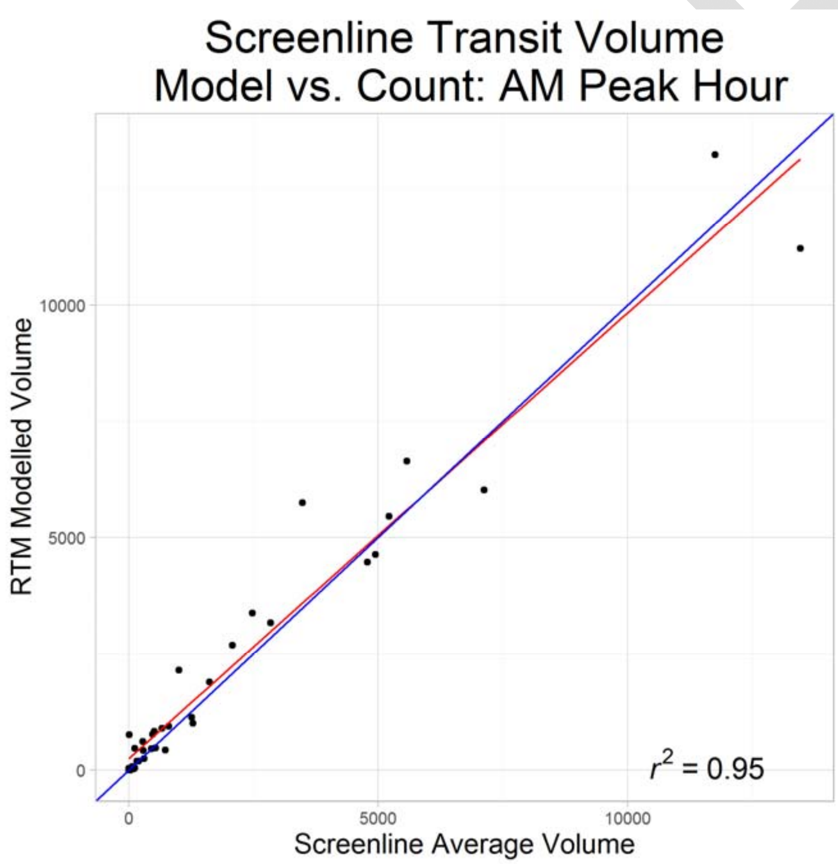

Figure 9-12: RTM Screenline Transit Volume vs APC – AM Peak Hour

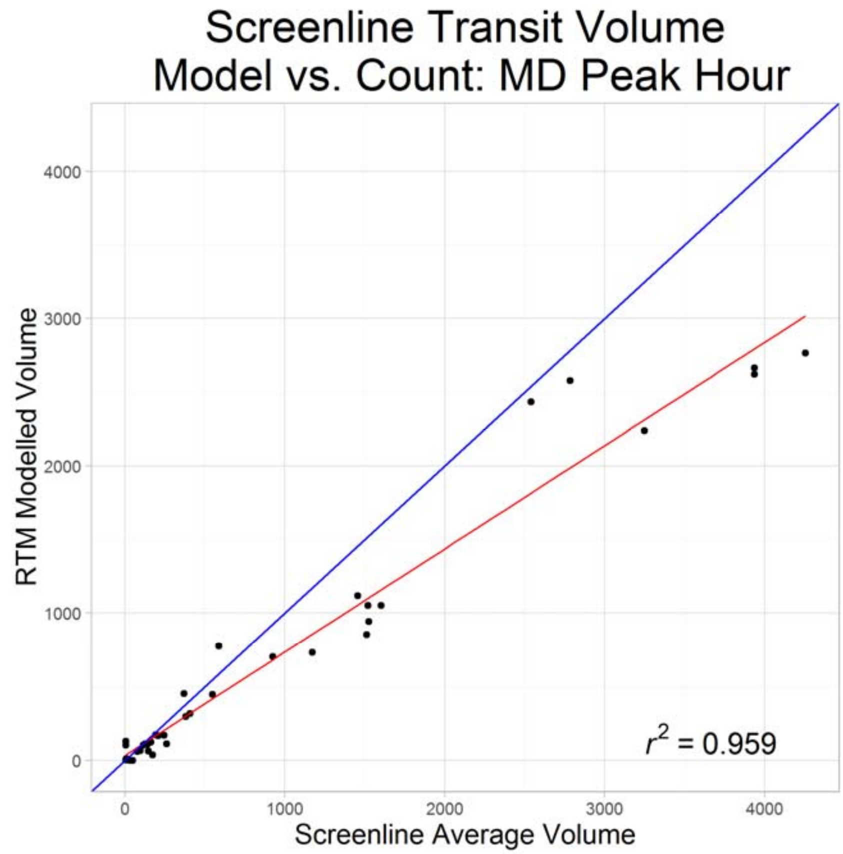

Figure 9-13: RTM Screenline Transit Volume vs APC – MD Peak Hour

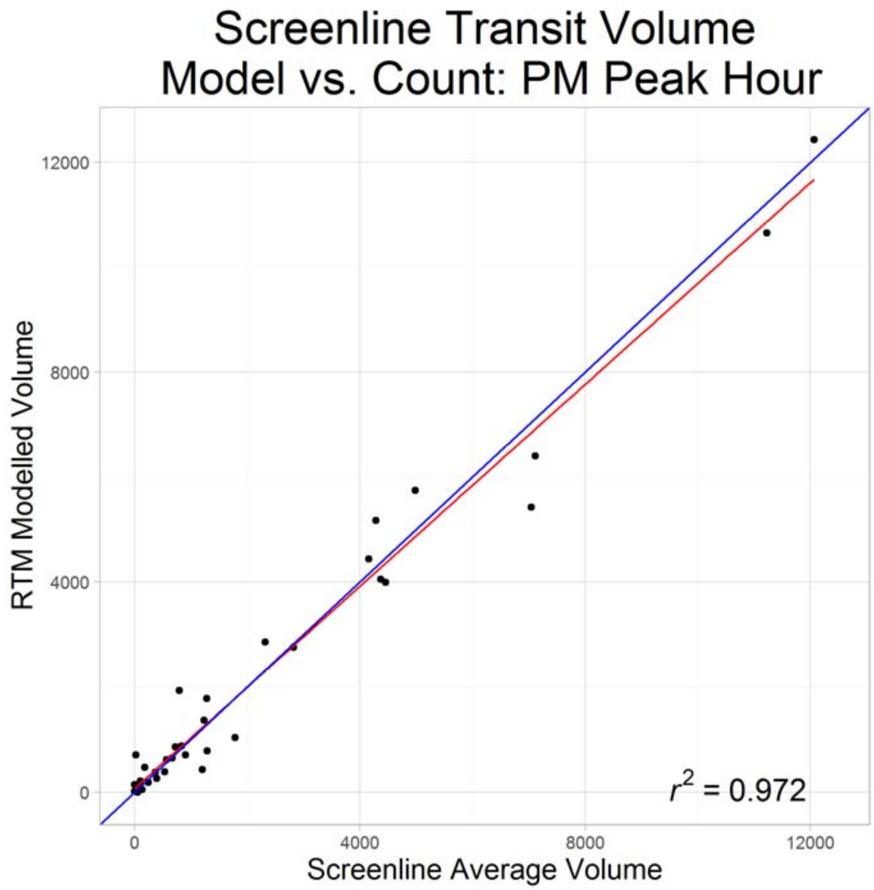

Figure 9-14: RTM Screenline Transit Volume vs APC – PM Peak Hour

Bus boardings at the line level were also compared with observed APC data. These comparisons are shown in Figures 9-15 – 9-17. Again, the AM and PM RTM3 volumes fit the data well, while the MD RTM3 volumes under-predict the observed data.

