UNIVERSITY OF TORONTO
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Demand Modelling of Cross-Regional Intermodal Commuting Trips in the Greater Toronto and Hamilton Area

Submitted to

METROLINX

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Table of Contents

PROJECT SUMMARY 1

INTRODUCTION AND LITERATURE REVIEW 2

STUDY OBJECTIVES 5

STUDY AREA 6

SURVEY INSTRUMENT DESIGN 7

Section A: Revealed Preference Survey 10

Section B: Stated Preference Survey 12

Section C: Socioeconomic Attributes 13

Respondents' Feedback 13

SURVEY IMPLEMENTATION 17

MODE CHOICE MODELLING 21

EMPIRICAL MODELS 23

RP-Only Model 25

SP Models 27

SP-Only Model 27

Joint RP-SP Model 27

MARGINAL EFFECTS OF TRAVEL COST AND TRAVEL TIME 35

MODEL VALIDATION 42

POLICY ANALYSIS 45

CONCLUSIONS 48

REFRENCES 50

List of Figures

Figure 1 Polices Under Investigation 5
Figure 2 The Greater Toronto Hamilton Area 6
Figure 3-a SCRIPT Data Model 8
Figure 3-b SCRIPT Data Model 9
Figure 4 Snapshot of a Sample SP Experiment 16
Figure 5 Spatial Distribution of Cross-Regional Trip Ends 19
Figure 6 Mode Choice Split 19
Figure 7 Level in Confidence in SP Choice 20
Figure 8 Mode Availability 20
Figure 9 The Artificial Nested Structure of Joint RPSP Models 22
Figure 10 Marginal Effects of Travel Cost and In-Vehicle Travel Time 37
Figure 11-a Marginal Effects of RP Travel Cost for Local Transit with Walk Access Mode Identification of Sample Segments 41
Figure 11-b Marginal Effects of Parking Cost at Park-and-Ride Stations for Regional Transit with Auto Driver Access Mode 41
Figure 12-a Joint RPSP Model Validation – RP Data 43
Figure 12-b Joint RPSP Model Validation – SP Data 44
Figure 13 Calibrated Joint RPSP Model 46

List of Tables

Table 1 Mode Feasibility 11
Table 2-a Mode Attribute Definition 14
Table 2-b Mode Attribute Levels 15
Table 3 SCRIPT and TTS Sample Distribution 19
Table 4 Definitions of Variables 23
Table 5 RP-Only Model 26
Table 6 SP-Only Model 29
Table 7 Joint RPSP Model 30
Table 8 Value of Travel Time Savings 34
Table 9 Average Direct Elasticities for Travel Cost and In-vehicle Travel Time 36
Table 10 Predicted GO Transit Mode Shares 47

Glossary

Revealed Preference (RP) Survey	Collects information about the actual choices made by survey respondents
Stated Preference (SP) Survey	Collects information about choices of respondent when presented with hypothetical choice scenarios
RP-Only Models	Use only RP data of individuals' choices
SP-Only Models	Use only SP data of individuals' choices
Joint RP-SP Models	Use both RP and SP data of individuals' choices
Regional Transit	Transit services that operate across the region, i.e., GO Transit
Local Transit	Transit services that operate within one jurisdiction of the region (e.g. Toronto Transit Commission)
Intermodal/Multimodal Trip	A trip that involves the use of different: • travel modes such as car and transit, or • types of transit services such as local transit bus and regional transit train, or • local transit services such as Toronto Transit Commission (TTC) bus and York Region Transit (YRT) bus.
Cross-Regional/Inter-Regional Trips	Trips that involve crossing jurisdictional borders and/or the use of different local transit service providers
Heteroscedastic Model	A model that captures the variance across different sub-groups in the population
Elasticity	A measure of how responsive travel demand is to a unit change in one service attribute
Experimental Design	An experiment in which one or more process variables (or factors) are changed in order to observe the effect on one or more response variables
Orthogonal Experimental Design	An experimental design is orthogonal if each factor can be evaluated independently of all the other factors
D-Efficient Experimental Design	D-optimal designs are constructed to minimize the generalized variance of the estimated regression coefficients and therefore maximizes the information from each choice situation

Target Population	The target population is the entire group of individuals which is under investigation
Strata	Homogeneous groups of the target population
GAUSS ®	A matrix programming language for mathematics and statistics, developed and marketed by Aptech Systems
MAXLIKE	A package that provides a likelihood-based approach to estimate model parameters
Ngene®	A software for generating experimental designs that are used in stated choice experiments for the purpose of estimating choice models, particularly of the logit type

PROJECT SUMMARY

This study presents an investigation on mode choice behaviour of cross-regional commuters in the Greater Toronto and Hamilton Area (GTHA). With the aim of improving transit services with more emphasis placed on transit modal integration across the region, a policy-sensitive evaluation framework is developed and presented herein. This framework allows to evaluate the effectiveness of various policy initiatives and quantify the effect of changes in level of service attributes (such as travel time and cost) on commuters' mode choice. The framework adopts the state-of-the-art survey methods to develop an online survey, namely the Survey of Cross-Regional Intermodal Passenger Travel (*SCRIPT*).

SCRIPT collects data on respondents' current commuting trips as well as their stated mode choice in response to hypothetical changes in the current mode attributes. An innovative multimodal trip planner tool is developed to generate feasible travel options for each choice experiment using information of households' auto ownership level, proximity to transit, work start time, and total travel time from home to work. The survey platform adopts pre-developed access location choice models to identify potential park-and-ride access stations for intermodal travel modes.

The gathered data is used to develop a set of econometric choice models that can explain the changes in individuals' probabilistic responses as a result of introducing new policies. The developed models provide an extensive understanding of cross-regional commuters' mode choice behaviour. In addition, an Interactive Model for Policy Analysis of Cross-Regional Travel (*IMPACT*) is developed to predict corresponding changes in aggregate modal shares in response to the policy initiatives under consideration.

INTRODUCTION AND LITERATURE REVIEW

The continual expansion of major metropolitan areas due to the inexorable urban sprawl away from city centres has produced a persistent growth of inter-regional commuter trips (i.e., trips originating from and destined to different regions) (*1; 2*). As a result, a growing group of commuters experience long travel times especially for travel modes other than driving. The complexity of cross-regional trips stems from the multimodal nature of such long distance travel. Cross-regional trips may involve the use of multiple transit services or the interaction between two travel modes which often result in delays due to the typical lack of service coordination. Improving transit modal integration is one of the promising strategies that have been under investigation by regional transit operators (*3*). Such improvements can be achieved at the intra-modal integration level (e.g. local transit with regional transit) by providing easier access to major stations in areas where transit accessibility is inadequate, synchronized transfers, integration of stations areas with supporting land uses, and introducing advanced fare integration schemes *via* smart cards. Similarly, improvements at the transit intermodal integration level (e.g. transit with automobiles or active modes) can be achieved through a system of connected mobility hubs where parking facilities are available for park-and-ride or passenger drop-off/pick-up areas (kiss-and-ride) to provide seamless transfers between different modes of travel. Evaluating the effectiveness of such initiatives and supporting policies requires a proper understanding of individuals' travel choices, especially for a hard-to-reach target population with unique travel characteristics as cross-regional commuters.

The literature on cross-regional travel behaviour is evidently limited. Previous studies defined cross-regional trips as long-distance trips and confirmed their significant growth over time (*4*). Earlier studies highlighted the importance of dedicating special research efforts to investigate long-distance inter-regional commuting since typical travel demand models are inadequate in terms of explaining the travel behaviour of this special market segment (*5*). Based on results from a set of logistic regression models, a more recent study emphasized that long-distance commuters have distinct characteristics relative to other types of commuters (*6*). According to these studies, long-distance commuting trips can be classified based on a predefined travel distance or time threshold. However, such definitions do not appropriately take into account the interaction between different travel modes across regional boundaries and how that might affect individuals' choice behaviour. That is, models developed to explain long-distance trip patterns cannot represent specifically the travel behaviour of cross-regional commuters, and as such in-depth research to fill this gap in the literature is required.

Studying cross-regional trip makers' behaviour requires an extensive data on their trip patterns including detailed information on each trip leg such as access, transfer and egress times. Typical commuting travel surveys do not provide sufficient data to conduct this type of analysis. This is due to several reasons: cross-regional trips are often underrepresented in survey samples, the collected data does not provide the necessary level of detail on inter- and intra-modal trips, and the majority of typical travel surveys rely predominantly on Revealed (observed) Preference (RP) trip data. Previous research efforts showed that RP data does not capture adequately the behavioural trade-offs involved in the travellers' decision making process. Therefore, demand models developed based on RP data only are incapable of accurately forecasting individual choices in response to new transportation policies or the introduction of new modes (*7; 8*).

In order to overcome the limitations of RP models, some researchers have replaced RP data with Stated Preference (SP) data. SP surveys are used to measure individuals' preferences towards hypothetical scenarios by asking the respondents questions on services or policies that do not exist (*9-11*). A summary of the advantages of using SP data over the conventional RP data for travel behaviour analysis can be found in (*12*). However, SP data has its own drawbacks as well. Previous studies showed that individuals' stated preferences may not be consistent with their actual choices which induce a systematic bias in the data (*13*). Alternatively, using joint RP-SP data allows for scale adjustment of parameter estimates in order to correct the systematic bias of the SP data (*10*). As it stands now, joint RP/SP surveys represent the state-of-the-art approach for travel behavioural data collection, in which behavioural factors along with typical socioeconomic attributes are gathered to accurately develop econometric models that can explain the probabilistic response in accordance with changes in transportation level of service attributes as a result of introducing new policies.

Several studies investigated individual's travel behaviour using RP-SP data (*14-17*). In a recent study (*18*), data form an RP-SP survey on parking price levels at park-and-ride stations was used to develop a heteroscedastic mode choice model. The study shows that a relatively small dataset of RP/SP data can provide a good understanding of individuals' elasticity towards policy changes. In a recent study, data from an RP-SP commuting survey was used to investigate the influence of transit service attributes on mode switching behaviour (*19*). Results of SP-Only and joint RP-SP mode shift models were compared and the study concluded that the inclusion of joint RP-SP data has a positive effect on improving the goodness of fit and explanatory power of the SP-Only model.

The purpose of performing an SP experiment is to quantify the independent effects of the design attributes on respondents' choices (*20-22*). In general, the experiment design gets more complex as the number of attributes and their levels increase. Therefore, it is desirable to keep the number of attribute levels as low as possible. Although the minimum number of attribute levels is two, if the attribute is expected to have a non-linear influence on the dependent variable then at least three levels are required (*23; 24*). In addition, maintaining balanced utilities and attribute level ranges are desirable properties to increase the efficiency of the SP experiment design. Previous research shows that while it is statistically preferred to have a wide range of attribute levels, extremely wide ranges may result in choice situations with one dominant alternative (*20; 25*). As such, striking a balance in the alternatives' utilities help reduce the chances of having a dominant alternative within any of the choice scenarios and therefore maximizes the information gathered from each choice task (*26*). Also, maintaining a balance among the attribute levels, by equally showing all levels at the same time across the choice tasks, provides sufficient data for parameter estimation (*25; 27*).

Many previous studies relied on orthogonal experimental design to develop SP surveys. However, recent studies showed that efficient designs outperform orthogonal designs (*24*). In general, efficient designs aim at finding SP experiments that allow for parameter estimation with the lowest asymptotic standard error (*28*). Such designs require prior estimates of attribute parameters based on a specific model structure which can be obtained from similar studies or a pilot survey. While different measures of design efficiency have been used in the literature, the D-efficient design is the most common. Details on efficient SP choice experiments and survey design can be found in (*8*).

STUDY OBJECTIVES

The goal of this project is to conduct a thorough study of cross-regional commuting mode choice behaviour. As such, a policy analysis framework is developed. This framework allows to evaluate the effectiveness of various policy initiatives and quantify the effect of changes in level of service attributes on individuals' choices of transit as a travel or access mode. These changes in level of service attributes are tied to the policies under consideration. In this study, such policies aim at improving transit services with more emphasis placed on transit modal integration. Figure (1) shows the list of strategies that are considered in this study.

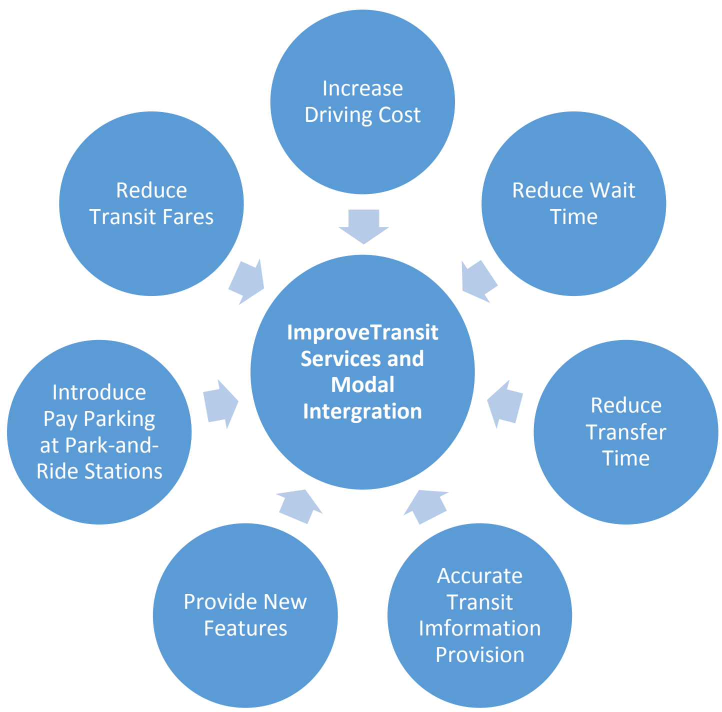

Figure 1 Polices Under Investigation

As explained above, joint revealed and stated preference surveys are capable of capturing behavioural factors along with typical socioeconomic attributes to accurately develop econometric models that are sensitive to changes in transportation level of service attributes as a result of introducing new policies. Accordingly, in order to achieve the study objectives, a joint RP-SP survey is designed with an SP experiment that is sensitive to the aforementioned policies. This report presents the framework of survey design which includes a new respondent-customized multimodal trip planner tool. The report describes details of the on-line survey design, trip planner tool development, SP experiment design using the state-of-the-art D-efficient method, sampling procedure, and data collection. Using the collected data set, a series of advanced mode choice models are developed and presented.

STUDY AREA

The survey is designed to be implemented in The Greater Toronto Hamilton Area (GTHA), Canada's largest urban region, although the framework is transferable to similar metropolitan areas. The GTHA, shown in Figure (2), consists of the City of Toronto and five other regional municipalities. It has nine local transit and one regional transit (i.e., GO Transit) services. As such, the GTHA provides a generic case study of a multimodal integrated transportation network.

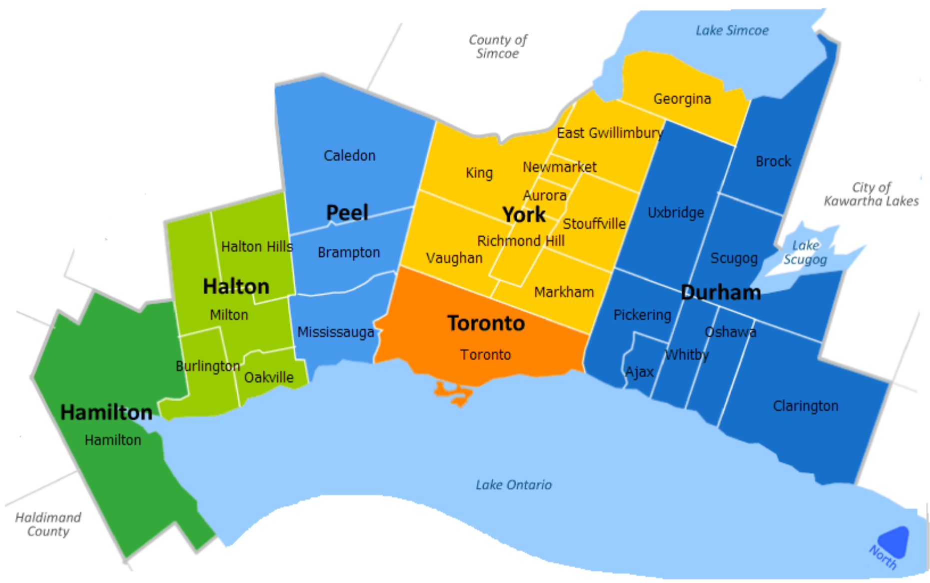

Figure 2 The Greater Toronto Hamilton Area[1]

A cross-regional trip is defined in this study as a trip originating from one municipality and destined to another. As such, it may involve the use of multiple transit services or the interaction between two different modes. For instance, a transit trip from the City of Mississauga to the City of Brampton involves the use of two transit services which are operated by two agencies (i.e., MiWay Transit and Brampton Transit). This trip is considered a cross-regional trip despite being conducted within the same region (i.e., Peel Region). On the other hand, a trip within different local municipalities of York Region is not considered a cross-regional trip in this study since it can be conducted using one transit system (i.e., York Region Transit).