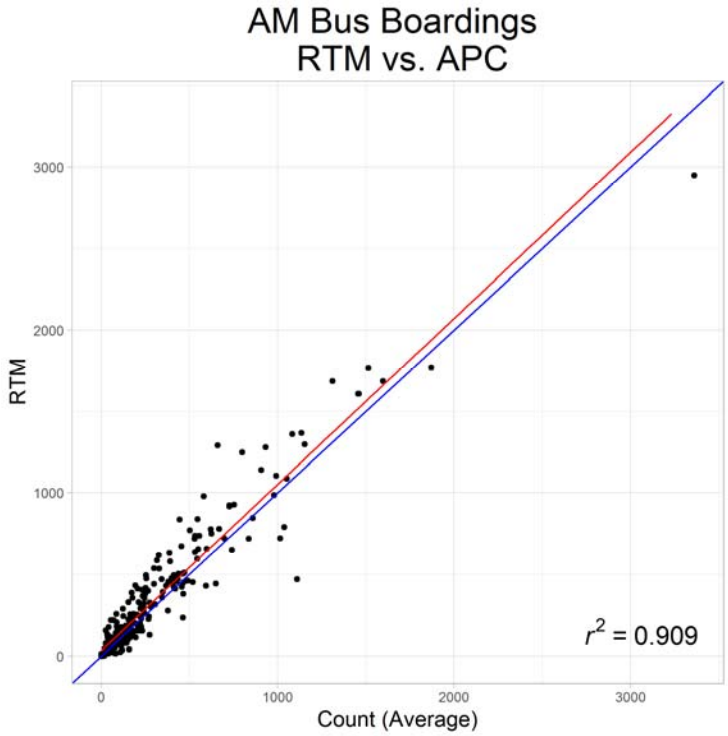

Figure 9-15: RTM Bus Boardings by Line vs APC – AM Peak Hour

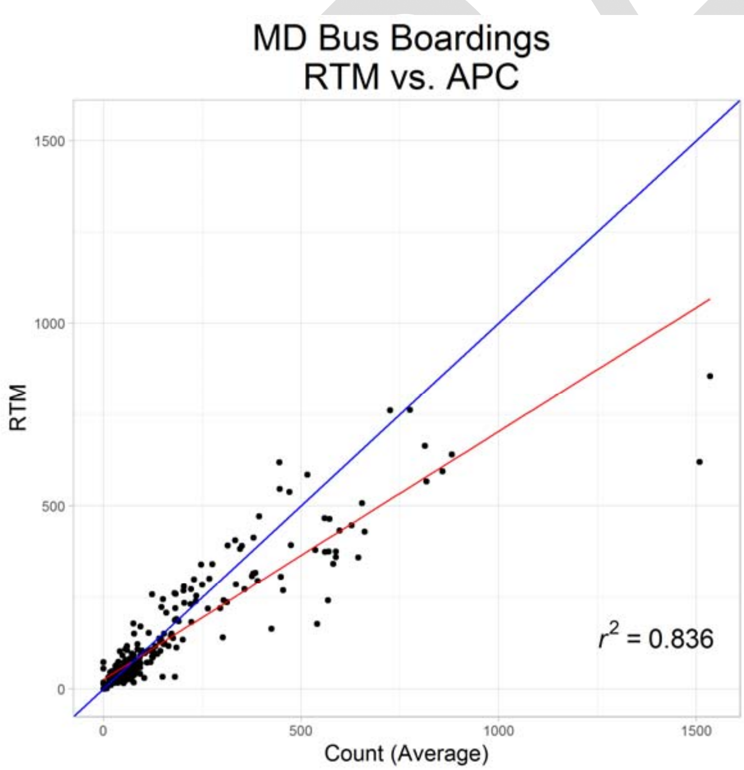

Figure 9-16: RTM Bus Boardings by Line vs APC – MD Peak Hour

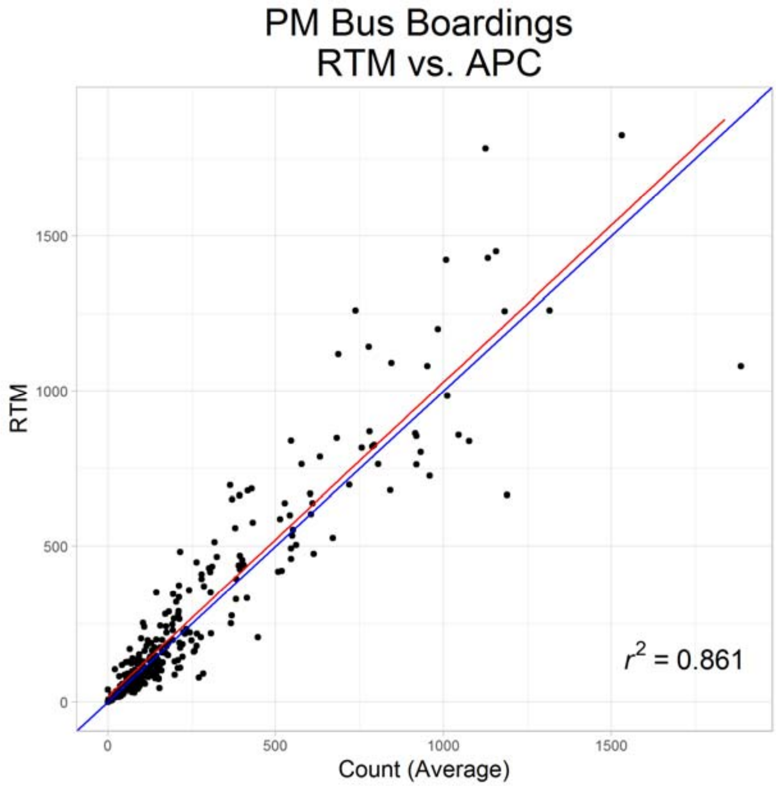

Figure 9-17: RTM Bus Boardings by Line vs APC – PM Peak Hour

10: Other Model Components

This chapter documents the additional sub-modules and data preparation work that contribute to RTM3 forecasts, but are outside of the standard 4-step modules. These sub-modules include:

- Parking price model
- Car share availability model
- Bike score

Parking Price Model

The parking sub-module forecasts future year parking rates. Parking rates are used as inputs to other RTM3 sub-modules. For instance, in the mode choice sub-module parking rates are added to the other costs of the driving modes. The parking sub-module was estimated using data collected for RTM3 development.

ESTIMATION

There are several factors that affect parking rates some of which are hard to measure including parking restrictions, capacity of free parking spaces, special events' rates, and discounted rates for employees. Parking spaces can be off-street (often managed by private vendors) or on-street (owned by municipalities). To capture the two types of parking spaces, a dataset was constructed from two data sources. Off-street parking data was acquired from a private vendor for Metro Vancouver and the Fraser Valley for a total of 495 parking lots during the period 2011-2016. The dataset includes parking rates and capacity. Rates for on-street parking meters and stations for 2016 were gathered from numerous municipalities in the region including Vancouver, Richmond, Surrey, New Westminster, North Vancouver City, Coquitlam, Burnaby and White Rock. This dataset does not include information about parking capacity at each parking meter/station. As such, parking capacity was assumed to be1.5 spaces at parking meters (as some meters can serve multiple parking spaces) and five spaces at parking stations.

The two datasets were combined and aggregated at the TAZ level. Figures 10-01 and 10-02 show two-hour and eight-hour parking rates at the TAZ level. The following points summarize the steps and assumptions to develop the combined dataset:

- An analysis of activity duration by trip purpose from the Trip Diary showed that the average activity duration for commuting is approximately 6.25 hours and the average activity duration for other trip purposes is approximately 1.6 hours. Therefore, two parking rates were developed: two hour (2hr) and eight hour (8hr) rates. The 8hr rate represents parking rates for commuting purposes while the 2hr rate represents parking rates for other trip purposes.
- The equivalent two hour and eight hour rates were calculated based on the parking rates provided for each lot/meter based on the available terms (per 30 minutes, hour, 4hrs, day, etc.) . The equivalent rates were calculated as follows:
    - If a two hour rate is available at the parking lot/meter, it is used; otherwise prorated rates are calculated linearly up to two hours and capped after that. For example, if a two hour rate is not available while 30-min, 1-hr and 3-hr rates are available, the two hour rate is calculated as the minimum of (30-min rate *120/30, 1-hr rate * 120/60, 3-hr rate).

  - Similarly, if an eight hour rate is available at the parking lot/meter, it is used; otherwise prorated rates based on the number of working days per month (22). For example, if an eight hour rate is not available while 10-hr, daily and monthly rates are available, the eight hour rate is calculated as the minimum of (10-hr rate, daily rate, and monthly rate/22). For cases where parking rates are not available for eight hours or more, eight hour parking is assumed not to be available.
- Parking capacity was used to calculate weighted average parking rates. For example, if a particular TAZ has three parking lots/meters with the following two hour rates (and capacities): $6 (10), $9 (50), and $12 (25), then the weighted average two hour parking rate is calculated as follows: (6*10 + 9*50 + 12*25)/(10+50+25) = $9.53
- The 8hr rate was capped at $15 per day since it is developed for commuting purposes and the maximum observed monthly parking rate was $350.
- The dataset was reviewed and a few adjustments were introduced to correct for data inconsistencies. For example, Vancouver International Airport has high parking prices, particularly for short-term (24-hr) parking facilities, which leads to high weighted average parking rates. However, most employees receive free or reduced parking rates so the 8-hr parking rates were adjusted to be in line with commuters to the area.