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[1] http://findtheway.ca/en/

SURVEY INSTRUMENT DESIGN

The Survey of Cross-Regional Intermodal Passenger Travel (*SCRIPT*) consists of three sections. Section “A” gathers RP information on the respondents’ daily commuting trips and current travel attributes. In section “B”, individuals are asked to respond to hypothetical scenarios where travel modes’ service attributes are different from the current state. Finally, section “C” collects the respondents’ socioeconomic and demographic characteristics. At the end of the survey, respondents are encouraged to give their feedback and suggestions for improvements in addition to ranking the survey’s complexity level.

Numerous survey tests and trials were conducted to arrive at a survey design that provides the respondent with a user-friendly experience. Early trials helped identify potential improvements to the survey design, several of which were implemented in later trials. For example, in order to reduce high-density text and improve readability, survey instructions and sample answers were embedded in hyperlinks, appearing only by hovering the mouse arrow over the “Help?” buttons which are located alongside the survey questions. In addition, illustration figures and videos are presented to provide guidelines and walkthrough examples to the survey respondents. The average complexity of the survey dropped by more than 30% after these improvements were adopted (on a scale from 1 to 5, the average complexity of the survey dropped from 4.2 to 2.9). The engagement of professional software and website developers, a comprehensive target market research, survey respondents’ feedback and lessons learned from similar studies in the literature have shaped the evolution of the survey interface from the early stages until the final design.

Figure (3) shows the survey’s data model, which explains the logic behind building the survey structure with its specific questions’ layout/order. The questions are tailored to accommodate all the possible travel mode options including trips that may involve multiple trip segments. Within the survey questions, different trip segments are clearly defined using distinctive colour codes for each category of questions. Whether the trip is as complex as using three different travel modes or as simple as driving all the way from home to work, the survey is interactively adjusted to accommodate all varying trip components.

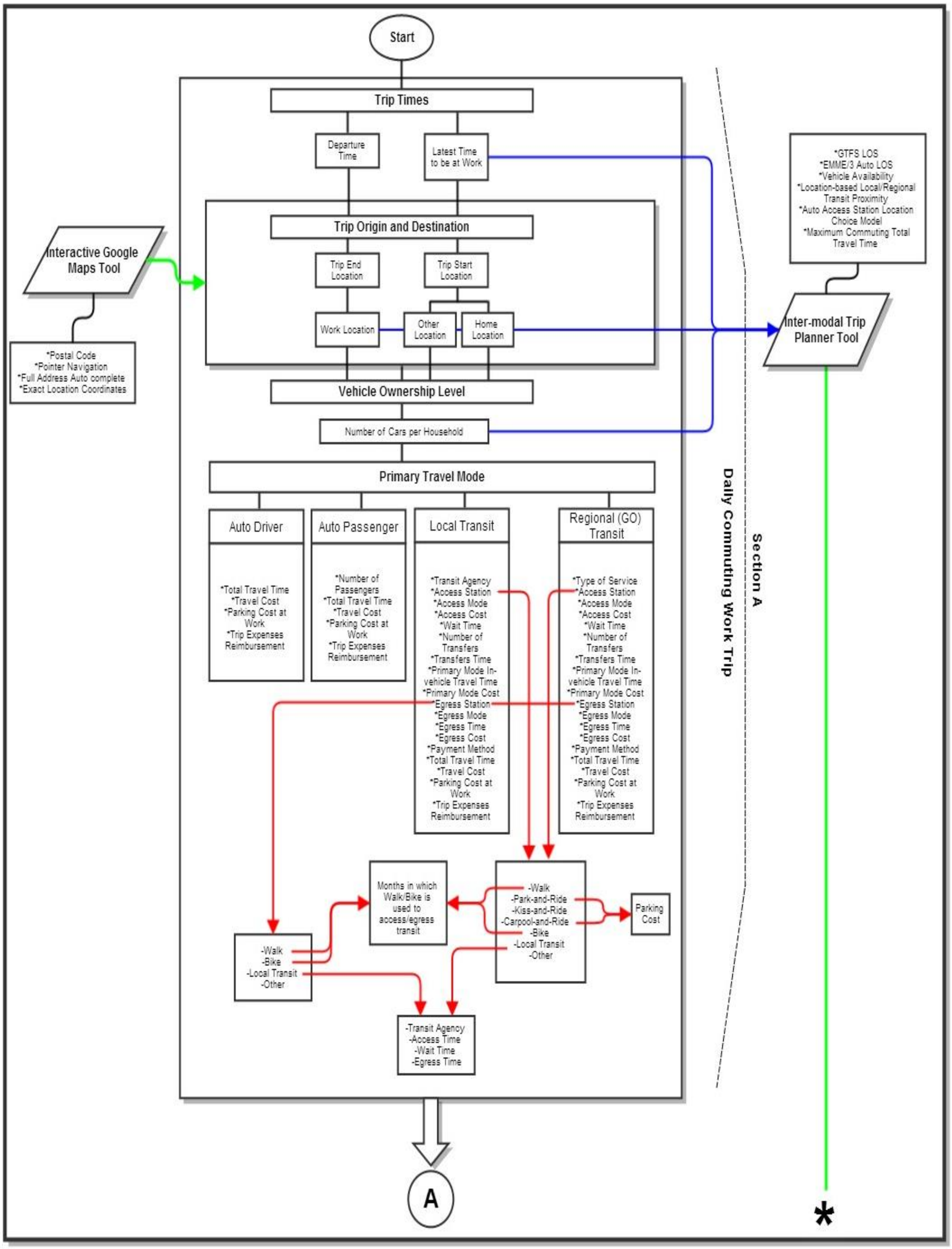


Figure 3-a SCRIPT Data Model

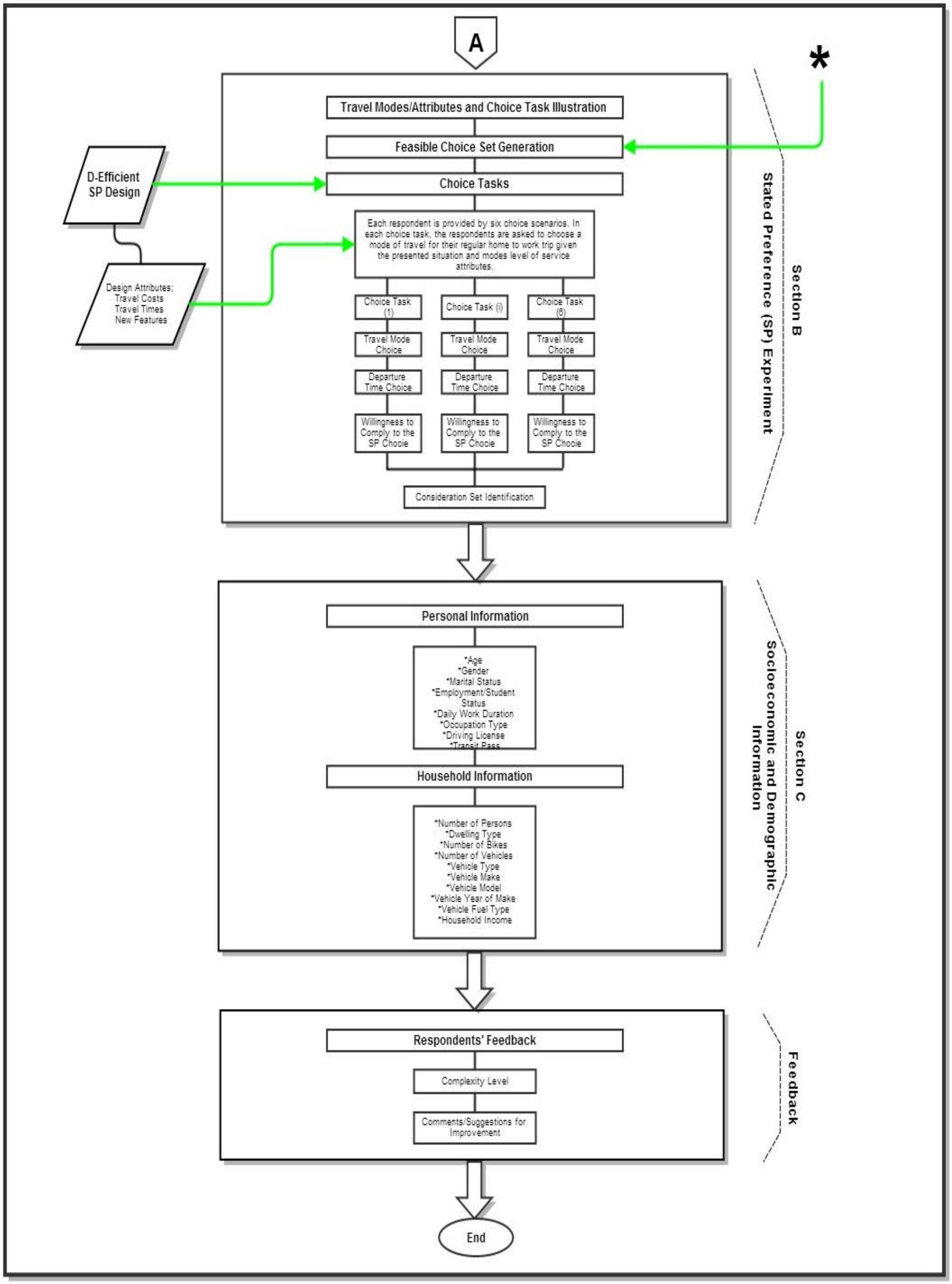


Figure 3-b SCRIPT Data Model

Section A: Revealed Preference Survey

In section “A”, the revealed preference section, the respondents are asked to provide detailed information about their work trip on the previous typical working day, including departure time, latest time they can be at work, trip start and end locations (location selection is done through an interactive map tool embedded in the survey webpage), vehicle ownership level, travel modes used, and other travel characteristics. The interactive map tool used in the survey is based on a Google Maps® interface which is enhanced with an auto complete address/postal code option in addition to the typical map navigation capabilities. Based on the selected primary mode of travel, a list of customized questions is dynamically shown to each respondent to capture all necessary trip details for cross-regional commuters. This allows for gathering detailed information on complex intermodal trips which involve the interactions of different transit modes/service providers and automobiles or active modes (i.e., walk and bike). Data on travel costs including gas, parking and transit fares, and methods of payments is also collected.

The gathered information in section “A” feeds into an innovative intermodal trip planner tool. This tool is developed to generate all feasible travel options for each SP choice experiment for use in Section “B” of the survey. The tool is embedded within the survey platform to link sections “A” and “B” of the survey. Firstly, a set of feasible modes for each respondent based on vehicle ownership level, proximity to transit, and total travel time from home to work is defined. Secondly, levels of service attributes, including different elements of travel cost and time component, are generated based on the specified arrival time at work for all feasible modes. Finally, those attributes are fed into the SP experiment design to adjust attribute levels before the final choice situations are presented to the respondents. Table (1) shows the list of conditions under which travel modes are considered unfeasible options. The number of feasible alternatives ranges typically from two to nine options.

The travel time components for the auto driver and auto passenger modes are obtained from an offline origin-destination travel time matrix based on the 2012 EMME3 traffic assignment for The GTHA. However, the travel time components for all transit-based modes are generated based on General Transit Feed Specifications (GTFS) using Google Maps Application Programming Interface (API). Unlike existing similar tools, this trip planner generates intermodal travel alternatives such as park- and-ride or kiss-and-ride, and transit trips that involve the use of two or more transit services (i.e., operated by different transit agencies), in addition to typical travel modes such as driving and transit with walk access. Furthermore, the tool provides detailed travel cost components for all travel options. Driving cost is determined based on network-based travel distance and average gas cost per km according to The Canadian Automobile Association (CAA) (*29*). Other cost components such as parking costs at trip destinations or park-and-ride stations (if any) are included as well as transit fares taking into consideration access and/or egress co-fares.

Table 1 Mode Feasibility

	Condition	Unfeasible Modes
1	No vehicles in the household	Auto Driver, Local Transit with Auto Driver Access, and Regional Transit with Auto Driver Access
2	Closest local transit stop is more than 2KM (i.e., walking access time is more than 24 minutes)	Local Transit with Walk Access, and Regional Transit with Local Transit Access
3	Closest regional transit stop is more than 2KM (i.e., walking access time is more than 24 minutes)	Regional Transit with Walk Access
4	Total travel time is more than 120 minutes	Case-specific

The choice of transit access station for auto driver access (park-and-ride or kiss-and-ride) is not a straightforward decision by just choosing the nearest station. Among the cross-regional commuters of the GTHA, more than 30% of the park-and-ride users choose a station that is not the closest station to their home locations *(2; 30).*Variables such as access distance, direction of travel to the station relative to home and work locations, parking cost, type of transit service, and the surrounding land use may affect users' choice of access stations (*30*). Two multinomial logit (MNL) models were developed for the regional commuter rail (GO Transit) users' and the Toronto Transit Commission subway (TTC Subway) users' access station location choice, respectively. The estimated parameters were found to be statistically significant with the expected correct signs. Access distance and the relative station direction were the primary factors that affected individuals' choices. These models are adopted in the survey's trip planner tool for transit trips with auto driver or passenger access.

As such, for individuals who have park-and-ride and/or kiss-and-ride options available in their feasible choice sets, the trip planner tool selects commuter rail and subway access stations based on the pre-developed discrete choice models before generating the associated level of service attributes for presentation to the respondent. Therefore, the trip is divided into two main components: a driving access from the trip origin to the chosen station and a transit trip from that station to the final destination. For any given respondent, the tool finds his/her optimal wait and transfer times between different modes by adjusting the departure time from home while ensuring that he/she arrives at the final destination before their previously stated arrival time at work (elicited in the RP section). To the authors' knowledge, this is the first attempt to integrate a multimodal trip planner with a set of pre-developed econometric models to develop a comprehensive respondent-customized data collection tool.

Section B: Stated Preference Survey

In section "B" of the survey, the stated preference section, each respondent is provided with six choice scenarios. In each scenario, the respondents are asked to choose a mode of travel to conduct their commuting trip based on a set of attributes and mode characteristics. Those attributes are altered according to the predefined polices in Figure (1). Table (2) shows the considered nine travel mode definitions and their attribute levels (where applicable). Throughout the report, the terms regional transit and GO Transit are used interchangeably, and so are local transit park-and-ride and TTC Subway park-and-ride. These scenarios are presented in tables as shown in Figure (4). The respondents are provided with an embedded instructional video within the survey webpage that explains the SP experiment with a walkthrough example. The mode attributes are categorized in three sections: travel cost components, information provision and special features/amenities, and travel time components.

In this study, each SP experiment presents up to nine travel mode options and up to 15 mode attributes out of which only nine attributes have different levels that vary across the experiments. The number of presented alternatives depends on the mode feasibility for each respondent and accordingly the corresponding mode attributes are shown or hidden. In order to maintain the requirements of D-efficient designs, as explained above in the introductory section, the Ngene® software package is used to develop the experiment design for this study (*31*). Based on the mode feasibility conditions presented in Table (1), eight SP designs are generated to cover all possible cases. A pilot survey is developed based on an orthogonal design and conducted among a random sample of the same target population sampling frame that was used later for the final survey. The number of choice scenarios generated by the orthogonal design to ensure attribute level balance is 108 which are blocked into 18 blocks of six scenarios each. Data from the pilot survey was used to obtain the prior parameter estimates which were required to develop the D-efficient design. After cleaning the dataset from incomplete or invalid records, 45 complete responses are used to estimate a pilot model. The model showed correctly signed coefficients for all variables. However, some parameters are found to be statistically insignificant due to the small size of the dataset. Based on the developed pilot model and the SP D-efficient, the target number of complete responses is estimated to be between 800 and 1000 data points.

Based on their new chosen mode and its estimated travel time for each choice scenario, respondents are asked to provide their new departure time. This allows for studying the effect of mode choice on departure time choice. In addition, after each choice scenario, the respondents are asked to provide their level of confidence in making their future home-work trip based on the selected travel mode on a five-level scale: not confident, somewhat confident, neutral, confident, and strongly confident. After the sixth and last choice scenario, the respondents are asked to choose travel modes that were truly considered while making the choice. As described above, this study considers a universal choice set of nine travel alternatives. However, based on the conditions adopted within the trip planner tool, only feasible modes are presented to each respondent. Yet, not all the feasible modes are considered (from a behavioural stand point) by the respondent while making their choice. Such information helps in developing a customized choice set for each respondent and therefore reduces the error of unrealistically assuming a uniform choice set across all individuals.

Section C: Socioeconomic Attributes

In section “C”, socioeconomic and demographic information is collected. On the individual level, the survey collects data on age, gender, marital status, employment/student status, daily work duration, occupation type, and the availability of driving license or transit pass. Similarly, household information such as the number of persons per household, dwelling type, number of bikes and vehicles per household and household income is gathered.

Respondents’ Feedback

Finally, the survey ends with acknowledging the respondents’ efforts followed by two optional questions. The respondents are asked to rank the complexity level of the survey on a scale from one (very easy) to five (very complex) and to leave comments/suggestions for improvements or report any problems encountered. Adding the feedback section at the end of the survey was extremely useful in developing the survey structure/layout as well as wording of questions.

Enormous test runs were conducted and respondents' feedback was considered carefully. As a result, the average complexity of the survey dropped from 4.2 (after the first pilot test) to 2.9 (after the final survey) based on respondents' revealed feedback.

Table 2-a Mode Attribute Definition

	Mode Attribute	Definition
Travel Cost Components	Travel cost/Transit fare	Travel cost including fuel cost and/or transit fare(s) (Canadian Dollars)
	Reserved parking at Park-and-Ride GO stations	The availability of a reserved parking option at Park-and-Ride GO Transit Station. This attribute takes the values of (Yes) for available and (NO) otherwise.
	Daily/Monthly parking cost at Park-and-Ride GO stations	Daily or Monthly parking cost at Park-and-Ride GO Transit Stations (Canadian Dollars). Daily parking rates are provided if reserved parking option is not available and *vice versa*.
	Parking cost at TTC Subway Park-and-Ride stations	Parking Cost at Park-and-Ride TTC Subway Stations per day per person (Canadian Dollars)
	Parking cost at trip destination	Daily parking cost at work location per person (Canadian Dollars)
	Local transit to GO co-fare	Co-fare of local transit if local transit is used to access GO transit (Canadian Dollars)
	GO to local transit co-fare	Co-fare of local transit if local transit is used after GO transit (Canadian Dollars)
Information Provision and New Features	Next bus information	The availability of information provision for the arrival of next bus (local transit buses only). This attribute takes the values of (Yes) for available and (NO) otherwise.
	Wi-Fi on GO Trains/Buses	The availability of Wi-Fi services on regional (GO) Train/Buses. This attribute takes the values of (Yes) for available and (NO) otherwise.
Travel Time Components	Transfer time(s)	Time taken to transfer between different transit lines, vehicles or modes (Minutes)
	Wait time	Time taken to wait for boarding a transit vehicle at the first (access) transit stop/station of the primary mode (Minutes)
	Access time	Time taken to travel from the trip origin location to the first (access) transit stop/station of the primary mode (Minutes)
	In-vehicle travel time	Time taken to travel from the first (access) transit stop/station to the last (egress) transit stop/station on a transit vehicle(s) of the primary mode (Minutes)
	Egress time	Time taken to travel from the last (egress) transit stop/station of the primary mode to the final trip destination (Minutes)
	Total trip time	Total trip time from the trip start location (origin) to the trip final destination (Minutes)

Table 2-b Mode Attribute Levels

Mode Attribute	Attribute Levels		
Travel Cost/Fare ($)	3	Low	Current
		Medium	+50% (Car) +20% (Transit)
		High	+75% (Car) +30% (Transit)
Reserved Parking (Regional Transit)	2	Yes	
		No	
Daily Parking Cost at Regional Transit Stations ($)	3	Low (Current)	0
		Medium	4
		High	8
Monthly Parking Cost at Regional Transit Stations ($)	3	Low	40
		Medium (Current)	80
		High	120
Parking Cost at Local Transit (TTC Subway) Park-and-Ride Stations	NA	Current	
Parking Cost at Trip Destination	NA	Current	
Local Transit-Regional Transit Access Fare ($)	3	Low	0
		Medium	-50%
		High	Current
Regional Transit-Local Transit Egress Fare ($)	3	Low	0
		Medium	-50%
		High	Current
Next Bus Information of Local Transit Vehicles	2	Yes	
		No	
Wi-Fi on Regional Transit Vehicles (Go Bus/Train)	2	Yes	
		No	
Transfer Time (at Transfer Stations between Local and Regional Transit)	3	Low	-50%
		Medium	Current
		High	+50%
Wait Time	3	Low	-50%
		Medium	Current
		High	+50%
Access Time	NA	Current	
In-Vehicle Travel Time	NA	Current	
Egress Time	NA	Current	
Total Trip Time	NA		

Choice Scenario: 1

Mode Attributes	Auto Driver Help?	Auto Passenger/ Carpool Help?	Local Transit - Walk Access Help?	TTC Subway - Auto Driver Access Help?	TTC Subway - Auto Passenger Access Help?	GO Transit - Auto Driver Access Help?	GO Transit - Auto Passenger Access Help?
Travel cost/Transit fare of the primary mode Help?	5.50	2.75	6.25	5.25	4.42	5.03	4.67
Reserved parking at park-and-ride GO stations Help?	--	--	--	--	--	No	--
Daily/Monthly parking cost at park-and-ride GO stations Help?	--	--	--	--	--	4	--
Parking cost at TTC Subway park-and-ride stations Help?	--	--	--	5	--	--	--
Parking cost at trip destination Help?	5	2.5	--	--	--	--	--
GO transit to local transit co-fare (egress) Help?	--	--	--	--	--	0.0	1.50
Next bus information Help?	--	--	No	Yes	Yes	--	--
Wi-Fi on GO Trains/Buses Help?	--	--	--	--	--	No	Yes
Transfer time(s) Help?	--	--	5	2	2	8	8
Wait time Help?	--	--	5	2	2	0	0
Access time Help?	--	--	5	10	10	6	6
In-vehicle travel time Help?	42	42	44	23	23	5	5
Egress time Help?	--	--	4	4	4	4	4
Total trip time (Minutes) Help?	**42**	**42**	**63**	**41**	**41**	**23**	**23**
Choice	☑	☐	☐	☐	☐	☐	☐

Based on the chosen mode for your work trip, what is the expected departure time from home?

Please enter your new departure time from home (Hour:Minute): 08 : 15

In the future, what would be your propensity to make your work trip using the option selected above?

☐ Not Confident ☐ Somewhat Confident ☐ Neutral ☑ Confident ☐ Strongly Confident

Next

Figure 4 Snapshot of a Sample SP Experiment

SURVEY IMPLEMENTATION

The target population of this survey is identified as cross-regional commuters (i.e., trip makers with trip ends of home and work in different regions), 18 years and older, within the study area. Cross-regional commuter trips represent around 35% of the total daily commuting trips in the GTHA (*30*). The sample selection is done based on simple random sampling. In general, probability sampling methods reduce selection bias by randomly selecting individuals based on a certain inclusion probability (*23*). Data from the 2011/2012 Transportation Tomorrow Survey (TTS), a trip-based household survey conducted every five years in the GTHA among 5% of its population, is used to identify sampling probabilities based on spatial location, mode split, and gender (*2*). Other attributes such as age, vehicle ownership level and occupation type are considered as well. The sampling probabilities of each stratum are used as guidelines to ensure collecting a representative sample of the target population. The sample size is determined based on the prescribed sampling procedure. Initially, the required sample size is estimated as 960 complete responses. However, after conducting the pilot survey and developing the SP experiment D-efficient design, the required number of complete responses is estimated to be between 800 and 1000 records in order to estimate statistically significant variables at the 95% confidence interval). The N-proportional allocation method is used to determine the required sample size from each stratum.

The data collection was done during the spring season of 2014 and a supplementary subset was collected during the fall season of the same year. The average time required to complete the survey is about 20 minutes. Invitations to the online survey were randomly emailed to a panel of respondents who previously accepted to be contacted for similar studies either by enrollment in Air Miles reward programs or by telephone requirement. A market research company conducted the survey on behalf of the research team. The sampling criteria and reward system were reviewed and approved by the Research Ethics and Protection committee at the University of Toronto.

The total number of accepted invitations was 15,975 out of which only 2,986 respondents were qualified to participate in the study. The total number of complete responses was 1,203 with a completion rate (the rate of complete responses to number of respondents who qualified to participate in a survey) of 40.3%. The overall response rate (the rate of complete responses to the number of respondents who attempted to participate in a survey) was 7.5% which is an acceptable rate compared to similar studies in the literature *(23)*. This relatively small rate highlights the complex nature of the study given the specific hard-to-reach target population. After cleaning the data, a total of 845 complete records were prepared for empirical modelling.

Figure (5) shows a density distribution of trip origins and destinations based on the collected sample. The two distributions have a similar pattern in which the majority of the trips originate in or destined to the centre of each region. Table (3) shows sample statistics of the collected data and their corresponding records from the 2011/2012 TTS. The spatial distribution of trip origins, mode split, and gender split pertain to the collected RP data. As shown in Table (3), the collected data provides a representative sample with only marginal differences compared to the TTS records. The reason for those minor changes is perhaps due to the temporal changes and difference in sampling methods between the two surveys.

Figure (6) shows the mode split based on the TTS data for cross-regional commuters, *SCRIPT* RP data, and *SCRIPT* SP data. Figures (6-a) and (6-b) show similar mode share distributions of the sample RP data and the corresponding TTS data. Figure (6-c) shows a significant drop in auto driver mode share and increase of auto passenger as well as transit mode shares due to the changes in alternatives' level of service attributes. As shown in Figure (7), more than 50% of the respondents made their SP choices with high level of confidence. This indicates that the respondents would make similar choices in the future if similar choice satiations arise. Figure (8) shows the distribution of the available modes across the sample size based on the rules presented in Table (1). It was assumed that the auto passenger mode is available for all individuals.

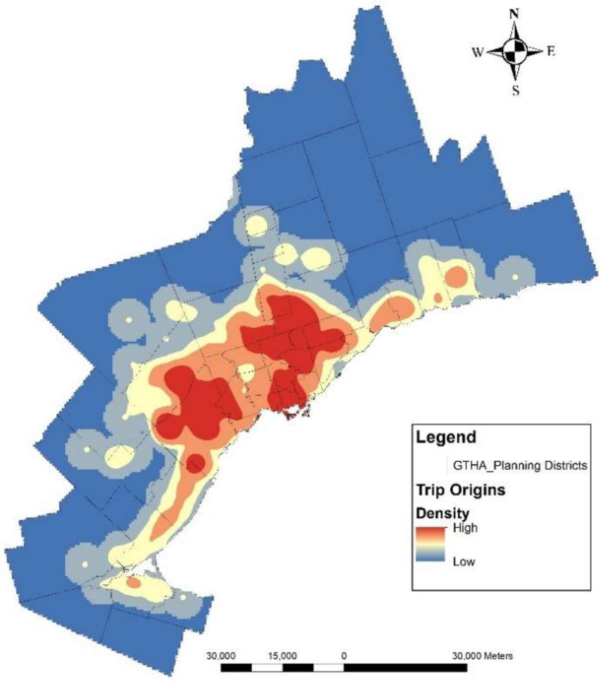


Figure 3-a Trip Origins Density Distribution

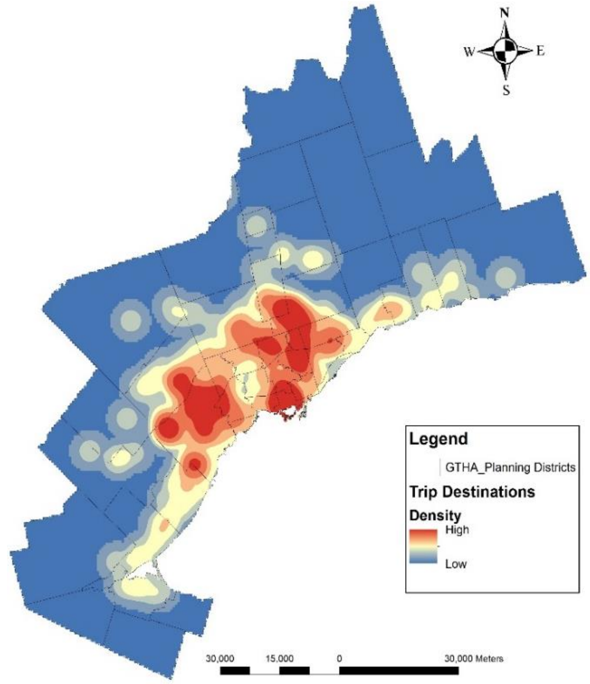


Figure 3-b Trip Destinations Density Distribution

Figure 5 Spatial Distribution of Cross-Regional Trip Ends

Table 3 SCRIPT and TTS Sample Distribution

	SCRIPT **Sample Distribution (%)**	**TTS Sample Distribution (%)**	**Difference (%)**
Trip Origin by Region			
City of Toronto	25	25	0
Durham Region	13	10	+3
York Region	26	20	+6
Brampton	10	11	-1
Mississauga	15	14	+1
Halton Region	9	14	-5
Hamilton	2	6	-4
Mode Split			
Auto Driver	82	85	-3
Transit	18	15	+3
Gender			
Male	59	62	-3
Female	41	38	+3

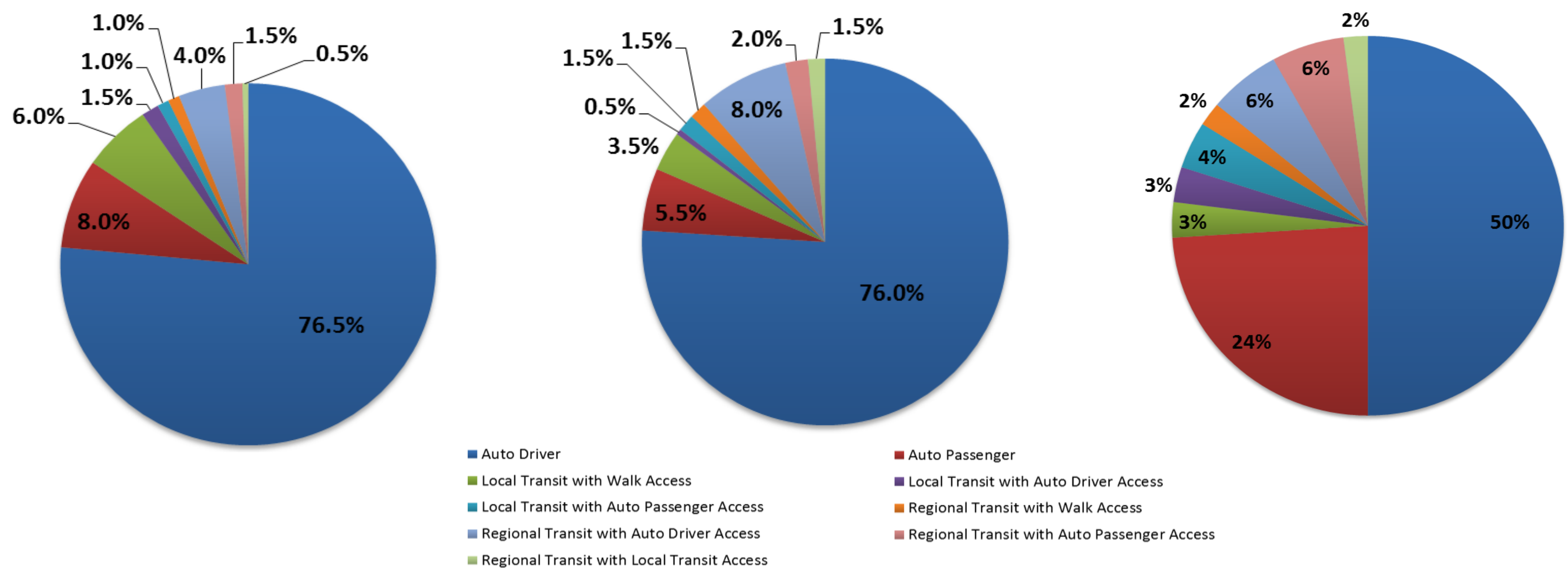


Figure 6-a TTS Cross-Regional Commuters   Figure 6-b *SCRIPT* RP Data   Figure 6-c *SCRIPT* SP Data