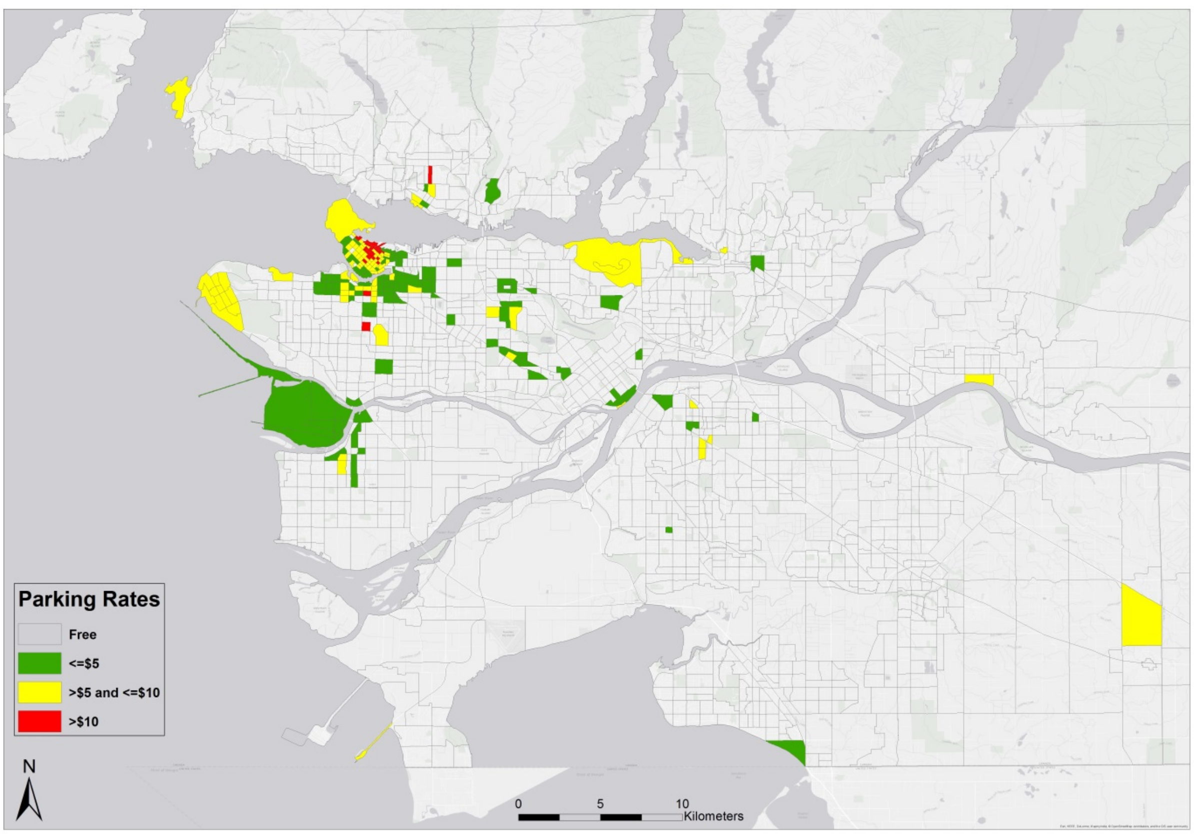

Figure 10-01: Average 2hr Parking Rates at the TAZ level

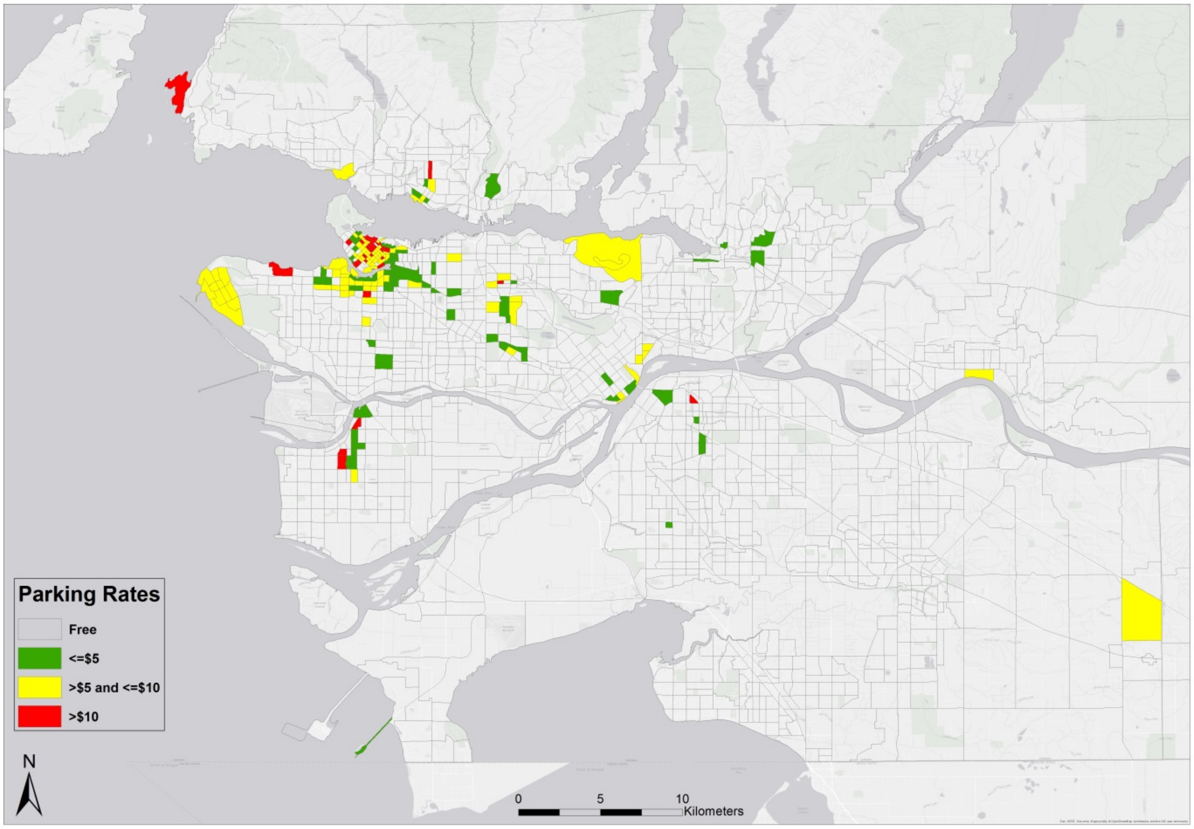

Figure 10-02: Average 8hr Parking Rates at the TAZ level

STRUCTURE

The model is developed and applied at the TAZ level. The model is structured as a binary logit model to forecast whether parking is free or paid at a given TAZ, followed by a linear regression model to forecast the average parking cost for paid parking TAZs.

PARKING MODEL FORM AND EXAMINATION

As mentioned earlier, two parking rates, 8hr and 2hr, were calculated and used in subsequent models. The two parking rates correspond to commuting and discretionary activities, respectively. As such, two sets of models were developed to forecast the two parking rates of interest.

CLASSIFICATION MODEL: FREE OR PAID PARKING

A binary logit model was estimated to classify TAZs to one of two groups: free and paid parking for each set of parking rates: 2hr and 8hr. The model takes the form:

$$V_i = ASC + \sum_{j}^{m} \beta_j * x_j$$

Where:

'V_i' is the systematic utility of each alternative defined in a linear form in which
'ASC' is the alternative-specific constant,
'x_j' represents a set of explanatory variables and
'β_j' represents their corresponding estimated coefficients.