Figure 6 Mode Choice Split

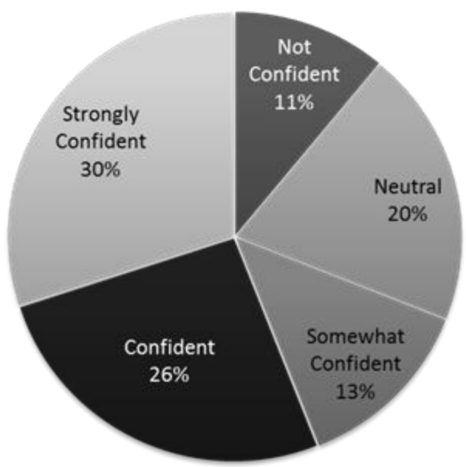


Figure 7 Level of Confidence in SP Choice

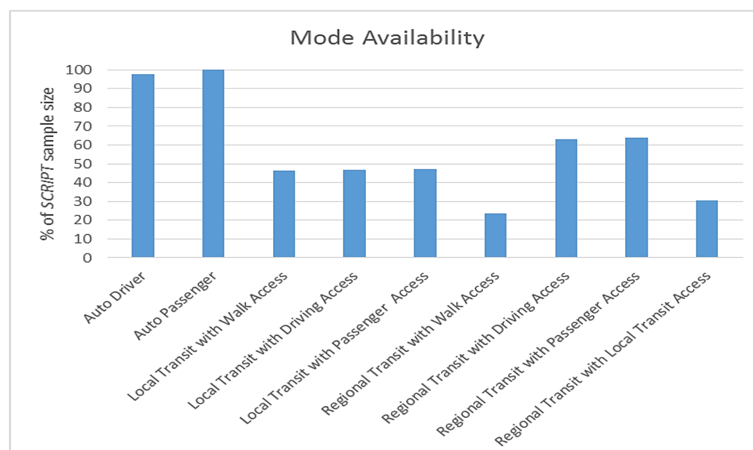


Figure 8 Mode Availability

MODE CHOICE MODELLING

Each respondent has a customized choice set which ranges from two to nine alternatives. We assume that individuals achieve a certain level of utility by choosing one alternative from their variable choice set. According to the Random Utility Maximization (RUM) Theory (*32*):

$$U_m = V_m + \varepsilon_m = (\beta \cdot x)_m + \varepsilon_m \qquad [1]$$

where "U" is the utility function, "V" is the systematic utility component which is a linear-in-parameters function of the observed variables "χ" and their corresponding coefficients "β", "ε" is the random error component which is assumed to follow the Independent and Irrelevant Distribution (IID) of Type I Extreme Value distribution, and the subscript "m" indicates one of the mode alternatives in the choice set.

It was assumed that trip makers are rational in making their decisions by choosing the alternative with the highest utility value among a set of feasible alternative. Such assumption results in the Multinomial Logit (MNL) model (*33*) of the form of:

$$\Pr(m) = \frac{\exp(\mu \cdot V_m)}{\sum_{m'=1}^{M} \exp(\mu \cdot V_{m'})} \qquad [2]$$

where,"Pr(*m*)" is the probability of choosing one mode alternative "*m*", "*M*" indicates the maximum number of mode alternatives under consideration by each respondent, and "μ" is the scale parameter.

In order to jointly estimate an RP-SP model, an artificial tree structure, as shown in Figure (9), is assumed to identify the differences between the two data sets; RP and SP data. This is captured through a scale parameter which is estimated for the SP data relative to a normalized (fixed to 1) scale parameter for the RP data. In addition, the scale parameter allows capturing the heteroscedasticity in individuals' responses. As such, the scale parameter was parameterized as an exponential function of the respondents' attributes (*18*):

$$\mu = \exp(\alpha \cdot \tau) \qquad [3]$$

where, τ refers to attributes that can explain scale variation and α refers to their corresponding coefficients.

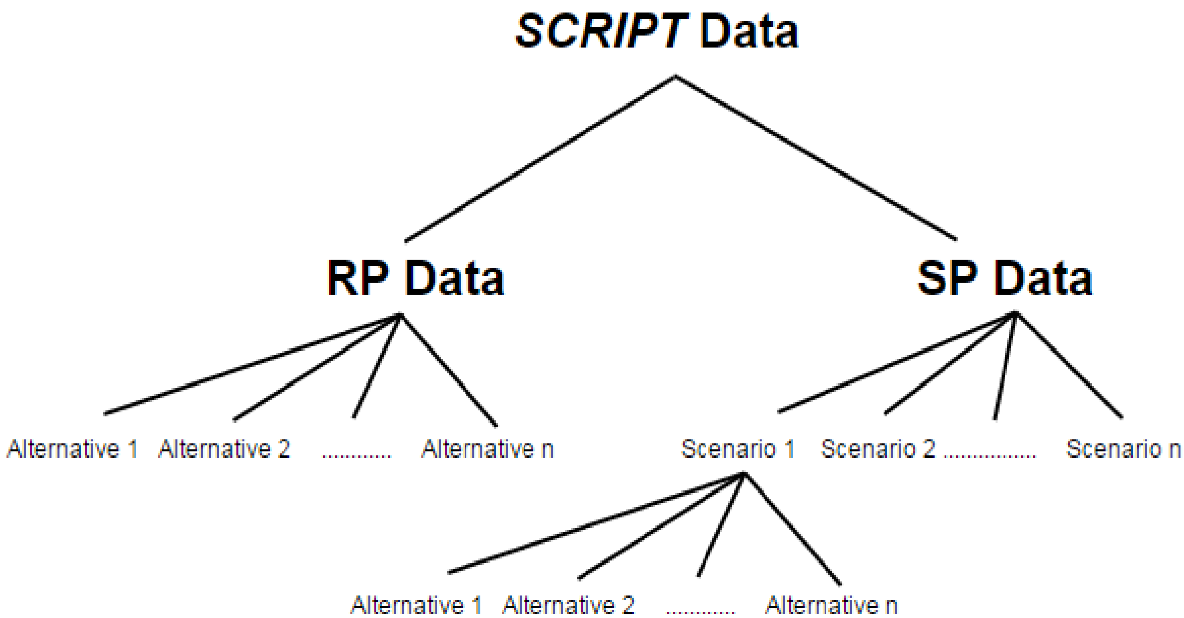


Figure 9 The Artificial Nested Structure of Joint RPSP Models

For a sample of N individuals with multiple responses (RP choice and six SP choices), assuming that each individual's choice decision is independent, the joint probability of each person choosing the observed choice can be expressed as *(36)*:

$$L(\beta) = \prod_{d=1}^{D} \prod_{n=1}^{N} \prod_{i}^{C} (P_{ni})^{y_{ni}} \qquad [4]$$

where, y_{ni}=1 if person "*n*" chose alternative "*i*" from a variable choice set "C" and zero otherwise, and "*d*" is the dataset used for estimation (i.e., "*d*" represents either the RP data or one of the six choice situations of the SP data).

All the empirical models were estimated using codes written in GAUSS® using the MAXLIK component for maximum likelihood estimation (*34*).

EMPIRICAL MODELS

To ensure the availability of all variables of concern, a subset of the collected data was selected to develop three multinomial logit mode choice models. The full sample size used for models estimation is 704 individuals. As the names imply, the RP-Only and SP-Only models are restricted models including only RP and SP data, respectively, while the joint RP-SP model considers both RP and SP information. The variables used in models' specifications are presented in Table (4) along with the corresponding polices tied to each variable.

Table 4 Definitions of Variables

Variable Name	Description	Corresponding Policy
Travel Cost/Fare	Travel cost including gas and parking cost at work location or transit fares	Increase driving cost/reduce transit fares
P&R Cost at TTC Stations	Parking cost at TTC park-and-ride locations per day	Increase parking cost at TTC park-and-ride stations
P&R Cost at GO Stations	Parking cost at GO Transit park-and-ride locations per day	Introduce pay parking at GO Transit park-and-ride stations
In Vehicle Travel Time (no Wi-Fi)	In vehicle travel time if Wi-Fi is not available on GO Transit vehicles	Reduce transit travel time
In Vehicle Travel Time (Wi-Fi)	In vehicle travel time if Wi-Fi is available on GO Transit vehicles	Provide new transit features (Wi-Fi on GO Transit)
Access and Egress Times	The sum of access and egress travel times	Improve transit accessibility
Wait and Transfer Times	The sum of waiting and transfer travel times	Reduce waiting and transfer times
Next Bus Information Provision	1 if the next transit vehicles' arrival time information is available; 0 otherwise	Provide accurate transit information
The Need for a 2nd Transfer	1 if the individual needs to make more than one transfer between GO Transit and other travel modes ; 0 otherwise	Reduce number of intermodal transfers
Number of Vehicles per Household	Number of vehicles per household	N/A
Transit Pass Possession	1 if the individual owns a transit pass; 0 otherwise	N/A
Trip O/D: City of Toronto	1 if the trip origin/destination is from/to the City of Toronto; 0 otherwise	N/A
Age	Individuals age	N/A
Gender (Male)	1 if male; 0 otherwise	N/A

These variables are carefully selected in accordance with the policies under investigation. For instance, the parking cost at park-and-ride stations variable is defined as a separate cost component (i.e., not aggregated with the total travel cost). Therefore, the developed models are sensitive to corresponding policies such as the introduction of pay parking at park-and-ride stations. Similarly, the out-of-vehicle travel time components are divided into access and egress times, and wait and transfer times. As such, the effectiveness of policies that aim at improving different level of services attributes can be appropriately quantified. The chosen variables are also consistent with the travel mode alternatives under consideration. The modelling frameworks considers nine alternatives; it explicitly distinguishes between auto driver and auto passenger modes, regional and local transit modes, and different access modes. Each travel mode has its own level of service characteristics and therefore different target customers. That is, various policy initiatives that target specific travel modes (such as High Occupancy Vehicle (HOV) policies for auto passenger modes or the introduction of transit mode-specific new features) can be analyzed.

The final empirical models' specifications are presented in Tables (5), (6) and (7). In addition to the presented models below, several specifications were tested to find the best specifications across the three models while providing the highest explanatory power and statistical significance. In the following section, results of the three models are presented. Results of the joint RP-SP model are discussed in greater detail while analogous conclusions can be drawn for the two other models.

RP-Only Model

Table (5) presents the parameter estimates of the RP-Only MNL mode choice model using the RP data of individuals' actual mode choice. A total of 17 parameters are estimated using the full sample size. The rho-squared (with respect to a constant-only model), as a measure of the model goodness-of-fit, indicates how much of an improvement the estimated model offers over a naïve model that assumes all parameters are zero while allowing for constants. The reported rho-squared value is 0.31 which indicates an acceptable goodness of fit. According to the literature on discrete choice models, a rho-squared value in the range of 0.2 to 0.4 is considered a good fit *(7)*. In addition, the log likelihood ratio test shows a test statistics value of 336, which indicates that the reported models fit the data significantly better than the constant-only model.

All the reported parameters are estimated with the expected signs and found to be statistically significant (with t-statistics higher than 1.96) at the 95% confidence interval, except for the parking cost at local transit park-and-ride locations due to the low number of park-and-ride users within the sample. However, it was kept in the model as it was estimated with the expected sign and to ensure specification consistency with the SP models. The relative values of the estimated parameters indicate that out-of-vehicle travel times are perceived 1.2 to 2 times higher than in-vehicle travel time.

These findings show consistency with corresponding mode choice models which verify the validity of the survey design, sampling procedure and data quality (23; 38). As such, the developed RP-Only model sets the ground as the first step towards developing policy-sensitive behavioural models. However, as explained above, RP-Only models are incapable of accurately forecasting individuals' choices in response to new transportation policies or the introduction of new modes. In other words, predicting/forecasting users' behaviour due to change in level of service attributes beyond the ranges observed in the RP data, addition of new service features (e.g. on-board Wi-Fi), or introduction of new modes is beyond the scope of traditional RP-Only models. Therefore, policy-sensitive SP models are developed to capture the associated changes in travel demand with respect to changes in the level of service attributes as shown in the following section.

Table 5 RP-Only Model

MNL Logit Model		RP-Only Model	
Log likelihood of Full Model		-380.225	
Log likelihood of Constant-only Model		-548.111	
Rho-squared value		0.31	
Number of Observations		704	
Variable	**Mode**	**Parameter**	**t-Statistics**
Systematic Utility Function:			
Alternative Specific Constant	Auto Driver	2.6051	6.839
Alternative Specific Constant	Auto Passenger	0 (fixed)	0 (fixed)
Alternative Specific Constant	Local Transit with Walk Access	-0.4003	-0.597
Alternative Specific Constant	Local Transit with Auto Driver Access (TTC Park-and-Ride)	-4.3841	-1.297
Alternative Specific Constant	Local Transit with Auto Passenger Access (TTC Kiss-and-Ride)	-2.6383	-1.456
Alternative Specific Constant	Regional Transit with Walk Access	-0.9951	-1.272
Alternative Specific Constant	Regional Transit with Auto Driver Access (GO Park-and-Ride)	-0.9548	-1.299
Alternative Specific Constant	Regional Transit with Auto Passenger Access (GO Kiss-and-Ride)	-1.4855	-2.166
Alternative Specific Constant	Regional Transit with Local Transit Access	-0.6875	-0.868
Travel Cost/Fare	All Modes	-0.0838	-4.519
P&R Cost at TTC Stations	Local Transit with Auto Driver Access (TTC Park-and-Ride)	-0.0458	-0.066
In Vehicle Travel Time	All Modes	-0.022	-2.977
Access and Egress Times	All Transit Alternatives	-0.044	-2.513
Wait and Transfer Times	All Transit Alternatives	-0.0259	-1.974
The Need for a 2nd Transfer	Regional Transit with Walk Access, Regional Transit with Auto Driver Access (GO Park-and-Ride), Regional Transit with Auto Passenger Access (GO Kiss-and-Ride), and Regional Transit with Local Transit Access	-0.8691	-2.475
Number of Vehicles per Household	Auto Driver, Local Transit with Auto Driver Access (TTC Park-and-Ride), and Regional Transit with Auto Driver Access (GO Park-and-Ride)	0.4598	2.359
Transit Pass Possession	All Transit Alternatives	3.1088	9.651
Trip O/D: City of Toronto	All Transit Alternatives	1.3774	2.738

SP Models

The following section presents results of the developed SP models including results of an SP-Only model and a joint RP-SP model. The reported models are compared and results of the joint RP-SP model are analyzed in greater detail. A randomly selected subset of the full sample data set is prepared for parameter estimation using data of 560 individuals (80% of the full sample data set size). The remaining records are used for model validation and forecasting.

SP-Only Model

Table (6) presents the results of the SP-Only MNL mode choice model which is estimated using the SP data only. The estimation routine takes into consideration the repeated observations by each individual across the six SP choice situations. The reported model is consistent with the RP-Only model specification except for the new features that were added to the SP experiment including the introduction of parking cost at park-and-ride GO Transit stations, the availability of Wi-Fi on GO Transit vehicles, and the provision of real-time information of local transit vehicles' arrival times. All parameters are estimated with the expected signs and relative values, and found to be statistically significant at the 95% confidence interval, except for the provision of information of local transit vehicles' arrival times which is statistically significant at the 90% confidence interval. The reported rho-squared value is 0.11 and the log likelihood ratio test show a test statistics value of 915, which indicates that the reported models fit the data significantly better than the constant-only model.