The systematic utility of the free parking alternative is set to 0. The probability of each alternative is defined as:

$$P_i = \frac{exp^{V_i}}{\sum_j^k exp^{V_j}}$$

Where 'k' is number of alternatives. In this case $k = 2$. Figure 10-03: shows the variables' definitions and the estimated coefficients for each model. All variables' coefficients are statistically significant at the 95% confidence level and estimated with the expected sign. The overall model accuracy is 94.9% and 93.5% for the 2hr and 8hr models, respectively.

Variable	2hr Model	8hr Model
Constant	-1.07	-3.65
Log Employment Density	0.93	1.19
Log Distance to CBD	-2.00	-1.23
Town Centres*	1.99	0.88
Rail Stations*	2.46	2.40
Point of Interest* Including: Hospitals, Universities, Ferry Terminals, Airports	5.14	NA
Downtown Eastside*	-1.82	-1.39
Hospitals*	NA	2.59
Universities*	NA	5.82

* Dichotomous variable

Figure 10-03: Free/paid Parking Classification Model Variables and Coefficients

REGRESSION MODEL: PARKING RATES FOR PAID TAZS

A linear regression model for each set of parking rates, 2hr and 8hr, was estimated to forecast parking prices for the paid parking classified TAZs. The model takes the form:

$$y = intercept + \sum_j^m \beta_j * x_j$$

Where:

'y' represents the continuous dependent variable, in this case: $Log(Parking\ Cost)$,
'x_j' represents a set of explanatory variables and
'β_j' represents their corresponding estimated coefficients.

Figure 10-04 shows the variables' definitions and the estimated coefficients for each model. All variables' coefficients are statistically significant at the 95% confidence level and estimated with the expected sign.

Variable	2hr Model	8hr Model
Intercept	1.8168	2.0042
Log Employment Density	0.0005	0.0003
Log Distance to CBD	-0.136	-0.1172
Point of Interest* Including: Hospitals, Universities, Ferry Terminals, Airports	0.2469	0.1225

* Dichotomous variable

Figure 10-04: Parking Rate Model Variables and Coefficients

The residuals of both models were found to be normally distributed and do not have concerning non-linear patterns thanks to the non-linear variables' transformation. The adjusted r-squared is 0.40 and 0.21 for the 2hr and 8hr models, respectively.

Car Share

Car share services create a new mobility option, particularly for households without an available vehicle. Metro Vancouver has several car share companies providing two types of service:

- One-way: The car operates within a certain geographic boundary and the driver does not have to drop the vehicle back where it was picked up
- Two-way: Vehicles have designated parking lots. The driver has to pick up and drop off the vehicle at those locations

In 2011, Vancouver had three car share companies; Modo, Zip Car, and Car2Go. Modo and Zip Car provide two-way service and Car2Go provides one-way service. Figure 10-05 shows the location of Modo and Zip Car lots as well as the Car2Go geographic boundaries in 2011. At the time, most shared vehicles were located in the City of Vancouver.

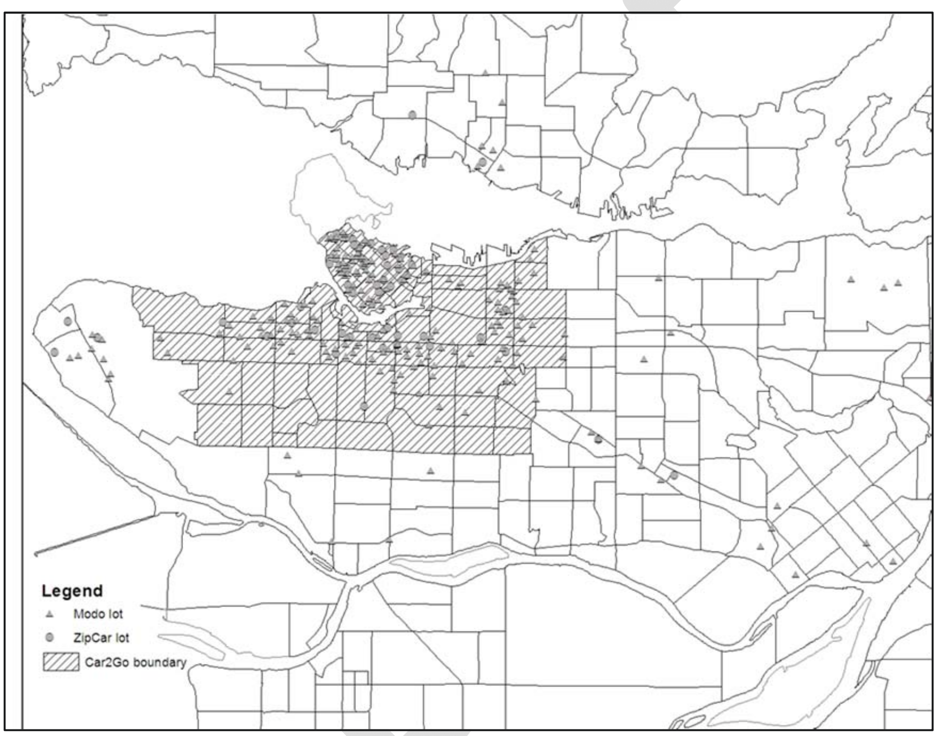

Figure 10-05: 2011 Car Share Availability

In March 2015, a fourth company, EVO, entered the market providing one-way service.

CAR SHARE IN RTM3

Car share is an exogenous variable in the auto ownership and mode choice models in RTM3. In the auto ownership model, the availability of car share services in a TAZ reduces the likelihood of a household owning a vehicle, or an additional vehicle, all else being equal. In the mode choice model, the SOV mode is available for zero vehicle households that reside in TAZs served by car share services. RTM3 does not model household car share membership or use of car share as a separate mode because the 2011 Trip Diary did not include that information. The 2017 Trip Diary did however include car-share related questions so more accurate car share modeling should be possible for the next version of the model.

For RTM3 application each TAZ is given an ordinal score, ranging from 0 to 3 with 3 indicating high availability of car share services.

CAR SHARE SCORE CALCULATION

TAZ level car share scores are calculated outside the RTM using GIS software as follows:

1) Create 500 meter circular buffers around the Modo and Zip Car point shapefile (lot locations)
2) Load the Car2Go polygon shapefile
3) Load the TAZ polygon shapefile
4) The table below describes how the scores are calculated

Two-way service: Modo/Zip Car Score	Criteria
0	TAZ does not intersect any buffer
1	TAZ only intersects one type of lot (either Modo or Zip Car)
2	Buffer intersects both types of lots
One-way service: Car2Go Score	**Criteria**
0	TAZ falls outside Car2Go polygon boundary
1	TAZ falls within Car2Go polygon boundary

Figure 10-06: Car Share Scoring Method

Figure 10-07 shows 2011 car share scores at the TAZ level.