Joint RP-SP Model

The final jointly-estimated RP-SP MNL mode choice model results are shown in Table (7). The model is estimated using both actual RP mode choice data and SP data. Various model specifications are tested and compared to one another until reaching the reported final model specification with the highest explanatory power. The estimation routine takes into consideration the repeated observations by each individual across the RP data and the six SP choice situations. As mentioned before, the survey respondents were asked to provide information about their level of confidence in making their SP choices. Choice scenarios where low confidence levels were reported by the respondents are not considered in the estimation process.

A total of 31 parameters were estimated with the expected signs and relative values, and found to be statistically significant at the 95% confidence interval, except for the provision of information of local transit vehicles' arrival times which is statistically significant at the 90% confidence interval. The reported rho-squared value is 0.16 which is significantly better than the reported value for the SP-Only model. Clearly, the use of the combined RP-SP data enhanced the goodness of fit and explanatory power of the joint model. The log likelihood ratio test show a test statistics value of 1279, which indicates that the reported models fit the data significantly better than the constant-only model.

The estimated parameters of the joint RP-SP model are classified into three groups: parameters that are exclusively estimated by either the RP or the SP data sets, parameters that are estimated with different coefficients in each data set, and parameters that are estimated with the same coefficient (before taking the scale parameter effect into consideration) in the RP and the SP data sets. Typically, alternative specific constants (ASC) dataset-specific coefficients are estimated while variables that belong to one data set and scale parameter factors are uniquely estimated by one (usually the SP data) data set *(37).* Other level of service attributes that appear in both data sets as well as socioeconomic attributes are estimated with the same coefficients. As such, different RP/SP coefficients are estimated for ASC, exclusive SP coefficients are estimated for the introduction of parking cost at park-and-ride GO Transit stations, the availability of Wi-Fi on GO Transit vehicles and scale parameter factors, and same (expect for the scale parameter effect) RP/SP coefficients are estimated for all other variables as shown in Table (7).

Assuming a unit scale parameter for the RP data, the SP scale parameter is relatively estimated as a parameterized exponential function of a constant, logarithm of individuals' age, and gender. The SP scale factor parameters are found to be statistically significant verifying the assumed tree structure of the two data sets. The SP scale parameter is estimated to be less than 1 for all individuals in the data set. In other words, the SP scale parameter is lower than the RP scale parameter which indicates that the variance within the SP data is higher than the RP data. This typical finding explains that the SP data encompasses an induced variation due to the nature of the hypothetical choice experiment in which the survey respondents were making their decisions while some elements of the current transportation system were altered. More insights of the variance across the SP data is discussed in the following sections.

Table 6 SP-Only Model

MNL Logit Model		SP-Only Model	
Log likelihood of Full Model		-3622.91	
Log likelihood of Constant-only Model		-4080.26	
Rho-squared value		0.11	
Number of Observations		560	
Variable	**Mode**	**Parameter**	**t-Statistics**
Systematic Utility Function:			
Alternative Specific Constant	Auto Driver	0.5999	5.808
Alt0ernative Specific Constant	Auto Passenger	0 (fixed)	0 (fixed)
Alternative Specific Constant	Local Transit with Walk Access	-0.6315	-2.472
Alternative Specific Constant	Local Transit with Auto Driver Access (TTC Park-and-Ride)	-0.0202	-0.02
Alternative Specific Constant	Local Transit with Auto Passenger Access (TTC Kiss-and-Ride)	-1.008	-3.466
Alternative Specific Constant	Regional Transit with Walk Access	-0.6263	-2.142
Alternative Specific Constant	Regional Transit with Auto Driver Access (GO Park-and-Ride)	-0.751	-2.692
Alternative Specific Constant	Regional Transit with Auto Passenger Access (GO Kiss-and-Ride)	-0.7095	-3.034
Alternative Specific Constant	Regional Transit with Local Transit Access	-0.8398	-2.64
Travel Cost/Fare	All Modes	-0.0493	-7.081
P&R Cost at TTC Stations	Local Transit with Auto Driver Access (TTC P Park-and-Ride)	-0.4301	-2.305
P&R Cost at GO Stations	Regional Transit with Auto Driver Access (GO Park-and-Ride)	-0.0699	-2.244
In Vehicle Travel Time (no Wi-Fi)	All Modes	-0.0284	-9.775
In Vehicle Travel Time (Wi-Fi)	Regional Transit with Walk Access, Regional Transit with Auto Driver Access (GO Park-and-Ride), Regional Transit with Auto Passenger Access (GO Kiss-and-Ride), and Regional Transit with Local Transit Access	-0.0234	-6.773
Access and Egress Times	All Transit Alternatives	-0.0679	-9.066
Wait and Transfer Times	All Transit Alternatives	-0.0253	-3.866
Next Bus Information Provision	Local Transit with Walk Access, Local Transit with Driving Access (TTC Park-and-Ride), Local Transit with Passenger Access (TTC Kiss-and-Ride), and Regional Transit with Local Transit Access	0.1963	1.698
The Need for a 2nd Transfer	Regional Transit with Walk Access, Regional Transit with Auto Driver Access (GO Park-and-Ride), Regional Transit with Auto Passenger Access (GO Kiss-and-Ride), and Regional Transit with Local Transit Access	-0.4538	-3.197

Number of Vehicles per Household	Auto Driver, Local Transit with Auto Driver Access (TTC Park-and-Ride), and Regional Transit with Auto Driver Access (GO Park-and-Ride)	0.2707	5.3
Transit Pass Possession	All Transit Alternatives	1.6337	14.416
Trip O/D: City of Toronto	All Transit Alternatives	0.4124	2.644

Table 7 Joint RP-SP Model

MNL Logit Model – Joint Estimation		RPSP Model			
Log likelihood of Full Model		-3477.48			
Log likelihood of Constant-only Model		-4116.38			
Rho-squared value		0.16			
Number of Observations		560			
Variable	**Mode**	**Parameter**	**t-Statistics**	**Parameter**	**t-Statistics**
Systematic Utility Function:		**RP Coefficients**		**SP Coefficients**	
Alternative Specific Constant	Auto Driver	2.8022	10.548	0.8137	5.269
Alternative Specific Constant	Auto Passenger	0 (fixed)	0 (fixed)	0 (fixed)	0 (fixed)
Alternative Specific Constant	Local Transit with Walk Access	1.7581	3.888	-0.7417	-2.156
Alternative Specific Constant	Local Transit with Auto Driver Access (TTC Park-and-Ride)	0.0999	0.082	-0.6783	-0.686
Alternative Specific Constant	Local Transit with Auto Passenger Access (TTC Kiss-and-Ride)	-0.648	-1.033	-1.3036	-3.329
Alternative Specific Constant	Regional Transit with Walk Access	1.3622	2.445	-0.7658	-1.961
Alternative Specific Constant	Regional Transit with Auto Driver Access (GO Park-and-Ride)	0.8796	2.025	-0.8114	-2.282
Alternative Specific Constant	Regional Transit with Auto Passenger Access (GO Kiss-and-Ride)	0.385	0.839	-0.8418	-2.714
Alternative Specific Constant	Regional Transit with Local Transit Access	1.0062	1.575	-0.7131	-1.688
Travel Cost/Fare	All Modes	-0.0716	-6.853	-0.0716	-6.853
P&R Cost at TTC Stations	Local Transit with Auto Driver Access (TTC P Park-and-Ride)	-0.4409	-2.225	-0.4409	-2.225
P&R Cost at GO Stations	Regional Transit with Auto Driver Access (GO Park-and-Ride)	0 (fixed)	0 (fixed)	-0.0983	-2.31
In Vehicle Travel Time (no Wi-Fi)	All Modes	-0.0404	-8.363	-0.0404	-8.363
In Vehicle Travel Time (Wi-Fi)	Regional Transit with Walk Access, Regional Transit with Auto Driver Access (GO Park-and-Ride), Regional Transit with Auto Passenger Access (GO Kiss-and-Ride), and Regional Transit with Local Transit Access	0 (fixed)	0 (fixed)	-0.0338	-6.518
Access and Egress Times	All Transit Alternatives	-0.0952	-8.187	-0.0952	-8.187

Wait and Transfer Times	All Transit Alternatives	-0.0484	-5.587	-0.0484	-5.587
Next Bus Information Provision	Local Transit with Walk Access, Local Transit with Driving Access (TTC Park-and-Ride), Local Transit with Passenger Access (TTC Kiss-and-Ride), and Regional Transit with Local Transit Access	0.2126	1.798	0.2126	1.798
The Need for a 2nd Transfer	Regional Transit with Walk Access, Regional Transit with Auto Driver Access (GO Park-and-Ride), Regional Transit with Auto Passenger Access (GO Kiss-and-Ride), and Regional Transit with Local Transit Access	-0.6191	-3.322	-0.6191	-3.322
Number of Vehicles per Household	Auto Driver, Local Transit with Auto Driver Access (TTC Park-and-Ride), and Regional Transit with Auto Driver Access (GO Park-and-Ride)	0.3796	5.174	0.3796	5.174
Transit Pass Possession	All Transit Alternatives	2.3783	9.305	2.3783	9.305
Trip O/D: City of Toronto	All Transit Alternatives	0.4679	2.272	0.4679	2.272
Exponential Function of Scale Parameter:					
Constant	SP Scale Factor	0 (fixed)	0 (fixed)	-1.2816	-3.584
Ln (Age)	SP Scale Factor	0 (fixed)	0 (fixed)	0.3064	3.346
Gender	SP Scale Factor	0 (fixed)	0 (fixed)	-0.1786	-3.677

The joint RP-SP model shows consistency in general with previous research findings and in particular with the previously presented models. However, the values of the estimated parameters of the RP-Only and SP-Only models are different than their corresponding parameters in the RP-SP model. This indicates the effect of incorporating the full information (i.e., the combined RP-SP data) on capturing the scaled (corrected) relative influence of each variable on the probability of mode choice. Travel costs including gas cost, transit fares, and parking costs and different travel time components including in-vehicle and out-of-vehicle travel times are estimated with the expected negative signs. The relative values of the estimated parameters indicate the perceived relative importance of different travel cost and time components by trip makers. For instance, the unit parking cost at park-and-ride locations is perceived with higher influence compared to the unit travel cost. In addition, the need of a second transfer between GO Transit and other travel modes has a strong negative effect on the probability of choosing GO Transit modes. Similarly, the model results indicate that out-of-vehicle travel times (including access, egress, wait and transfer times) are perceived 1.2 to 2.3 times higher than in-vehicle travel time. In addition, access and egress travel times have a stronger negative effect than transfer and wait times on transit modes choice, perhaps due to the relatively higher access and egress travel times for this specific segment of the population (i.e., cross-regional commuters).

It is worth mentioning that former tested specifications (prior to the final reported model) considered access, egress and transfer times as one variable representing out-of-vehicle travel time component and waiting time as a separate variable. Such specifications showed that waiting time was found to be statistically insignificant while other travel time components were found to be statistically significant. This is, possibly, because cross-regional commuters who use regional transit or local transit services (other than TTC) which are relatively low frequency services, plan their trips according to service schedules to avoid long waiting times. In addition, the trip planner tool, which was used to develop the SP choice scenarios, optimized respondents' departure times in order to minimize waiting times at transit stations. Therefore, it comes as no surprise that waiting time was found to be statistically insignificant for this specific segment of the population. Hence, another model structure was tested to capture the effect of all travel time components on mode choice. This model structure considers two major travel time components: in-vehicle, and out-of-vehicle travel times. The latter is divided into two sub-components: access and egress times, and transfer and wait times. In the context of cross-regional trips, it seems (based on the empirical model results) that the proposed travel time components' structure is more suitable to represent the data.

The effect of the introduction of paid parking at GO Transit park-and-ride stations, information provision of local transit vehicles' arrival time and the introduction of Wi-Fi service on GO transit vehicles on the probability of commuting mode choice is captured through the SP component of the model. Different model specifications have not shown a significant difference between the monthly and the daily parking schemes. Therefore, equivalent daily parking rates were used for monthly parking schemes. The model results show that parking cost at GO Transit park-and-ride stations is perceived approximately 1.4 times higher than the travel cost.

Initially, the information provision of the next local transit vehicles' arrival time variable was estimated with an exclusive SP coefficient since it represents a new feature that is not currently available and therefore cannot be captured through the RP data. However, this feature is currently provided by few transit service agencies within the study area. So in order to account for the current un/availability of information provision of local transit vehicles' arrival time, this parameter is estimated with a pooled coefficient from the RP and the SP data sets. The model results show that providing individuals with real-time information of the next transit vehicles' arrival time would increase the probability of choosing local transit as their travel mode.

Similarly, introducing Wi-Fi service for regional transit users is expected to increase the modal shares of GO Transit. Several model specifications were tested in order to quantify the effect of the availability of Wi-Fi on commuters' mode choice. Results of preliminary models showed that the introduction of Wi-Fi on GO Transit modes is only statistically significant for individuals who spend 40 minutes or more on GO transit vehicles (i.e., individuals whose in-vehicle travel time is greater than or equal to the average in-vehicle travel time for GO Transit users within the sample). This finding triggered further investigation of in-vehicle travel time interaction with the availability of Wi-Fi on GO Transit vehicles. The final model specification shows two in-vehicle travel time parameters, one if Wi-Fi is available and the other if Wi-Fi is not. The two coefficients are estimated with the expected negative sign and found to be statistically significant. In addition, the estimated coefficient of in-vehicle travel time if Wi-Fi is available has a smaller negative effect on the probability of choosing GO Transit modes than the estimated coefficient of in-vehicle travel time if Wi-Fi is not available. This indicates that individuals are more likely to choose GO Transit if a Wi-Fi service is available on GO Transit vehicles.

For linear-in-parameters specifications of the utility function (similar to the formulation used in this study), the marginal rate of substitution (i.e. the trade-off) of attributes are estimated as the ratio of the estimated coefficient of each variable to the estimated coefficient of travel cost. As such, the willingness to pay (i.e., the amount that an individual would pay for a particular good) in order to receive real-time information of local transit vehicles' arrival time is calculated and found to be up to $3 per trip. Similarly, the value of travel time savings (VOT) which is the extra cost that a person would be willing to pay in order to save one hour of travel time *(36)*, is calculated for the different travel time components based on the results of the three developed models as shown in Table (8). The estimated VOT (based on the Joint RP-SP model) is $33.85/hr which is a reasonable value compared to the average wage rates within the sample data (more than 50% of the sample's household yearly income is found be to $100,000 and above). Similarly, the VOT for GO Transit modes if Wi-Fi is available is lower than the VOT if Wi-Fi is not available. Results indicate that individuals are willing to pay up to 9 cents per minute usage of Wi-Fi on GO Transit vehicles.

Table 8 Value of Travel Time Savings

Value of Travel Time Savings (VOT) ($/hr)	RP-Only Model	SP-Only Model	Joint RPSP Model
In-Vehicle Travel Time (no Wi-Fi)	15.75	34.56	33.85
In-Vehicle Travel Time (Wi-Fi)	N/A	28.48	28.32

In terms of personal and household attributes, the model results show that the number of vehicles per household has a positive impact on the probability of choosing car-dependent modes such as auto driver and park-and-ride. Similarly, transit pass possession increases the probability of selecting transit as a travel mode. Further, individuals who commute from/to the City of Toronto are more likely to use transit. This is likely due to the city's unique multimodal transit system, high density land use, and supportive transit policies.

MARGINAL EFFECTS OF TRAVEL COST AND TRAVEL TIME

In order to investigate the sensitivity of travel cost and in-vehicle travel time of each mode alternative, the direct elasticities are estimated based on the joint RP-SP model results and kernel densities are plotted as shown in Figure (10).The kernel density estimator provides an approximate probability density function (PDF) using the data observations. Therefore, a kernel density distribution has the same properties as the probability density function. In other words, the area under the curve is equal to 1 and the value of the density function is proportional to the probability that a data point is approximately equal to its corresponding value. The point disaggregate (of each individual) direct elasticity is estimated for linear-in-parameter utility functions based on equation (5) *(36)*. For the SP data, the average of six elasticity values corresponding to the six SP scenarios is estimated for each individual. The direct elasticity estimates the effect of a unit change in an observed factor of a choice alternative on the probability of choosing this alternative.

$$E_{i_{Xni}} = \beta_X . X_{ni} . (1 - P_{ni}) \quad [5]$$

where, "E_{iXni}" is the direct elasticity of a unit change in the observed factor "X_{ni}" with a parameter estimate "β_X" on the probability that individual "n" chooses alternative "i", "P_{ni}".

In general, SP elasticity density charts show more variance as compared to RP elasticity density charts. Nevertheless, both RP and SP elasticity density charts are consistent in terms of their distributions across the two samples. For instance, the elasticity density charts of travel cost and in-vehicle travel time of the auto driver mode, presented in Figures (10-a) and (10-b), show that the majority of the RP sample is inelastic (less sensitive) to changes in travel cost and in-vehicle travel time, which is an expected result given the high modal share of the auto driver mode within the sample as well as the high vehicle ownership level per sampled household. However, the corresponding density charts of the SP sample show considerably flatter distributions which indicates that individuals are likely to become more elastic to such changes when other mode alternatives are presented with altered level of service attributes.

Table (9) presents the average direct elasticities of travel cost and in-vehicle travel time for the nine mode alternatives across both RP and SP data sets. For instance, the estimated average direct elasticity of travel cost of the auto driver mode (based on the SP data set) is -0.32. That is, for an additional $1 of the auto driver travel cost, there would be a decrease of 0.32% in the auto driver mode share. In other words, over repeated choice situations, the auto driver mode would be used 1 time less in 100 per approximately $3 increase in travel cost. The elasticity density charts of in-vehicle travel time for GO Transit modes show the average SP elasticity of in-vehicle travel time and SP elasticity of in-vehicle travel time where Wi-Fi is available or unavailable. These charts indicate that individuals are less sensitive to changes in-vehicle travel times in the presence of Wi-Fi.

The elasticity density chart of travel cost for the local transit with walk access mode, as presented in Figure (10-e), shows a clear bi-modal distribution which suggests two groups of users with different mean travel costs. A further investigation showed that such a distribution results from the co-fare structure across the different transit agencies. Group (1) is identified as individuals whose commuting trips originate in or destined to the City of Toronto where they have to pay two "full" transit fares, and group (2) is identified as individuals who commute from/to other cities where they have to pay one "full" transit fare and a "co-fare". As shown in Figure (11-a), the two groups are perfectly identified indicating that individuals of group (1) are more sensitive to changes in travel cost than those of group (2). Similarly, the elasticity density chart for parking cost at regional transit park-and-ride stations is plotted as shown in Figure (11-b). The density distribution indicates two groups of users/parking schemes; free parking and paid parking. The average elasticity of parking cost at GO Transit park-and-ride stations -0.28.

Table 9 Average Direct Elasticities for Travel Cost and In-vehicle Travel Time

Mode Alternative	RP Data		SP Data	
	Travel Cost	In-vehicle Travel Time	Travel Cost	In-vehicle Travel Time
Auto Driver	-0.22	-0.43	-0.32	-0.66
Auto Passenger	-0.27	-1.54	-0.21	-0.97
Local Transit with Walk Access	-0.30	-1.74	-0.30	-1.44
Local Transit with Auto Driver Access	-0.46	-1.15	-0.46	-0.88
Local Transit with Auto Passenger Access	-0.46	-1.14	-0.32	-0.86
Regional Transit with Walk Access	-0.42	-1.42	-0.34	-1.04
Regional Transit with Auto Driver Access	-0.37	-1.33	-0.34	-0.97
Regional Transit with Auto Passenger Access	-0.39	-1.47	-0.32	-0.99
Regional Transit with Local Transit Access	-0.49	-1.64	-0.36	-1.20

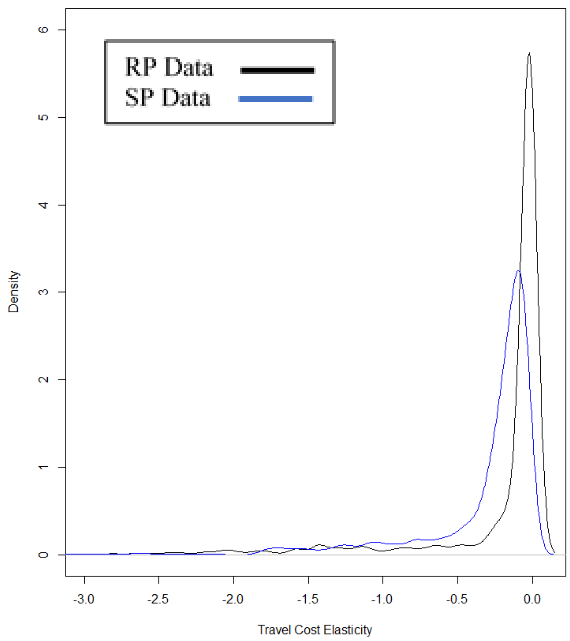


Figure 10-a Marginal Effects of Travel Cost for Auto Driver Mode

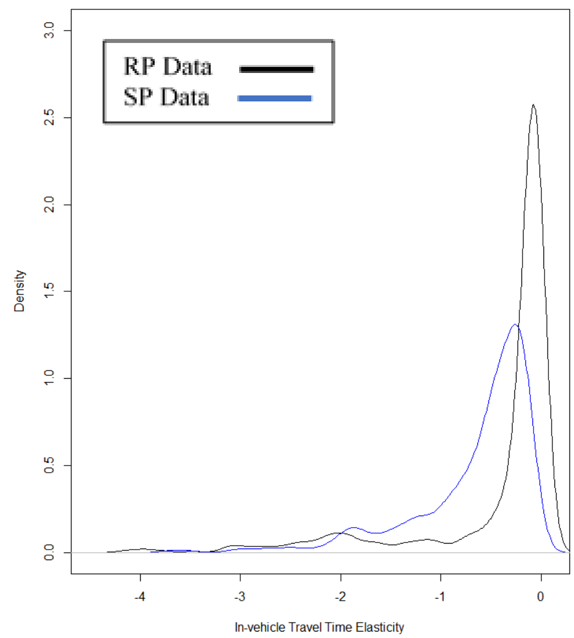


Figure 10-b Marginal Effects of In-Vehicle Travel Time for Auto Driver Mode

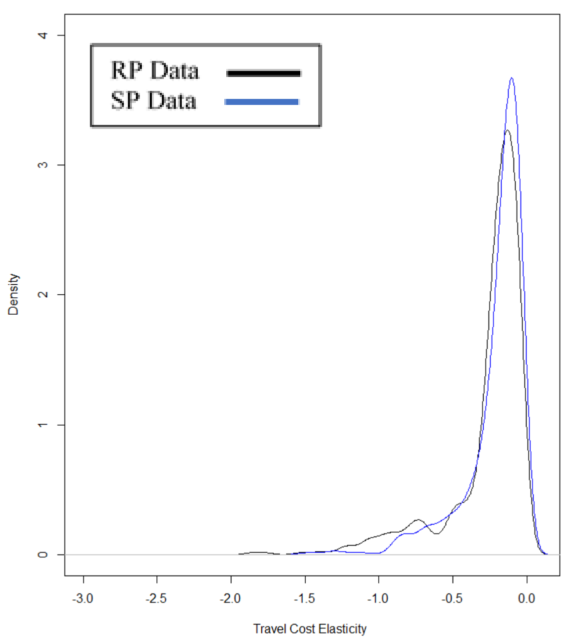


Figure 10-c Marginal Effects of Travel Cost for Auto Passenger Mode

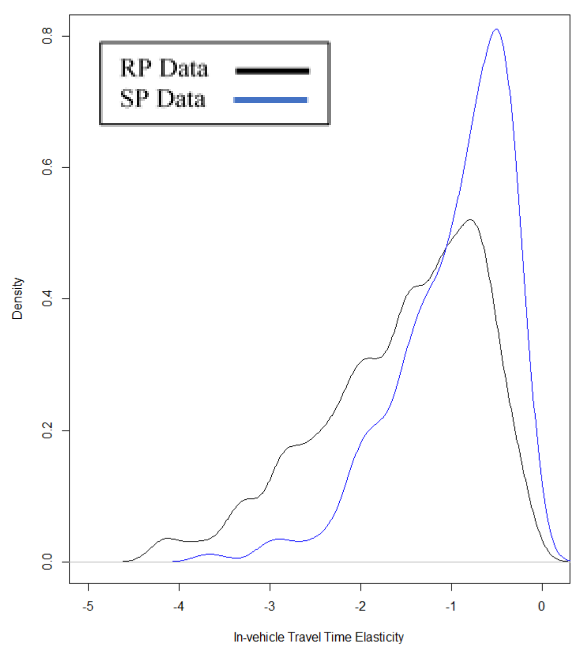


Figure 10-d Marginal Effects of In-Vehicle Travel Time for Auto Passenger Mode

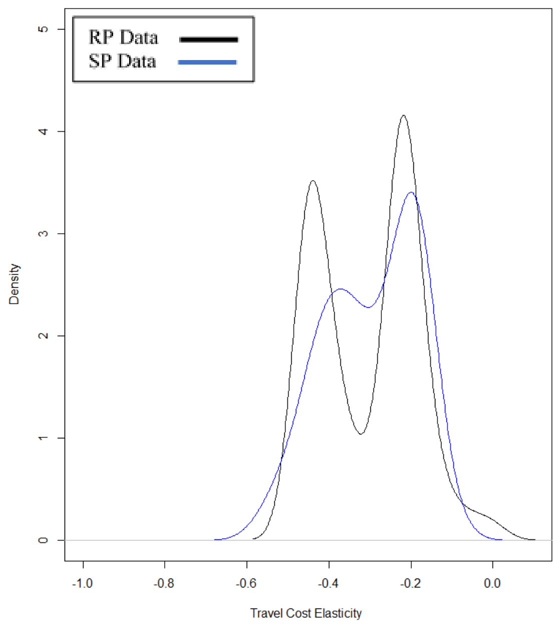


Figure 10-e Marginal Effects of Travel Cost for Local Transit with Walk Access Mode

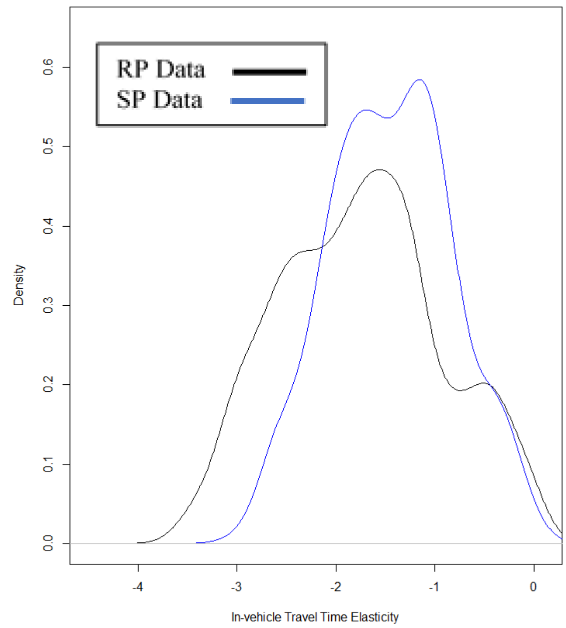


Figure 10-f Marginal Effects of In-Vehicle Travel Time for Local Transit with Walk Access Mode

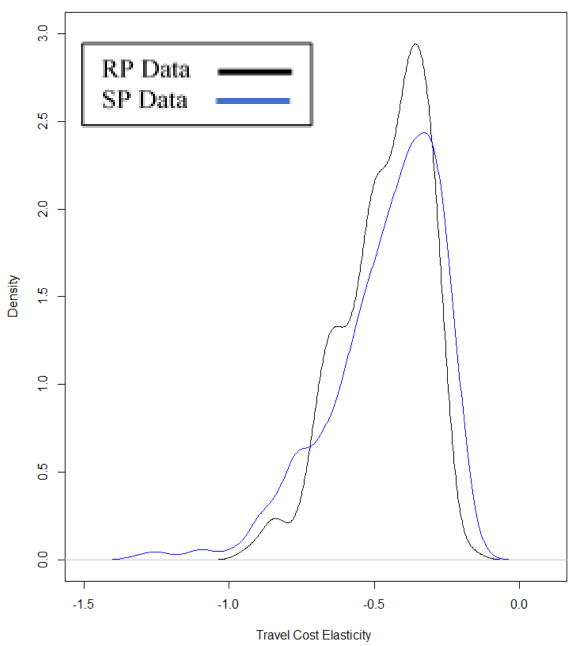


Figure 10-g Marginal Effects of Travel Cost for Local Transit with Auto Driver Access Mode

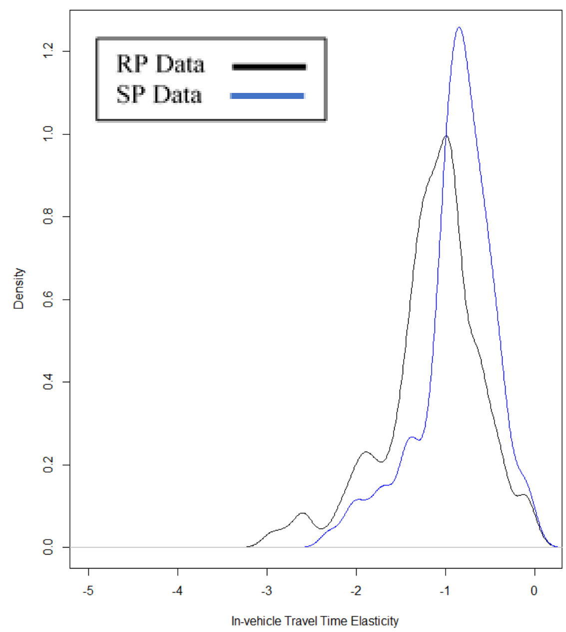


Figure 10-h Marginal Effects of In-Vehicle Travel Time for Local Transit with Auto Driver Access Mode

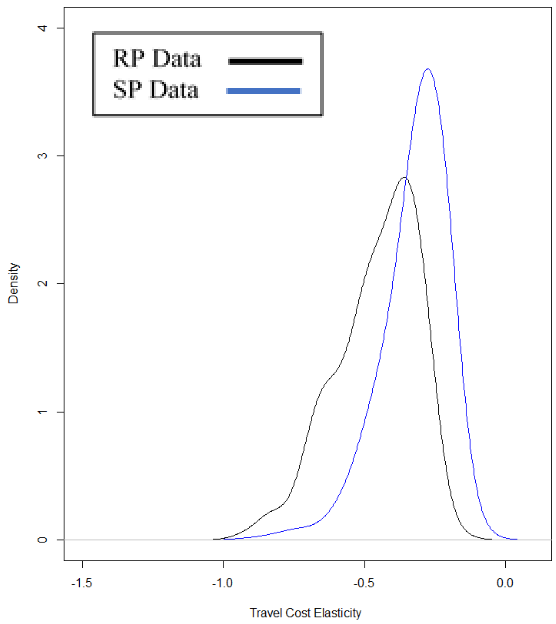


Figure 10-i Marginal Effects of Travel Cost for Local Transit with Auto Passenger Access Mode

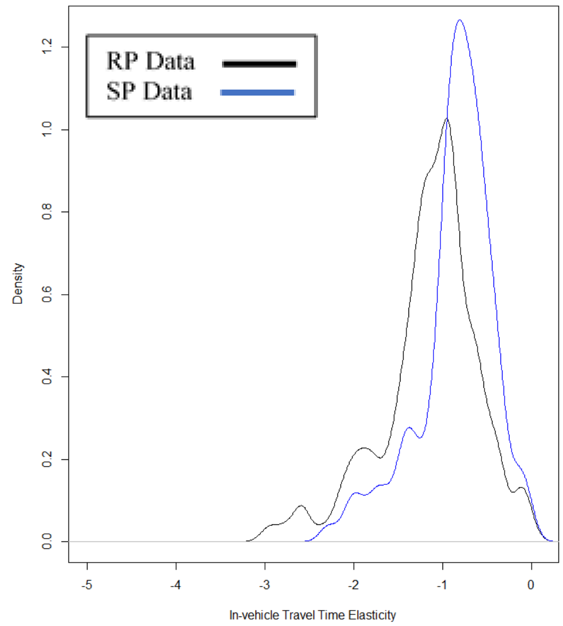


Figure 10-j Marginal Effects of In-Vehicle Travel Time for Local Transit with Auto Passenger Access Mode