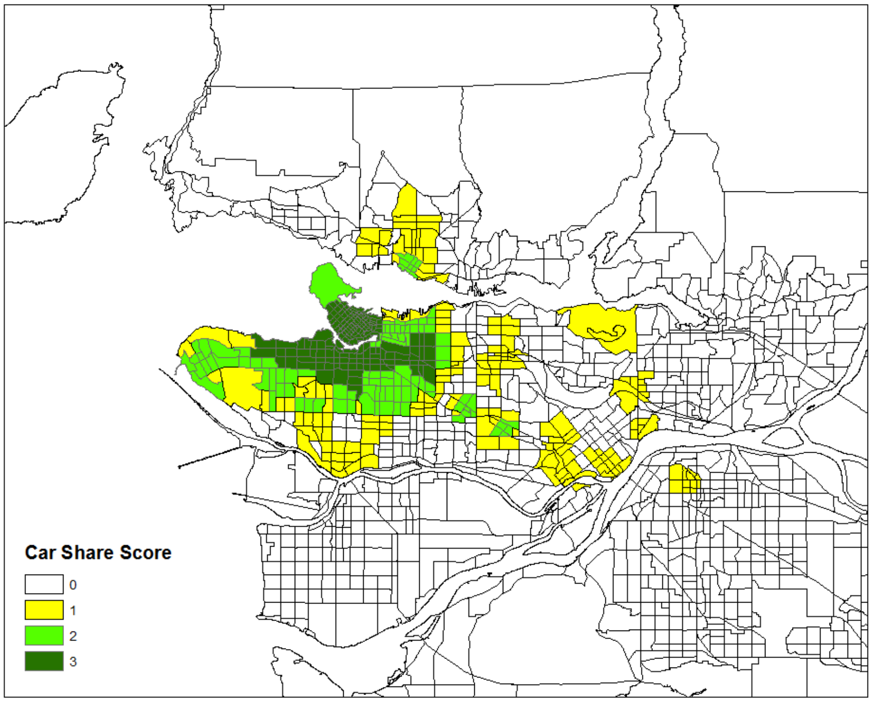

Figure 10-07: 2011 TAZ Car Share Scores

FORECASTING TAZ CAR SHARE SCORE

In order for the car share variable to have a meaningful impact on long-term forecasts, car share service availability needs to be projected for each horizon year. Calculating future TAZ car share scores requires predicting the location of future lots and one-way services boundary expansion.

RTM3 future year car share scores were pivoted from RTM2 (which is based on the 641 TAZ system) future year values. In RTM2, future lots and car share boundaries were forecasted based on the change in composite (population and employment) density:

Two-way lots (Modo and Zip car)

- Composite densities of all zones are calculated for the base year, 2030 and 2045
- Whenever, a zone crossed a density threshold, moving above 75 persons per hectare in composite density, these zones were flagged for further review
- A 75 composite density score indicates a neighbourhood that might support a car share lot within 500 metres
- Professional judgment was used to decide which of those TAZs would have car share availability
- The difference between base and future year RTM2 car share scores was calculated
- If a centroid fell within the boundaries of TAZ641 whose score increased then the car share score of the 1700 TAZ centroid was incremented accordingly

Based on the outlined method, car share is forecast to expand into new areas such as the Tri-cities, Surrey, and Richmond, as shown in Figure 10-08, which maps predicted 2045 car share scores.

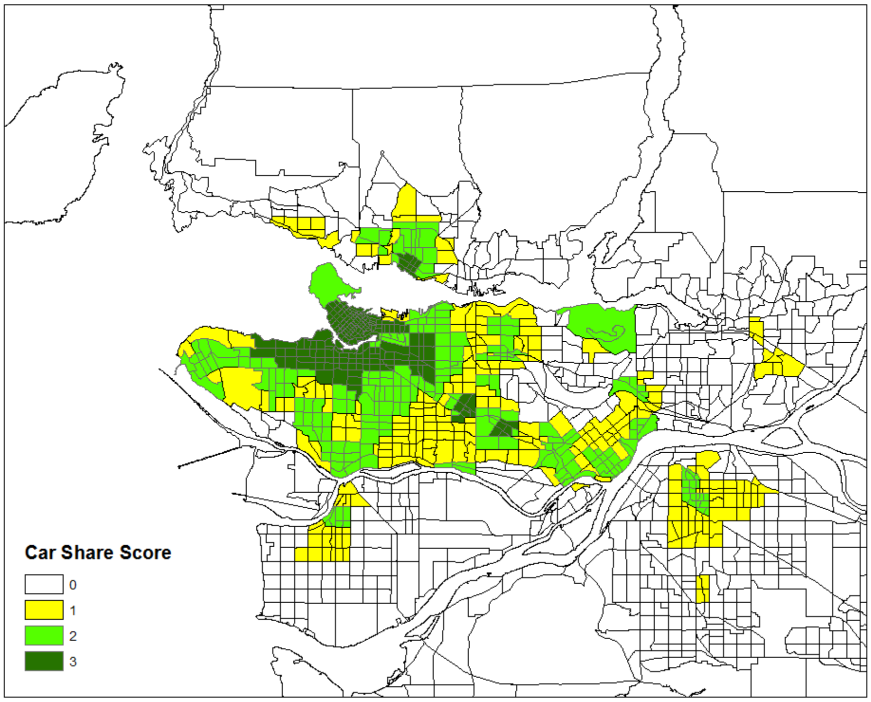

Figure 10-08: 2045 Forecast Car Share Scores

Bike Score

Bike score is an index of the suitability of a geographic area to support bike trips. Geographic areas are scored from 1 (poor) to 5 (good) based on a set of metrics including:

- Route connectivity
- Route network density
- Bikeway quality
- Supportive land use.