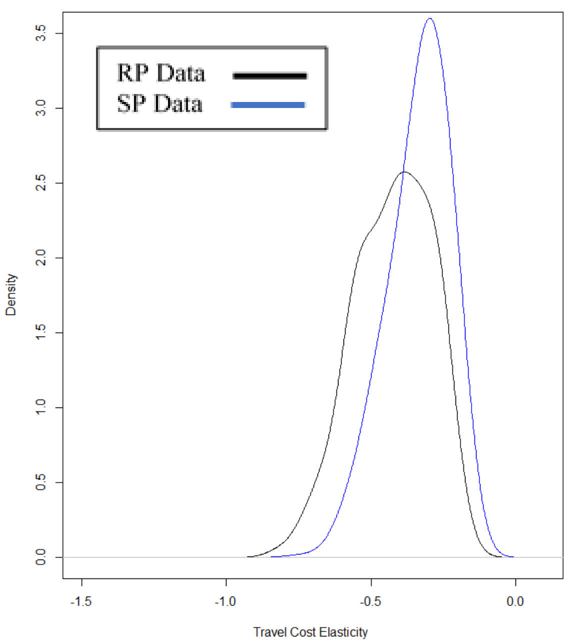


Figure 10-k Marginal Effects of Travel Cost for Regional Transit with Walk Access Mode

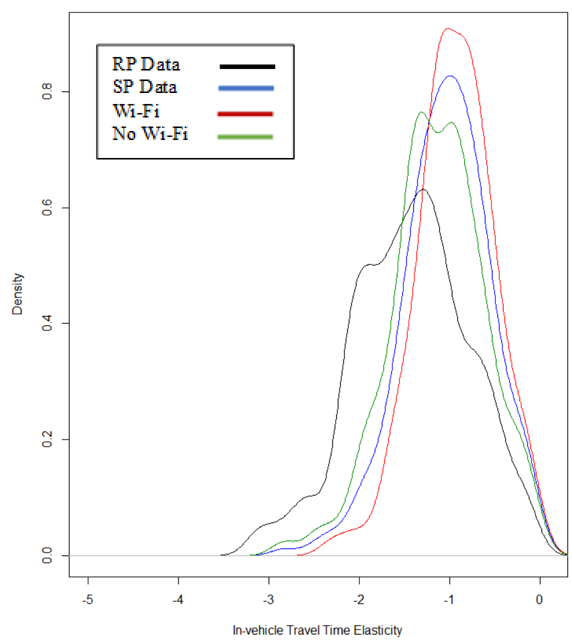


Figure 10-l Marginal Effects of In-Vehicle Travel Time for Regional Transit with Walk Access Mode

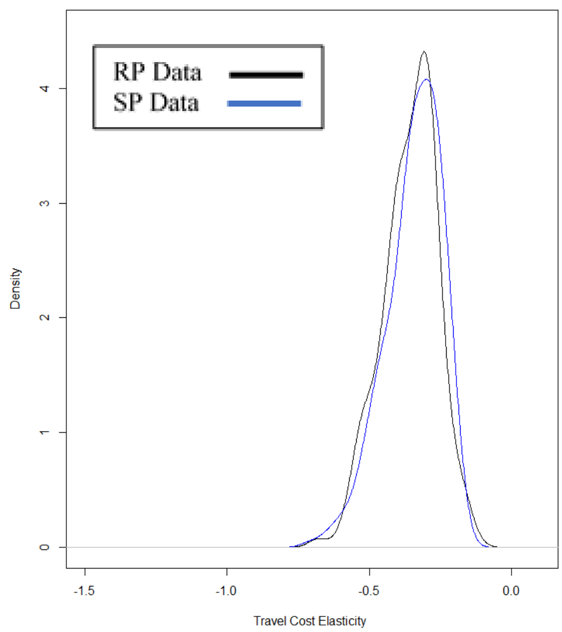


Figure 10-m Marginal Effects of Travel Cost for Regional Transit with Auto Driver Access Mode

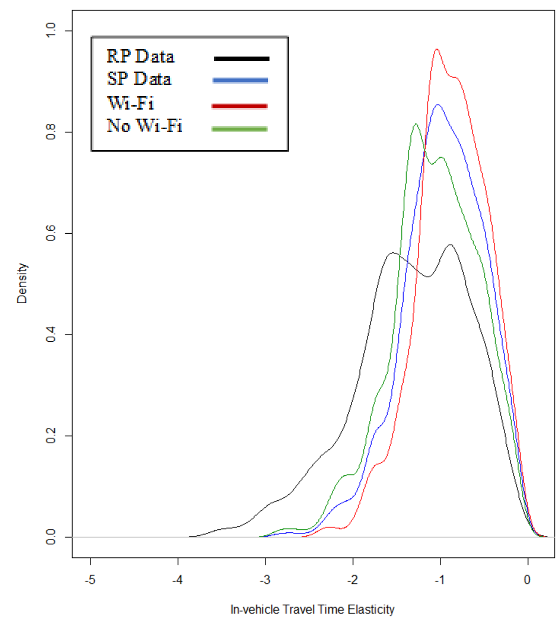


Figure 10-n Marginal Effects of In-Vehicle Travel Time for Regional Transit with Auto Driver Access Mode

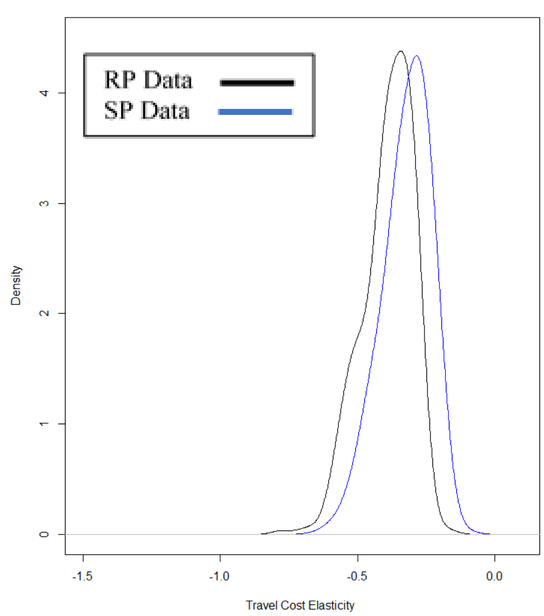


Figure 10-o Marginal Effects of Travel Cost for Regional Transit with Auto Passenger Access Mode

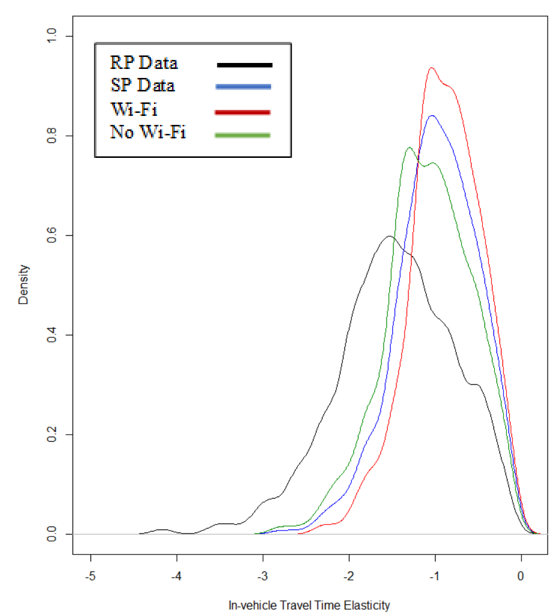


Figure 10-p Marginal Effects of In-Vehicle Travel Time for Regional Transit with Auto Passenger Access Mode

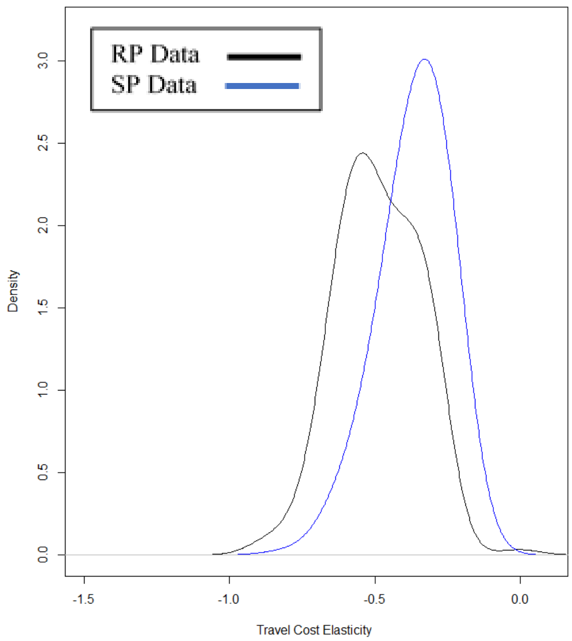


Figure 10-q Marginal Effects of Travel Cost for Regional Transit with Local Transit Access Mode

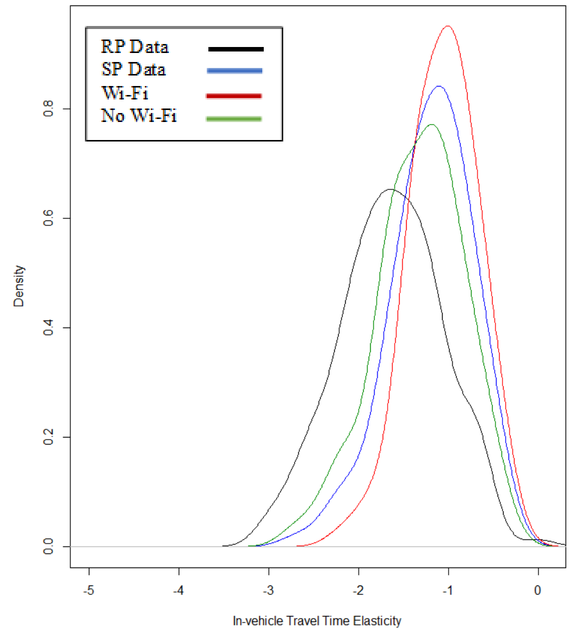


Figure 10-r Marginal Effects of In-Vehicle Travel Time for Regional Transit with Local Transit Access Mode

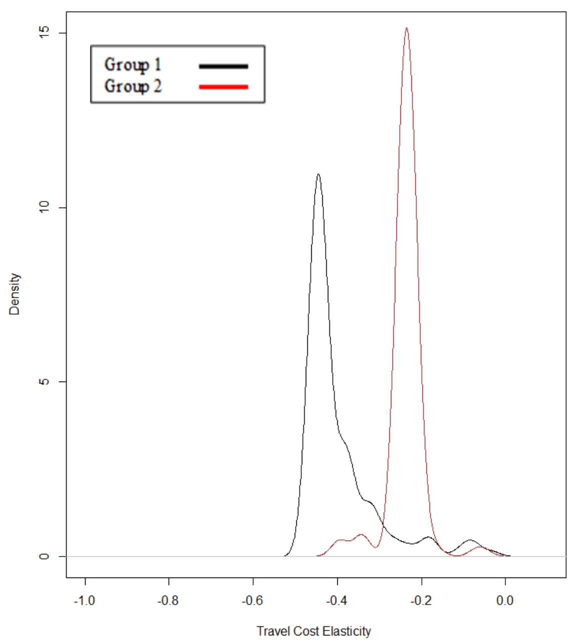


Figure 11-a Marginal Effects of RP Travel Cost for Local Transit with Walk Access Mode Identification of Sample Segments

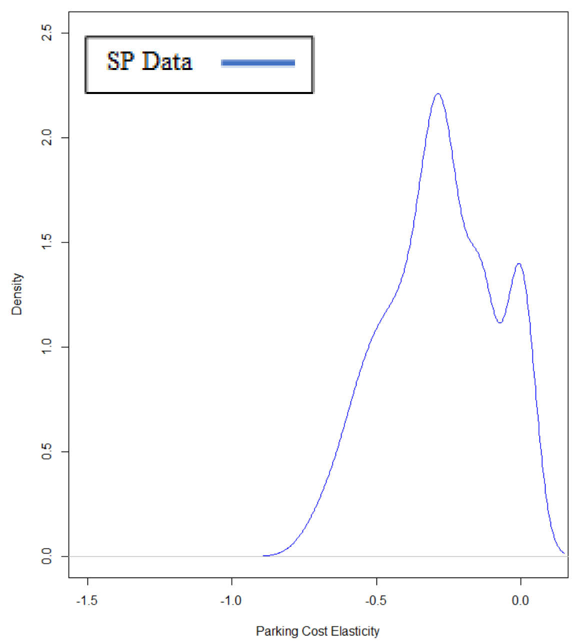


Figure 11-b Marginal Effects of Parking Cost at Park-and-Ride Stations for Regional Transit with Auto Driver Access Mode

MODEL VALIDATION

An independent subset of the collected RP-SP data was randomly selected and retained for model validation. This subset was not used in the joint RP-SP model estimation process in order to accurately investigate the predictive performance of the developed model against a holdout sample. The subset consists of 144 individuals (around 20% of the full sample data set). In general, the estimation and validation data sets are consistent in terms of their modal shares of both RP and SP data sets. However, the SP validation data set contains a slightly higher share of the auto passenger mode at the expense of a lower share of the auto driver mode.

In order to investigate the predictive performance of the joint RPSP model, the developed model was used to predict the modal share using the holdout sample of the RP and SP data sets. The resulting aggregate modal shares of the joint RP-SP model and the actual modal shares of the data set are shown in Figure (12). The developed model appears to predict the observed modal shares accurately with minor variations in the auto driver and auto passenger modes. The model results showed an overestimation of the auto passenger mode by 3% and an underestimation of the auto driver mode by approximately 8% which corresponds to the difference in aggregate modal shares between the estimation and validation data sets. In addition, the underlying assumption of the auto passenger mode being available to all individuals in the data set contributes to this variation. Rationally, with the same travel time and half of the travel cost, the auto passenger mode is a “better” option as compared to the auto driver mode. However, other unobserved variables including the household interactions and tasks allocation may affect individuals’ choices.