These metrics are weighted based on importance to biking and the weighted metrics are converted to the bike scores index as follows:

- Bike score 1: 0% - 25%
- Bike score 2: 25% - 50%
- Bike score 3: 50% - 65%
- Bike score 4: 65% - 75%
- Bike score 5: 75% - 100%

The full list of metrics and weights is shown in Figure 10-09. Changes to the metrics were estimated from planning data and used to prepare future year bike scores.

Factor	Weight			
	Cycling Potential	Existing Bicycle Network Conditions	Overall Existing Conditions	Future Cycling Conditions
a) Road Network Connectivity	20%		10%	
b) Road Network Density	20%		10%	
c) Topography	20%		10%	
d) Land Use	40%		20%	
e) Permeability			10%	
f) Bicycle Network Density (existing)		35%	14%	
Bicycle Network Density (planned)				50%
g) Bicycle Network Connectivity (existing)		35%	14%	
Bicycle Network Connectivity (planned)				50%
h) Bikeway Quality		15%	6%	
i) Intersection Quality		15%	6%	
TOTAL	**100%**	**100%**	**100%**	**100%**

Figure 10-09: Bike Score Metric Weighting

The bike scores were developed by TransLink staff and external consultants. TransLink's Forecasting group extended the bike score metric to create bike score skims. These skims take the weighted average bike score along the shortest path between two zones. Trips will have a greater skim value when the majority of the trip occurs in higher bike score areas. Conversely, a trip that starts and ends in high bike score zones, but traverses a substantial distance through lower bike score areas will have lower skim value.

The bike score skim value is used in mode choice and a higher value increases the likelihood that a trip will choose the bike mode.

TAZ level bike scores for 2011, 2030, and 2045 are shown in Figures 10-10 through 10-12

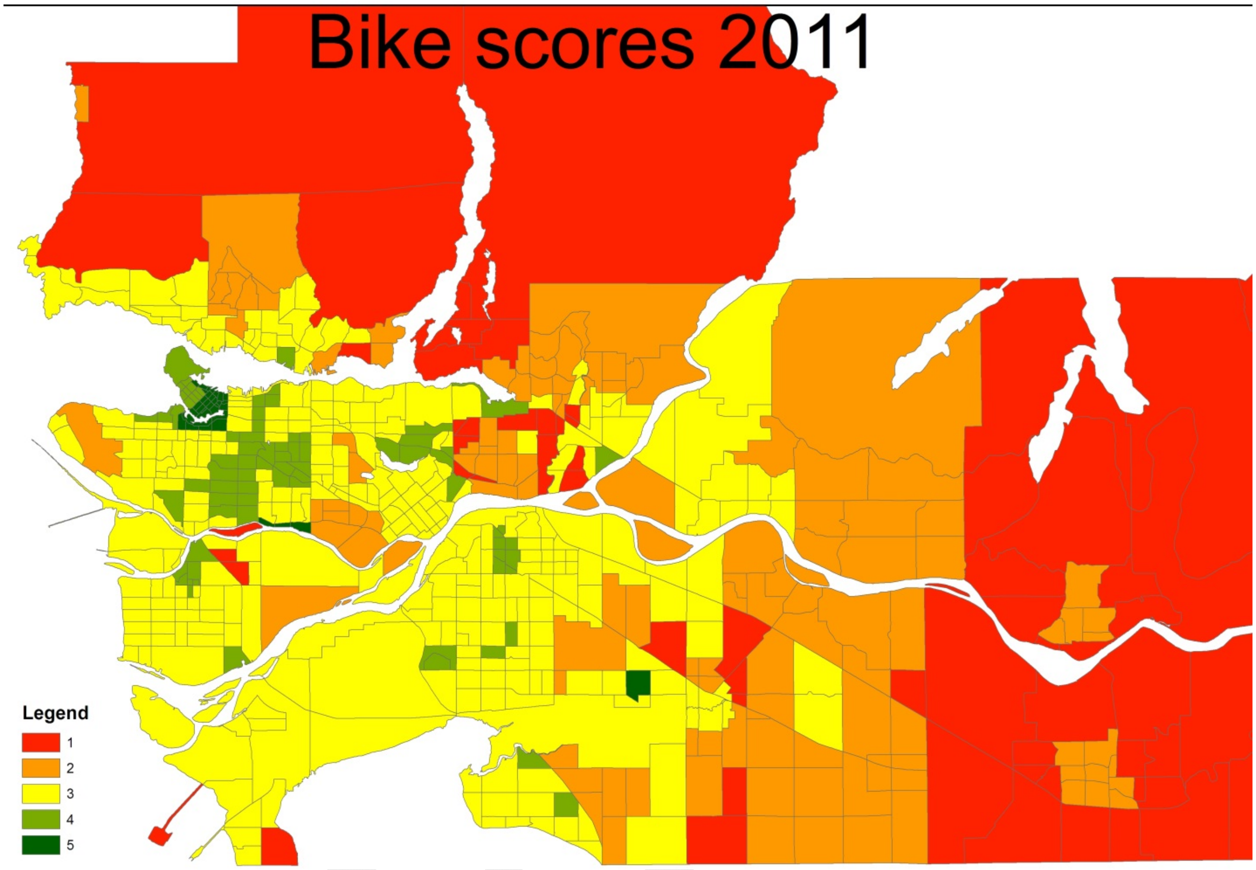

Figure 10-10: 2011 Bike Scores

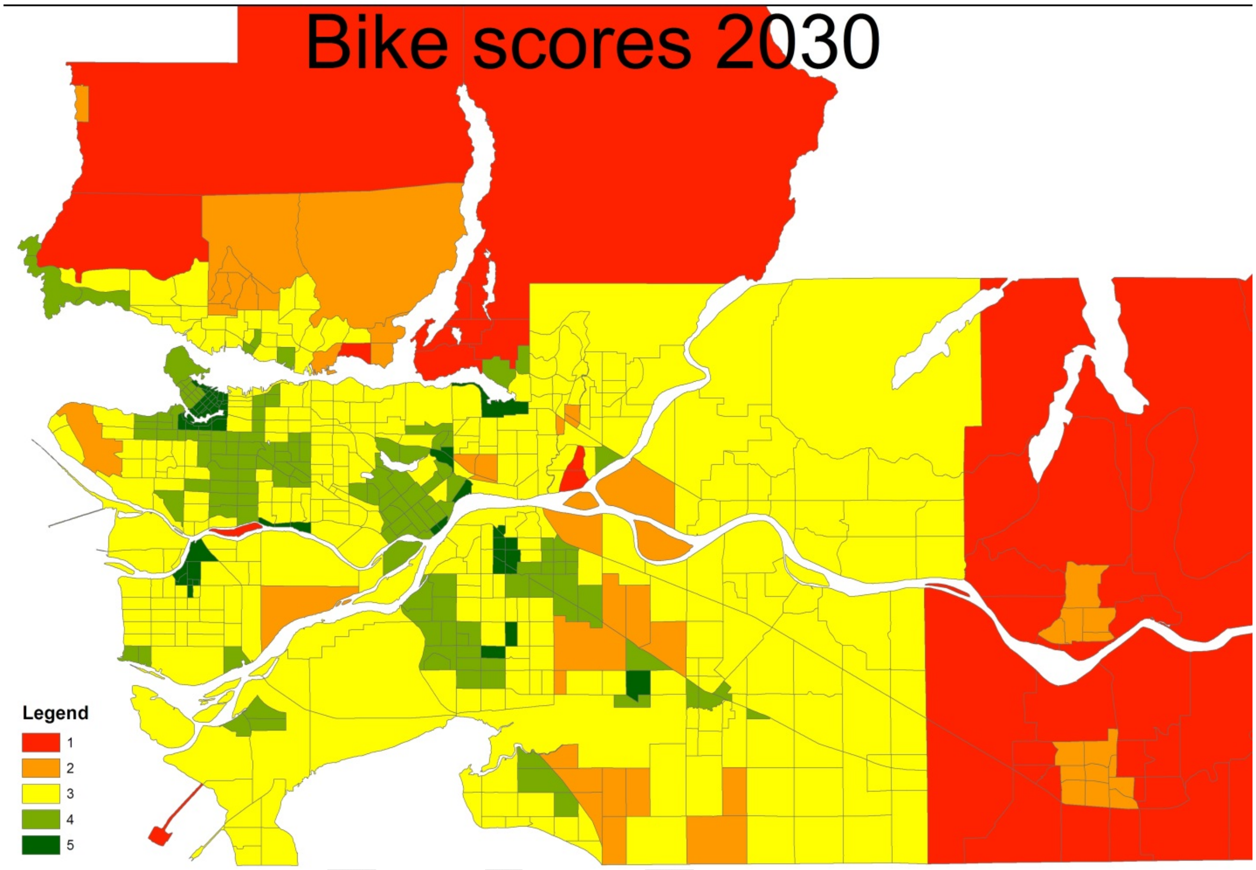

Figure 10-11: 2030 Bike Scores

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