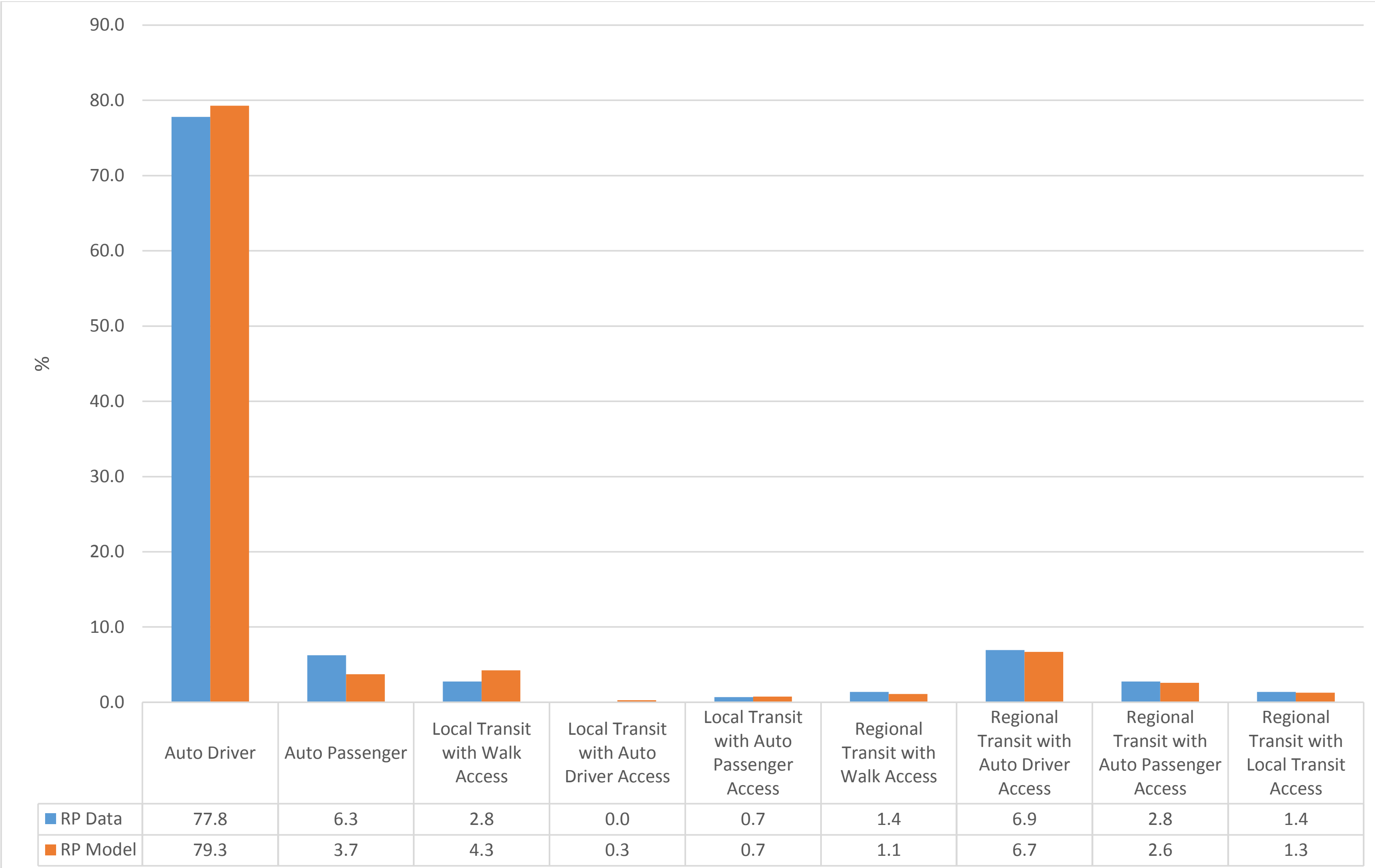
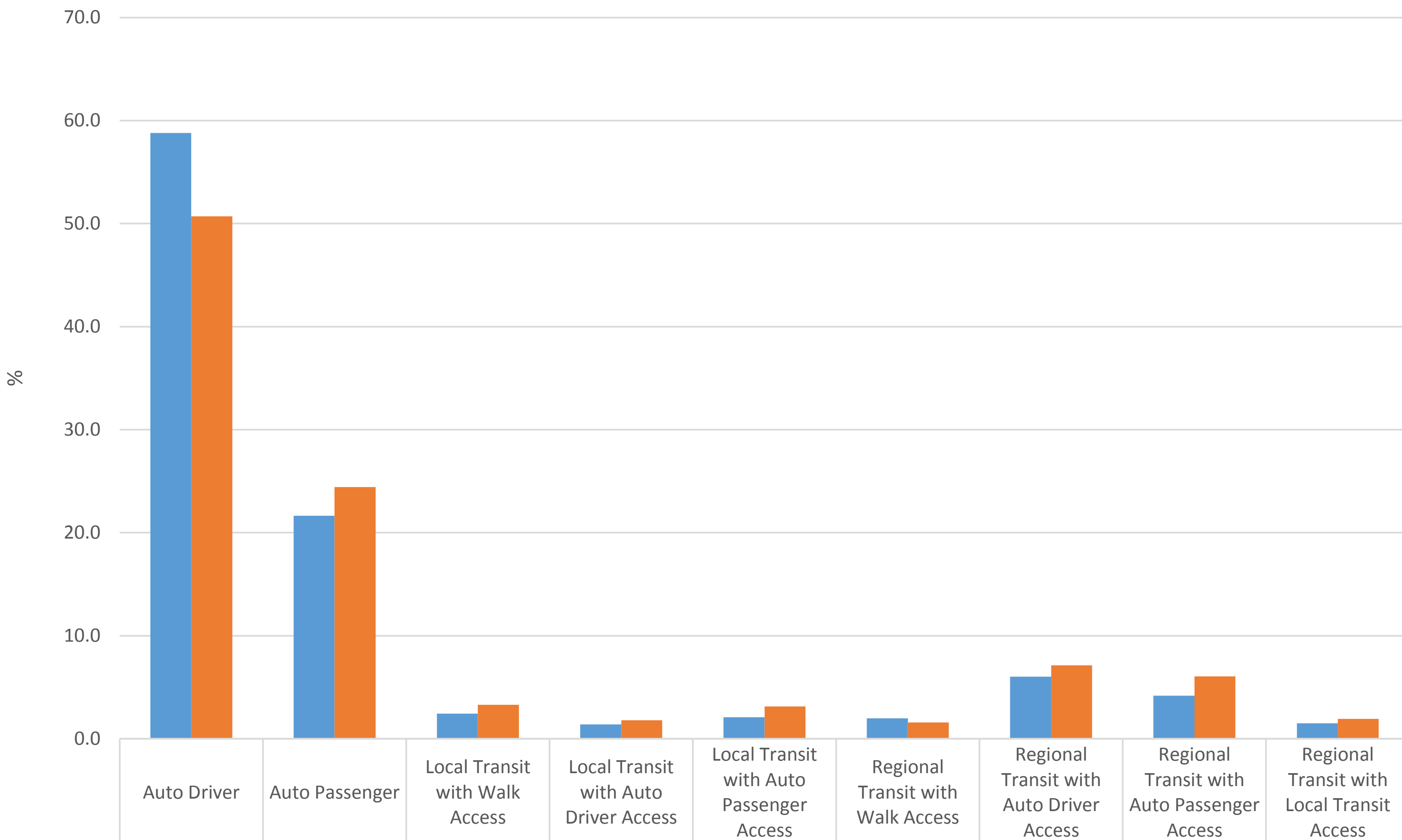


Figure 12-a Joint RP-SP Model Validation – RP Data



	Auto Driver	Auto Passenger	Local Transit with Walk Access	Local Transit with Auto Driver Access	Local Transit with Auto Passenger Access	Regional Transit with Walk Access	Regional Transit with Auto Driver Access	Regional Transit with Auto Passenger Access	Regional Transit with Local Transit Access
SP Data	58.8	21.6	2.4	1.4	2.1	2.0	6.0	4.2	1.5
SP Model	50.7	24.4	3.3	1.8	3.1	1.6	7.1	6.0	1.9

Figure 12-b Joint RP-SP Model Validation – SP Data

POLICY ANALYSIS

The developed joint RP-SP model is used to predict corresponding changes in aggregate modal shares in response to new transportation policies. In order to effectively use the developed model for predicting market shares, it is often useful to adjust the ASC to reproduce market shares that are sufficiently close to those of the sample data (36; 38). After the ASC are recalibrated, the calibrated model can be used for predicting demand changes in response to changes in the explanatory variables. Results of the base-case aggregate modal shares of the full sample RP data and the model predicts are presented in Figure (13).

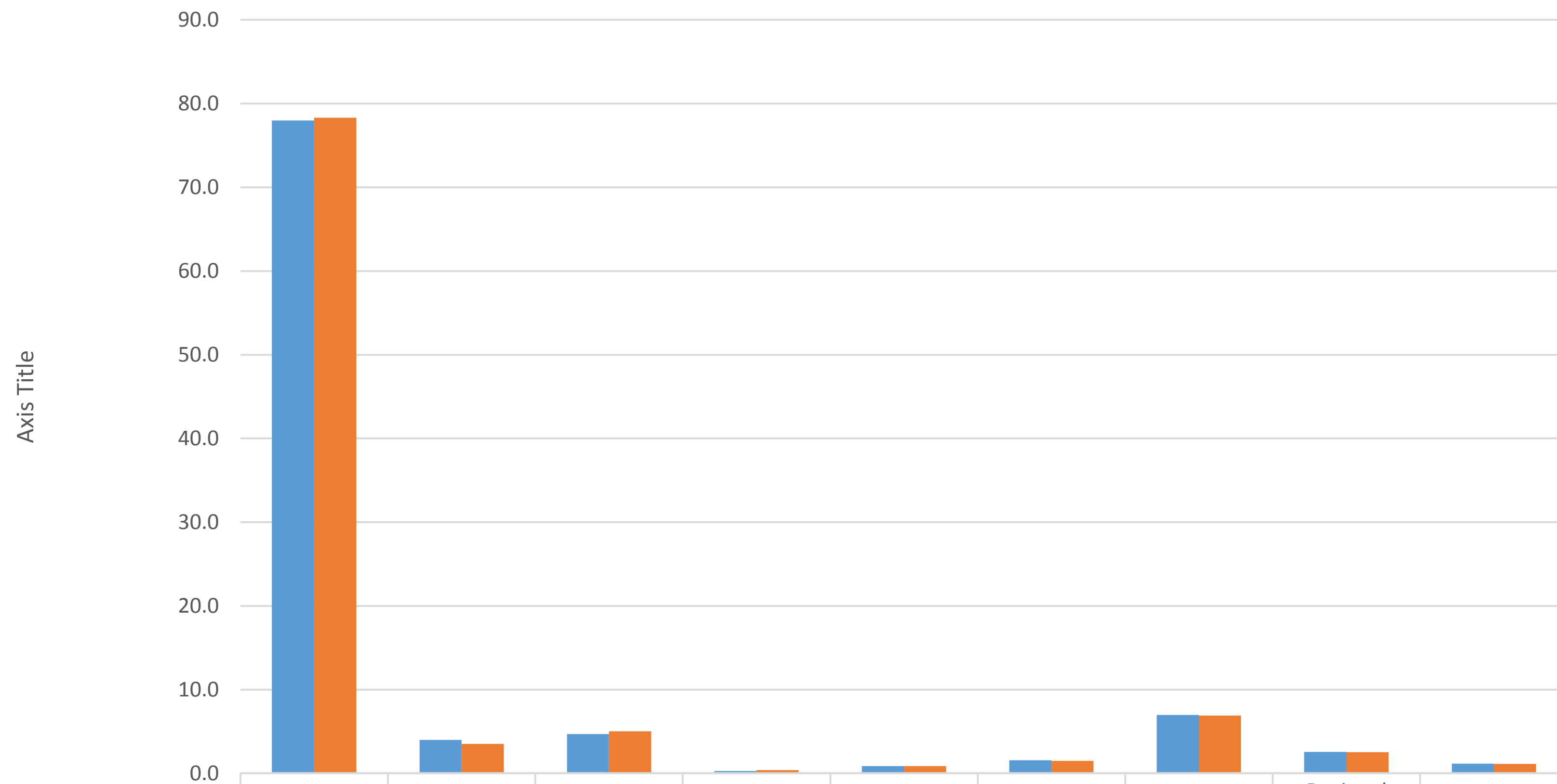
The calibrated model allows for testing the effectiveness of various policy initiatives. The Interactive Model for Policy Analysis of Cross-Regional Travel (*IMPACT*) is developed to facilitate testing the policies under investigation. In order to show-case the model prediction functionality, five independent (one policy at a time) policies are investigated. In each policy analysis, corresponding explanatory variables are adjusted and the predicted model shares are compared against the base-case aggregate modal shares.

Policy 1: "Introducing Wi-Fi on GO Transit"

In this policy analysis, it was assumed that all individuals in the data set will have access to a Wi-Fi service on all GO Transit modes. Based on the model's predicted modal shares, the modal share of GO Transit modes have increased from 12% to 13.4% (i.e., an increase of approximately 11% over the base-case). This increase in GO Transit modal share is associated with a 1.1% decrease in driving modal shares.

Policy 2: "Introducing Pay Parking at GO Transit Park-and-Ride Stations"

The effect of introducing pay parking at GO Transit park-and-ride stations is investigated. In general, the predicted modal shares show a decrease of GO Transit modal share and in particular a decrease of GO Transit park-and-ride with auto driver access modal share. Table (10) shows the predicted modal shares of GO Transit modes in response to introducing different parking cost at GO Transit park-and-ride stations.



	Auto Driver	Auto Passenger	Local Transit with Walk Access	Local Transit with Auto Driver Access	Local Transit with Auto Passenger Access	Regional Transit with Walk Access	Regional Transit with Auto Driver Access	Regional Transit with Auto Passenger Access	Regional Transit with Local Transit Access
Full Sample RP Data	78.0	4.0	4.7	0.3	0.9	1.6	7.0	2.6	1.1
Calibrated Model	78.3	3.5	5.0	0.4	0.8	1.5	6.9	2.5	1.1

Figure 13 Calibrated Joint RPSP Model

Table 10 Predicted GO Transit Mode Shares

Parking Cost at GO Transit Park-and-Ride Stations	GO Transit Modes*	GO Transit Park-and-Ride with Auto Driver Access Mode**
$1	11.7%	6.5%
$3	11.1%	5.7%
$5	10.7%	4.9%

*Base-case mode share is 12%
** Base-case mode share is 7.5%

Policy 3: "Reducing Transit Co-Fares to/from GO Transit"

In this policy analysis, GO Transit users are exempted from paying the co-fare in case a local transit is used for access/egress. Accordingly, the model predicts show an increase of GO Transit modal shares of approximately 0.6%.

Policy 4: "Reducing Waiting and Transfer Times"

For all individuals in the data set, waiting and transfer times of all transit modes are reduced by 50%. In response to this reduction, the results suggest that there would be an increase in the transit modal shares by 2.2%, out of which 1.6% increase in transit modal shares with non-driving access modes.

Policy 5: "Increasing Driving Cost"

Similarly, the current driving and parking costs at work locations for the driving mode alternatives (i.e., auto driver and auto passenger) are increased by 50%. Based on the new estimated modal shares, the modal shares of the driving mode alternative have decreased by 2.3% and, interestingly, a corresponding increase of GO Transit with driving access (park-and-ride and kiss-and-ride) modal shares by 1.4% is captured.

The above policy analysis is provided for demonstration purposes to illustrate how the model can be used for investigating individual policies. The model is capable of examining the likely effect of different changes than used above for each policy. Additionally, the model can predict the changes in mode choices as a result of introducing more than one policy combined.

CONCLUSIONS

This report presents a study on cross-regional commuters' mode choice behaviour. The objective of this study is to develop a policy-sensitive framework for modelling cross-regional commuting trips in the Greater Toronto and Hamilton Area (GTHA). This framework adopts a joint revealed and stated preference survey which is integrated with a respondent-customized multimodal trip planner tool. The Survey of Cross-Regional Intermodal Passenger Travel (*SCRIPT*) is developed and conducted in the GTHA during the spring and fall seasons of 2014. A sample size of 845 complete responses are collected. *SCRIPT* gathered information on the respondents' commuting trips (RP data) as well as their stated preferences towards mode choices with improved and/or new levels of service attributes (SP data). The survey is carefully designed to capture the changes in individuals' travel mode choices in response to a set of policies that aim at improving transit services with more emphasis on transit modal integration.

SCRIPT is respondent-customized, that is, the questions are tailored to accommodate all the possible travel mode options. The gathered information from the RP section feeds into an innovative intermodal trip planner tool. This tool generates only feasible travel options for each SP choice experiment based on households' auto ownership level, proximity to transit, work start time, and total travel time from home to work. For intermodal travel modes such as park-and-ride and/or kiss-and-ride, the trip planner tool selects the access stations based on pre-developed discrete choice models before generating the associated level of service attributes for presentation to the respondent. The SP experiments are developed based on the D-efficient design technique. Finally, socioeconomic and demographic information is collected.

The collected data is used to develop a set of econometric mode choice models that can explain the probabilistic responses to changes in transportation level of service attributes as a result of introducing those policies. The developed models reveal meaningful insights towards understanding cross-regional commuters' mode choice behaviour. In addition, elasticities of various policy variables are estimated which allows for investigating the effectiveness of the policy initiatives under consideration.

As a first step towards developing behavioural models, an RP-Only model is developed using only *SCRIPT*'s RP data. The estimation results show consistency with corresponding operational mode choice models, verifying the validity of the survey design, sampling procedure and data quality. Nevertheless, RP-Only models are incapable of accurately forecasting individuals' choices in response to the policies under investigation. Therefore, policy-sensitive SP models are developed to capture the associated changes in travel demand with respect to changes in level of service attributes. A joint RP-SP model is developed using *SCRIPT*'s RP and SP data. The estimated model outperformed the corresponding SP-Only model which indicates the effect of incorporating the full information (i.e., the combined RP-SP data) on capturing changes in individuals' preferences according to policy implications. In general, the estimated parameters are reported with the expected signs and found to be statistically significant (with t-statistics higher than 1.96) at the 95% confidence interval, except for a few variables.

An independent subset of the collected RP-SP data was randomly selected and retained for model validation. The developed model appear to predict the observed modal share accurately with only minor variations. Furthermore, the developed joint RP-SP model is calibrated and used to develop an Interactive Model for Policy Analysis of Cross-Regional Travel (*IMPACT*) to predict corresponding changes in aggregate modal shares in response to a sample of five transportation policies. In each policy analysis, corresponding explanatory variables are adjusted within the data set and the predicted model shares are compared against the base-case aggregate modal shares.

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