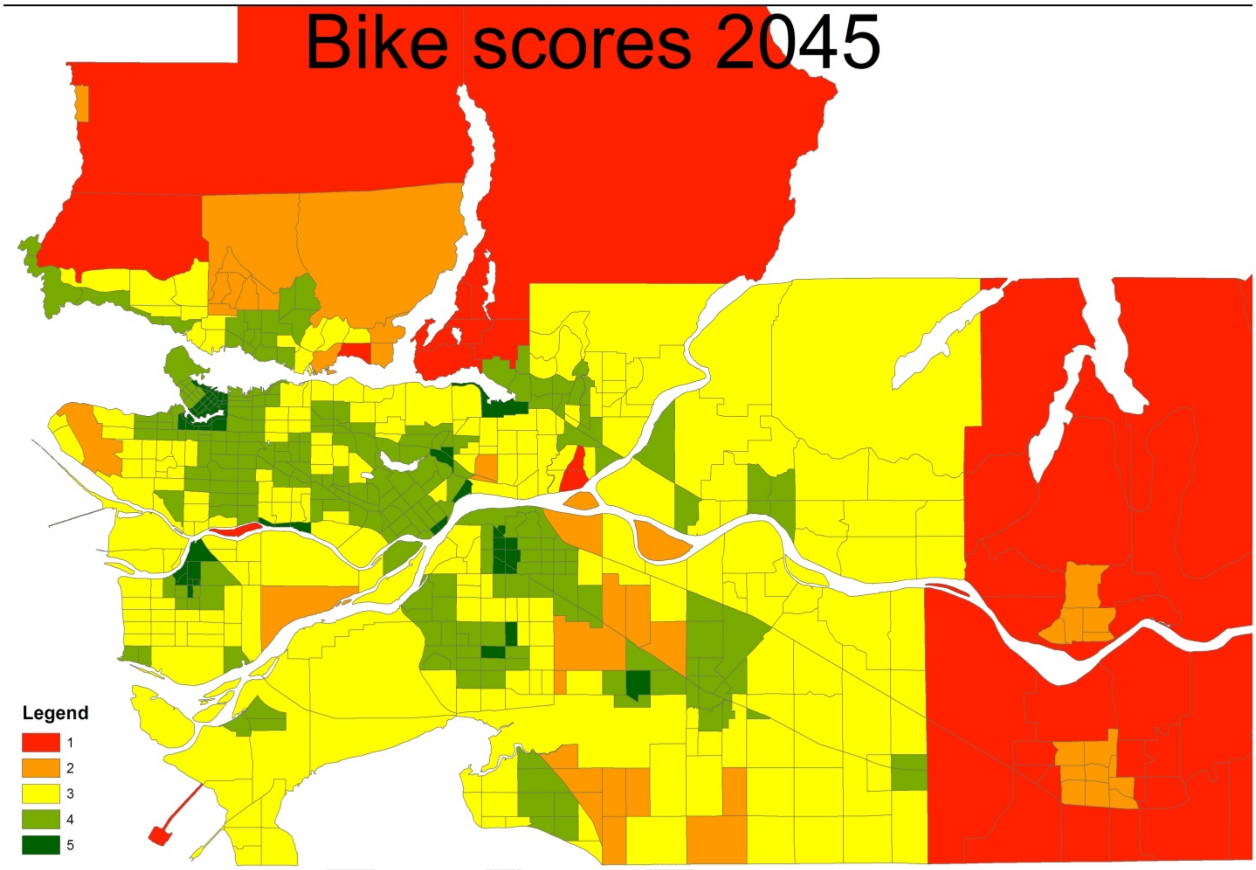

Figure 10-12: 2045 Bike Scores

Appendix A

Appendix B

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Appendix C

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